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GLOBAL WAREHOUSE MANAGEMENT: A METHODOLOGY TO DETERMINE AN INTEGRATED PERFORMANCE MEASUREMENT

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GLOBAL WAREHOUSE MANAGEMENT: A METHODOLOGY TO DETERMINE AN INTEGRATED PERFORMANCE MEASUREMENT

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The growing warehouse operation complexity has led companies to adopt a large number of indicators, making its management increasingly difficult. It may be hard for managers to evaluate the overall performance of the logistic systems, including the warehouse, because the assessment of the interdependence of indicators with distinct objectives is rather complex (e.g. the level of a cost indicator shall decrease, whereas a quality indicator level shall be maximized). This fact could lead to biases in the analysis executed by the manager in the evaluation of the global warehouse performance.

In this context, this thesis develops a methodology to achieve an integrated warehouse performance measurement. It encompasses four main steps: (i) the development of an analytical model of performance indicators usually used for warehouse management; (ii) the definition of indicator relationships analytically and statistically; (iii) the aggregation of these indicators in an integrated model; (iv) the proposition of a scale to assess the evolution of the warehouse performance over time according to the integrated model results.

The methodology is applied to a theoretical warehouse to demonstrate its application. The indicators used to evaluate the warehouse come from the literature and the database is generated to perform the mathematical tools. The Jacobian matrix is used to define indicator relationships analytically, and the principal component analysis to achieve indicator's aggregation statistically. The final aggregated model comprehends 33 indicators assigned in six different components, which compose the global performance indicator equation by means of component's weighted average. A scale is developed for the global performance indicator using an optimization approach to obtain its upper and lower boundaries.

The usability of the integrated model is tested for two different warehouse performance situations and interesting insights about the final warehouse performance are discussed. Therefore, we conclude that the proposed methodology reaches its objective providing a decision support tool for managers so that they can be more efficient in the global warehouse performance management without neglecting important information from indicators.

Resumo da Tese apresentada à UFSC como parte dos requisitos necessários para obtenção do grau de Doutor em Engenharia de Produção.

GERENCIAMENTO GLOBAL DE ARMAZÉNS: UMA METODOLOGIA PARA MENSURAR O DESEMPENHO DE FORMA AGREGADA

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Outubro/2015

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A crescente complexidade das operações em armazéns tem levado as empresas a adotarem um grande número de indicadores de desempenho, o que tem dificultado cada vez mais o seu gerenciamento. Além do volume de informações, os indicadores normalmente possuem interdependências e objetivos distintos, as vezes até opostos (por exemplo, o indicador de custo deve ser reduzido enquanto o indicador de qualidade deve sempre ser aumentado), tornando complexo para o gestor avaliar o desempenho logístico global do sistema, incluindo o armazém.

Dentro deste contexto, esta tese desenvolve uma metodologia para obter uma medida agregada do desempenho global do armazém. A metodologia é composta de quatro etapas principais: (i) o desenvolvimento de um modelo analítico dos indicadores de desempenho já utilizados para o gerenciamento do armazém; (ii) a definição das relações entre os indicadores de forma analítica e estatística; (iii) a agregação destes indicadores em um modelo integrado; (iv) a proposição de uma escala para avaliar a evolução do desempenho global do armazém ao longo do tempo, de acordo com o resultado do modelo integrado.

A metodologia é aplicada em um armazém teórico para demonstrar sua aplicabilidade. Os indicadores utilizados para avaliar o desempenho do armazém são provenientes da literatura, e uma base de dados é gerada para permitir a utilização de ferramentas matemáticas. A matriz jacobiana é utilizada para definir de forma analítica as relações entre os indicadores, e uma análise de componentes principais é realizada para agregar os indicadores de forma estatística. O modelo agregado final compreende 33 indicadores, divididos em seis componentes diferentes, e a equação do indicador de desempenho global é obtido a partir da média ponderada dos seis componentes. Uma escala é desenvolvida para o indicador de desempenho global utilizando um modelo de otimização para obter os limites superior e inferior da escala.

Depois de testes com o modelo integrado, pôde-se concluir que a metodologia proposta atingiu seu objetivo ao fornecer uma ferramenta de ajuda à decisão para os gestores, permitindo que eles sejam mais eficazes no gerenciamento global do armazém sem negligenciar informações importantes que são fornecidas pelos indicadores.

Résumé de la thèse présenté à l'UFSC comme partie des exigences nécessaires pour obtenir le grade de Docteur en Génie Industriel.

GESTION GLOBALE DES ENTREPÔTS LOGISTIQUES: UNE MÉTHODOLOGIE POUR MESURER LA PERFORMANCE DE FAÇON AGRÉGÉE

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La complexité croissante des opérations dans les entrepôts a conduit les entreprises à adopter un grand nombre d'indicateurs de performances, ce qui rend leur gestion de plus en plus difficile. De plus, comme ces nombreux indicateurs sont souvent interdépendants, avec des objectifs différents, parfois contraires (par exemple, le résultat d'un indicateur de coût doit diminuer, tandis qu'un indicateur de qualité doit être maximisé), il est souvent très difficile pour un manager d'évaluer la performance globale des systèmes logistiques, comprenant l'entrepôt.

Dans ce contexte, cette thèse développe une méthodologie pour atteindre une mesure agrégée de la performance de l'entrepôt. Elle comprend quatre étapes principales: (i) le développement d'un modèle analytique d'indicateurs de performance habituellement utilisés pour la gestion de l'entrepôt; (ii) la définition de relations entre les indicateurs, de façon analytique et statistique; (iii) l'agrégation de ces indicateurs dans un modèle intégré; (iv) la proposition d'une échelle pour suivre l'évolution de la performance de l'entrepôt au fil du temps, selon les résultats du modèle agrégé.

La méthodologie est illustrée sur un entrepôt théorique pour démontrer son applicabilité. Les indicateurs utilisés pour évaluer la performance de l'entrepôt proviennent de la littérature, et une base de données est générée pour permettre l'utilisation des outils mathématiques. La matrice jacobienne est utilisée pour définir de façon analytique les relations entre les indicateurs, et une analyse en composantes principales est faite pour agréger les indicateurs de façon statistique. Le modèle agrégé final comprend 33 indicateurs, répartis en six composants différents, et l'équation de l'indicateur de performance globale est obtenue à partir de la moyenne pondérée de ces six composants. Une échelle est développée pour l'indicateur de performance globale en utilisant une approche d'optimisation pour obtenir ses limites supérieure et inférieure. Après des testes réalisés avec le modèle intégré, nous concluons que la méthodologie proposée atteint son objectif en fournissant un outil d'aide à la décision pour les managers afin qu'ils puissent être plus efficaces dans la gestion globale de la performance de l'entrepôt, sans négliger des informations importantes fournis par les indicateurs.

Contents

List of Acronyms

AHP	Analytic Hierarchy Process
CADES	Component Architecture for the Design of Engineering Systems
CBR	Case-Based Reasoning
CCA	Canonical Correlation Analysis
CFA	Confirmatory Factor Analysis
CSEM	Covariance Structural Equation Modeling
DC	Distribution Center
DEA	Data Envelopment Analysis
DEMATEL	DEcision-MAking Trial and Evaluation Laboratory Method
DFA	Dynamic Factor Analysis
DMU	Decision Making Unit
DSS	Decision Support System
DWMS	Digital Warehouse Management System
EDCs	European Distribution Centers
EFA	Exploratory Factor Analysis
FAHP	Fuzzy Analytic Hierarchy Process
FA	Factor Analysis

FR	Fuzzy Reasoning
GI	Goods Inwards
GP	Global Performance
ICO	Internet Connected Objects
IoT	Internet of Things
ISO	International Organization for Standardization
IT	Information Technology
JIT	Just in Time
KF	Kalman Filter
KPI	Key Performance Indicator
MACBETH	Measuring Attractiveness by a Categorical-Based Evaluation TecHnique
MARSS	Multivariate Autoregressive State Space Model
MLE	Maximum Likelihood Function
NIPALS	Nonlinear Iterative Partial Least Squares
NS	Normal Scale
OS	Optimized Scale
PCA	Principal Component Analysis
PCTM	KPI Cost Transformation Matrix
PC	Principal Component
PLS	Partial Least Squares regression
PMS	Performance Measurement Systems
PPS	Production Possibility Set
QFD	Quality Function Deployment
QMPMS	Quantitative Model for Performance Measurement System

RFID	Radio Frequency Identification
SCOR	Supply Chain Operations Reference-model
SEM	Structural Equation Modeling
SI	Internation Systems of Units
SKU	Stock Keeping Unit
SQP	Sequential Quadratic Programming
TOC	Theory of Constraints
TQM	Total Quality Management
V-A-T	Value-added Tax
VAL	Value Adding Logistic
WLI	Warehouse Logistics Index
WMS	Warehouse Management System

Chapter 1

Introduction

Science, my boy, is made up of mistakes, but they are mistakes which it is useful to make, because they lead little by little to the truth.

Jules Verne

Abstract

This chapter presents the context of the study and the research gaps which are basis for the work's objectives. Besides, the dissertation proposal is detailed, presenting the research methodology and the steps carried out to achieve these objectives. Finally, the research delimitations are discussed and the thesis structure is reported.

1.1 Context of the study

The literature about performance measurement is vast. Performance measurement or organizational performance has become an important issue in companies due to the pressure to give results (KENNERLEY; NEELY, 2002). The performance indicators, which form the performance measurement system, provide a tool to compare the current results with the present objectives and thus to eventually launch the necessary actions to carry out in order to reach these objectives (BERRAH et al., 2000). Summarizing the literature of the last 30 years, it is possible to identify four main phases of the performance measurement area (NEELY, 2005).

First, in the 1980s it was the “problem identification” phase, where the dominant theme was a discussion of the problems of performance measurement systems. Kennerley and Neely (2002) state that in this stage, there was a growing realization that, given the increased complexity of organizations and the markets in which they compete, it was no longer appropriate to use financial measures as the sole criteria for assessing success. The financial measures are concerned with cost elements and quantify performance solely in financial terms, but many enhancements are difficult to quantify monetarily, such as lead-time reduction, quality improvements and customer service (TANGEN, 2004). So, there has been a growing criticism of traditional performance measurement systems which tend to focus only on financial results (COSKUN; BAYYURT, 2008). The main reason is, according to Fernandes (2006), that organizations compete not just on financial efficiency, but also on social legitimacy. A company does not want just to maximize financial revenues, but also to be recognized and accepted in its environment.

By the early 1990s, the second phase “potential solutions” has proposed measurement frameworks such as the balanced scorecard (NEELY, 2005). Following these developments, researches have started to suggest other performance measures, since financial indicators could not meet expectations of all stakeholders and a good organizational performance should balance all organization dimensions which are related (FERNANDES, 2006). Then, the “methods of application” (third phase), involved the search for ways in which the proposed frameworks could be used (NEELY, 2005).

Beginning of the 2000s was marked by the “empirical investigation” phase, in which people have begun to look for more robust empirical and theoretical analysis of performance measurement frameworks and methodologies. The objective was to develop dynamic rather than static measurement systems and to ensure an appropriate focus on enterprise performance management, rather than simply performance measurement (NEELY, 2005). The performance measurement system is ultimately responsible for maintaining alignment and coordination. Alignment deals with the maintenance of consistency between the strategic goals and metrics as plans are implemented and restated as they move from the strategic through the tactical and operational levels (MELNYK; STEWART; SWINK, 2004).

Nowadays, we are in the information era. Internet has changed the way people and companies relate to each other. This situation also has an impact in performance management methods. Lam, Choy and

Chung (2011) argue that information systems, such as warehouse management system (WMS), are recognized as useful means to manage resources in the warehouse. The information technology enables, for example, the product tracking from raw materials production up to customer acquisition or products' end-of-life. The Internet of Things (IoT) is often considered to be part of the Internet of the future, consisting in billions of intelligent communicating "things" or Internet Connected Objects (ICO) which will have sensing, actuating, and often data-processing capabilities (NG et al., 2013).

One of the changes coming from communication development is the conversion of local competition to global competition. Companies seek constant improvement of their products and services to satisfy customers while trying to reduce costs. It has led companies to decentralize their production systems all over the world. So, supplying the correct product, in the right time and in the right quantity has become a challenge, requiring a very good management of all company areas. The logistics plays an important role by aggregating value to the products and it has become a critical factor to obtain competitive advantages. Manufacturing logistics chains consist of complex interconnections among several suppliers, manufacturing facilities, warehouses, retailers and logistics providers. Performance modeling and analysis become increasingly more important and difficult in the management of such complex manufacturing logistics networks (WU; DONG, 2007).

One of the important aspects under the responsibility of the logistics sector is the warehouse, where the main logistics operations take place: transportation, warehousing and stocking. Not only their number is increasing substantially but also their functionality is changing. Whereas in the past many European Distribution Centers (EDCs) primarily served as a warehouse with a distribution function, some of the current EDCs have European headquarters, call-centers, service centers or manufacturing facilities as well (De Koster; WARFFEMIUS, 2005). The connection of these activities in one place makes the performance measurement in the warehouse a key factor for the overall performance of the logistics operations.

The growing warehouse operation complexity and the easy information access have led companies to adopt a large number of indicators, making their management increasingly difficult. The reason for that is the misunderstandings that managers could have when assessing global warehouse performance, since different indicator characteristics make difficult the evaluation of their structural relationships. Also, today managers are confronted with greater uncertainty and unpredictability, complicating the decision making; wrong decisions can thus be more disastrous (SARDANA, 2008).

Regarding the quantity of indicators used to manage performance, the managers have to choose among a lot of indicators (having a complete set of informations to make decisions) or few indicators (e.g the KPIs, Key Performance Indicators). In the first case it is hard to evaluate the global performance with so many data but, if the manager chooses few indicators, the global evaluation is simplified and some important information can be lost. In both cases, there will be indicators with different objectives (e.g. the level of a cost indicator shall be minimized, while a quality indicator level shall be maximized). This fact may increase the difficulty of the analysis executed by the manager while evaluating the warehouse global performance, even if he chooses a lot or few indicators. Cai et al. (2009) confirm this conclusion affirming that it is difficult to figure out the intricate relationships among different KPIs and the order of priority for accomplishment of individual KPIs.

Nevertheless, even if managers would like to evaluate just few indicators, the more the process is complex, the more the indicators needed are numerous and different (MELNYK; STEWART; SWINK, 2004). Thus, the aggregation of indicators can considerably simplify the analysis of a system, summarizing the information of a given set of sub-indicators (FRANCESCHINI et al., 2006).

Therefore, the main motivation of this work is to support manager decisions in an effective way on the global warehouse performance, considering the existing indicators of the warehouse activities and knowing that there are limits in the decision-maker's ability to process large sets of performance expressions (CLIVILLÉ; BERRAH; MAURIS, 2007). In this context, the research proposal is to define an integrated warehouse performance measurement system which aggregates indicators, giving a summarized feedback about the overall performance of the warehouse considering all relevant information.

It is important to highlight that this global performance is related, in this dissertation, to the aggregation of operational indicators of the warehouse, since this area has the greatest quantity of indicators used.

Interestingly, the term "performance aggregation" has different meanings in the literature. For example, Böhm, Leone and Henning (2007) state that performance information used at higher decision levels is more aggregated than the one employed at lower levels due to various reasons (data availability and error minimization, etc.). In this dissertation, we consider performance aggregation as the mathematical union of several performance indicators in order to achieve a measure, representing all the performance indicators of the system. This definition is confirmed by Clivillé, Berrah and Mauris (2007), who state that the aggregation of the performance expressions is an operation that synthesizes the elementary performance expressions into a global performance expression.

The next section presents the literature supporting the research gaps which are fulfilled by this dissertation.

1.2 Research Problem

This section is divided in two subsections. First, we present the research gaps reported by previous works, explaining for which problems we propose solutions. Secondly, the complexity of the subject and the proposed solution are detailed.

1.2.1 Research Gap

The literature on warehouse performance assessment has been largely ignored (DOTOLI et al., 2009; JOHNSON; MCGINNIS, 2011). While there are widely accepted benchmarks for individual warehouse functions such as order picking, little is known about the overall efficiency of warehouses (JOHNSON; MCGINNIS, 2011). Gu, Goetschalckx and McGinnis (2010) present a review about design and performance evaluation of warehouses. The authors address important future directions for the warehouse research community, stating that "the total warehouse performance assessment models are themselves a considerable development challenge". Indeed, we found very few papers analyzing warehouse performance relationships and proposing frameworks to evaluate the global performance. The two main approaches used in the literature could be summarized as follows.

First, Sohn, Han and Jeon (2007) evaluate relationships among various influential factors to develop an Air Force Warehouse Logistics Index (WLI). This index evaluates the logistics support capability of ROKAF (Republic of Korea Air Force) warehouses. The authors apply questionnaires to warehouse workers, getting the necessary database to perform a Structural Equation Modeling to find relationships among the predefined factors.

The group of works in which Sohn, Han and Jeon (2007) is included presents as the main characteristic the acquisition of data from questionnaires in order to perform mathematical tools. After interviewing people related to the subject, the papers can use several statistical tools to confirm, or not, the proposed relationships. In most of the cases, the questionnaires do not contain indicators' information and in the cases where there are indicators, they are evaluated qualitatively.

The second approach evaluates the global warehouse performance without subjective judgments. The papers use basically DEA (Data Envelopment Analysis) tool. For example, Johnson, Chen and McGinnis (2010) investigate the factors that impact warehouse performance (using correlation method) and evaluate warehouses with regard to technical efficiency (i.e. inputs and outputs).

The DEA tool is usually used for benchmarking, and the database to perform it is related to production inputs and outputs. Also, indicators as customer satisfaction or perfect orders (related to more than one activity) are not included in the model.

We observe that the literature on warehouse subject does not provide an aggregated model to measure warehouse performance, intending its periodic management. Therefore, we also verify the literature concerning the aggregation of performance measurement systems (PMS) in enterprises.

Several authors discuss the aggregation of performance indicators and their relationships.

Rodriguez, Saiz and Bas (2009) state that performance indicators provide information as to whether the upstream objectives are being reached or not. However, no further information about the causes is provided by these KPIs (Key Performance Indicators). For these authors, the fact of discovering relationships between KPIs is potentially much more profitable for an organization if it is possible to discover the latent relationships that occur between objectives of the PMS. Then, cause-effect relationships between objectives could be explained and managers would have additional decision-making information. For Melnyk, Stewart and Swink (2004), while there are numerous examples of the use of various metrics, there are relatively few studies in operations management that have focused on the effects of metrics within either the operations management system or the supply chain.

Lauras, Marques and Gourc (2010) affirm that each KPI should be examined separately and then in related groups of indicators. Analysts such as the task leader or senior manager must simultaneously consider all these factors. Regarding the number of indicators analyzed simultaneously, Lohman, Fortuin and Wouters (2004) state that it is impossible for a manager to make decisions on the basis of 100 unstructured metrics. Furthermore, Melnyk, Stewart and Swink (2004) present the complexity of an individual's metrics set as a load imposed upon a person's finite mental capacity.

According to Lohman, Fortuin and Wouters (2004), a possible solution is to cluster the metrics in perspectives to facilitate manager's interpretation. Franceschini et al. (2008) assert that if the performance measurement area includes different processes, it is possible to define an aggregate indicator, which synthesizes the performance of the set of indicators. For Vascetta, Kauppila and Furman (2008), the aggregated indicator is an informative tool, able to provide general background in a format that is easy to create and to update. In addition, it should have an attractive and understandable format to be considered helpful for people of all sectors. Lauras, Marques and Gourc (2010) reinforce that an advantage of an aggregated indicator is to provide an immediate and global overview of the performance situation interpretable by an entity not familiar with the details of the activities.

Even if several authors have discussed the need of an aggregate measure, few works have tried to accomplish it. Thus, the main research gaps which this dissertation proposes to fulfill are: Using a set of ratio measures can lead to confusion; if some measures are good and some are poor, is the warehouse performing well? (JOHNSON; CHEN; MCGINNIS, 2010). The challenge is to design a structure to the metrics (i.e., grouping them together) and extracting an overall sense of performance from them (i.e., being able to address the question of "Overall, how well are we doing?") (MELNYK; STEWART; SWINK, 2004). In the same way, Lohman, Fortuin and Wouters (2004) affirm that a conceptual question is still not answered: What are the effects of combining several measures into an overall score?

Even if some questions are asked more than 10 years ago, they are still valid since there are a lot of developments to be made on this subject. One confirmation is the statement of Clivillé, Berrah and Mauris (2007), pointing out that as soon as managers use more than one KPI, problems of comparison and aggregation of the performance expressions will exist.

After the works of Melnyk, Stewart and Swink (2004) and Lohman, Fortuin and Wouters (2004), some papers have studied ways to aggregate performance. These researches usually use a mathematical tool based on manager's opinions or subjective judgments (e.g. Fuzzy, AHP - Analytic Hierarchy Process) to achieve this objective (see, for example, Luo, Liu and Shu-quan (2010)). Also, several works analyze relationships among enterprise areas/departments using questionnaires (see. Fugate, Mentzer and Stank (2010)). Unlike these earlier works, we propose, in this dissertation, a methodology to measure objectively the integrated warehouse performance without considering experience or subjective judgments inside the mathematical tools. For that, analytical models and statistical tools are used to relate and aggregate indicators, including all relevant indicators in the model.

The work of Rodriguez, Saiz and Bas (2009) is the closest we found to our proposition. Rodriguez, Saiz and Bas (2009) develop a methodology to define aggregated indicators without judgments, using the time series of indicators to measure their correlations and combine them in factors. The main goal of the work is to relate the aggregated performance indicators upstream towards the strategic objectives of the company, to analyze the objective achievement.

This dissertation differs from Rodriguez, Saiz and Bas (2009) in the following points: our purpose with the performance aggregation is to provide insights about warehouse performance management in the operational level instead of strategical level; the application area of our work is warehouses instead of enterprise administration; the statistical tool used by Rodriguez, Saiz and Bas (2009) is just one part of the analysis performed in our work, since in this dissertation, relationships are also determined analytically; we also develop a scale for the integrated performance, which can be used for comparison purposes.

The proposed work is relevant in the theoretical and practical points of view: this subject has received less attention and this dissertation brings new insights about this theme; companies can realize their global performance with the implementation of the proposed methodology and get more efficiency on the warehouse management.

The complexity and difficulty to get this solution to aggregate warehouse performance is detailed in the next section.

1.2.2 Complexity

The complexity of this theme is addressed in different ways by the literature.

Caplice and Sheffi (1994) report some trade-offs involving indicator's choice. One of them is usefulness versus integration of indicators. This trade-off indicates that as a metric becomes more aggregated it loses its direct usefulness. Moreover, if an indicator captures all of the details of a process it tends to become more complex and thus harder to understand.

Franceschini et al. (2006) state that the effectiveness of an aggregated indicator strongly depends on the aggregation rules, because sometimes its result can be questionable or even misleading. Two years later, Franceschini et al. (2008) confirm that the aggregation of several indicators into an aggregated indicator is not always easily achievable, especially when the information to synthesize is assorted.

Vascetta, Kauppila and Furman (2008) assert that the aggregation using mathematical equations necessarily requires many assumptions and simplifications which could lead to incorrect or uncertain analyses, misunderstandings and distortions of data, sometimes making experts reluctant to use and promote the indexes among decision-makers.

Beyond the strong criticism of indicator usefulness and the possible reluctance of managers to utilize aggregated indicators, the main challenge is to provide trustful relationships among indicators. We believe that once this last problem is solved, the others will be considerably minimized. Thus, the proposition of this thesis is to relate indicators considering just indicator equations and the time series of their results, without human judgments. Two different quantitative methods (analytical model and statistical tool) are performed, and an analysis of different results builds the solution.

It is hard to model indicator relationships since several factors influence their results. De Koster and Balk (2008) exemplify this situation affirming that common measures used in warehouses (e.g. order lines picked per person per hour, picking or shipment error rates, order throughput times) are not mutually independent and, additionally, each of them can depend on multiple inputs. The result is that the indicators do not only influence one another (e.g. order lines picked per person per hour and order throughput time), but they can be influenced by other warehouse parameters as system automation, the assortment size, and the size of the warehouse, as well.

Another potential problem is how to provide a general solution with many different kinds of warehouses. In this way, the first issue is to define the set of indicators to measure warehouse performance. Clivillé, Berrah and Mauris (2007) confirm that one major problem in the design of PMS (Performance Measurement Systems) concerns the determination of performance expressions which are useful for the control decision-making.

Finally, the aggregated performance result must have a meaning to be interpreted by managers. As elementary performance expressions are associated with the various heterogeneous indicators into a common reference, it is necessary to create a new scale to provide informations about the current warehouse situation and how far it is possible to go. The complexity remains especially in the determination of the scale boundaries since they are usually related to the companies' goals.

The next sections present the dissertation objectives and the development required to achieve the proposed results.

1.3 Dissertation Objectives

1.3.1 General Objective

The main goal of this dissertation is to develop a methodology for an integrated warehouse performance evaluation through indicator's aggregation.

1.3.2 Specific Objectives

To reach this objective, it is necessary to balance different indicators using mathematical tools in order to consider the particularities of each of them. From the general objective presented, specific objectives are proposed as follows:

- Definition and classification of warehouse performance indicators;
- Development of an analytical model of performance indicators and data equations;
- Creation of a methodology to determine an integrated warehouse performance measurement;
- Discovery of a method to determine indicator relationships analytically;
- Determination of an optimization model to design a scale for the integrated performance.

Each one of these specific objectives represents a contribution of this work. The next section details all steps to attain the objectives presented.

1.4 Methodology and Development

The general research methodology applied in this dissertation is a quantitative model based research. According to Bertrand and Fransoo (2002), this methodology is based on the assumption that we can build models which explain (part of) the behavior of real-life operational processes or that can capture (part of) the decision-making problems that are faced by managers in real-life operational processes.

Regarding the specific steps of this work, it is possible to define two other sub methodologies. The first one consists of a normative empirical quantitative research, defined as a "research in which policies, strategies and actions are developed" (BERTRAND; FRANSOO, 2002). This methodology encompasses from step one of Figure 1.1 ("Searches on Databases. Keyword: warehouse performance") up to the methodology development ("Methodology to determine an integrated performance measurement"). The second methodology encompassing the rest of the work phases (Figure 1.1) corresponds to the descriptive empirical research, which is "primarily interested in creating a model that adequately describes the causal relationships that may exist in reality, which leads to understanding the processes going on" (BERTRAND; FRANSOO, 2002).

The research is conducted as described in Figure 1.1. It shows a structured division of the work in three main columns: bibliographic research, development and outcomes. The bibliographic research steps performed in the left column of Figure 1.1 are related specifically to the knowledge taken from the literature. This knowledge is used as a basis for the development area (middle column). Finally, the outcomes are the results of the developments carried out in this dissertation, also called the main contributions of the work.

Figure 1.1 starts with a deep literature review carried out in order to verify the set of performance indicators used for warehouse performance measurement. We identify that the literature does not provide a clear classification of these warehouse indicators regarding their definitions. Thus, the first outcome of this dissertation is the classification and definition of the warehouse performance indicators. From this result, indicator definitions are transformed in measurable equations.

After evidencing which warehouse performance indicators will be aggregated, researches on different themes are carried out to develop the methodology to determine an integrative warehouse performance measurement (the main contribution of this dissertation, second outcome). The literature demonstrates some papers treating performance aggregation subject and, also, discussing adequate statistical tools which should be used to aggregate indicators and the way it should be made. To simplify the interpretation of the integrated warehouse performance, it is also necessary to develop a reference scale to allow the evaluation of performance results. These three themes (performance aggregation,

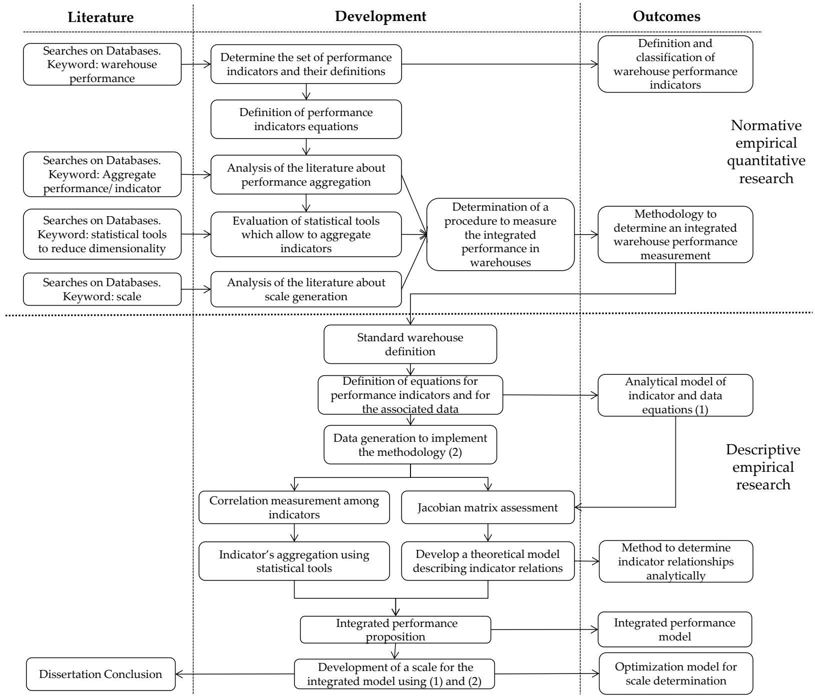


Figure 1.1: Research steps.

statistical tools and scale generation), together, structure the proposed methodology generating knowledge in this area.

The methodology is applied in a theoretical case. We define a standard warehouse, which contains the main processes/activities as usually found in real warehouses. The performance indicators used for warehouse management are defined based on the literature review findings and an analytical model of indicator and data equations is generated (third outcome).

To apply the mathematical tools and to find indicator relationships a historical time series of indicators is necessary. For that, data is generated representing the warehouse dynamics with indicator results changing monthly. From these data, two different analysis are performed to propose an integrated performance model (fifth outcome). The first analysis utilizes the analytical model and the data generated to verify indicator relationships from the Jacobian matrix result. As a result of this development, we have the fourth outcome, a method to determine analytically the indicator relationships. The second analysis is the application of statistical tools to aggregate indicators in components. Both results are analyzed carefully to determine the indicators which will make part of the integrated performance model.

Finally, a scale is developed for the proposed integrated model. This scale is the result of an optimization model which is based on the analytical equations of indicators and data as well as the data generated to implement the methodology. As this kind of analysis is quite new to design scales, the last outcome is the optimization model to define the integrated indicator scale. The conclusion of this dissertation with all developments return to the literature as new knowledge to be used by academics and practitioners.

1.5 Research Delimitations

The delimitations of this research and its results are divided in: methodology delimitations, theoretical case, indicators and scale.

For the proposed methodology, there are three main delimitations.

Firstly, the research boundaries are characterized by the performance analysis of an individual warehouse. It consists of the evaluation of one warehouse over a time period, measuring its own performance periodically. Thus, this dissertation does not encompass the benchmarking and comparisons among warehouses.

Secondly, the indicator set used in the standard warehouse (theoretical case) are taken from the literature. In a real case, warehouses determine indicators from company goals. As there are several developed frameworks to help managers with the indicators' choice (e.g. Franceschini et al. (2008)), this dissertation does not address this subject. Thus, to apply the methodology, it is considered that the selected indicators are the ones defined by the company.

Finally, the methodology is developed for operational performance measurement and the results depend on warehouse characteristics and indicators. Even if there is no limitation to use the methodology for indicators of higher levels or warehouses with different characteristics, the method has not been tested/ verified on different applications in this work.

The theoretical case study provides results that, initially, can not be generalized. The numerical results obtained in the integrated performance model are limited by the considerations made in data generation. However, regarding the analytical model, it is possible to adapt it to similar warehouse situations, once the characteristics and operations presented in the standard warehouse are the same.

Regarding the metric set definition and indicator relationships, the delimitations are as follows:

- The non-linear relationships among indicators are not measured in this work;
- Indicators for human resources performance measurement are not included in the metric set. Only the indicators that relate persons to operations (e.g. productivity indicators), are used;
- Indicators related to sustainable practices and reverse logistics activities are also not considered in the performance metric system.

Lastly, the numerical result of the developed scale can not be used in other warehouses since to create it, it is necessary to define low and high limits for data and indicators according to the warehouse conditions. In this dissertation, some limits are defined based on the restrictions proposed by the standard warehouse, as the maximum and minimum number of products processed by the warehouse per month, whereas other limits are determined from indicator times series. However, the methodology to create the scale remains a contribution of this work since its utilization is possible under the analytical model and limits adaptation.

1.6 Thesis Structure

From this first chapter which has presented the work proposition with its complexity and delimitations, the next chapters have their structure as follows.

Chapter 2 introduces the literature on warehouse performance measurement. A structured method is used to classify papers and to obtain the main characteristics of the literature concerning this subject. Furthermore, the indicators used for warehouse performance assessment are acquired from papers and classified according to their dimensions of measure.

Chapter 3 accomplishes a literature review on integrated performance measurement and their relations. The main focus is to show papers using mathematical tools to assess the global performance. These mathematical tools are classified and detailed, providing a discussion about their usefulness as well as application restrictions.

Chapter 4 presents the methodology to determine the integrated performance measurement, detailing the steps to follow to achieve it.

Chapter 5 describes the standard warehouse for which the performance measurement is assessed. The warehouse activities, layout and the unit of measure of indicators are detailed to allow indicator equations development. Furthermore, we develop an analytical model of indicator and data equations.

Chapter 6 utilizes mathematical methods to find indicator relationships. For that, we generate a database for the theoretical warehouse, which will be used for illustration purposes. After the database generation, the relationships among indicators are calculated using the Jacobian matrix, correlation matrix and Principal Component Analysis.

Chapter 7 analyzes the results of the mathematical tools application and proposes an integrated performance model. Also, a scale to evaluate the results of the integrated performance model is developed and tested for two different warehouse performance situations.

Chapter 8 presents the conclusions from the work results, highlighting the main contributions and future research directions.

Chapter 2

Literature Review on Warehouse Performance

Commence par faire le nécessaire, puis fais ce qu'il est possible de faire et tu réaliseras l'impossible sans t'en apercevoir.

François d'Assise

Abstract

This chapter carries out a deep literature review on warehouse performance. We perform a descriptive analysis of selected articles using content analysis method. The performance indicators acquired from these papers are divided initially as indirect or direct indicators. The indirect indicators are rather related to concepts and there is not a unique and simple equation to express them. The direct indicators are measured by equations like ratios and are also classified according to the dimensions of time, quality, cost or productivity. In order to clarify the direct indicators boundaries, we provide a framework positioning the measures according to the activity and dimension classification. Some conclusions made from this structured literature review are also presented.

2.1 Introduction

As the main objective of this dissertation is to study warehouse performance in an integrated way, a deep literature review is performed in this chapter to identify the main developments made by researchers as well as research gaps on this subject. Furthermore, this review synthesizes past works to recognize which kind of measures are mostly used on warehouse performance management. Due to the different kinds of indicators found in the literature, some classifications are performed to organize them according to what they measure (e.g. the performance of a specific activity) and how they do it (the mathematical tool used to calculate the performance).

In this work we refer to warehouse performance management as a short term analysis of the warehouse performance, usually done in short and regular time intervals (like months). These periodic results are used by managers to verify the evolution of the performance along the time and to take actions to enhance better results. We refer to the performance analysis as "the measurement and comparison of actual levels of achievement with specific objectives, measuring the efficiency and the outcome of corporation" (LU; YANG, 2010). In the following discussion, the terms "metric", "performance measure" and "performance indicator" are used as synonyms, as commonly done in the literature (FRANCESCHINI et al., 2006).

The reviews found treating warehouse subjects address technical issues as storage capacity and assignment policies (CORMIER; GUNN, 1992; GU; GOETSCHALCKX; MCGINNIS, 2007), order picking problems (CORMIER; GUNN, 1992; De Koster; LE-DUC; ROODBERGEN, 2007; GU; GOETSCHALCKX; MCGINNIS, 2007; GU; GOETSCHALCKX; MCGINNIS, 2010), routing problems (De Koster; LE-DUC; ROODBERGEN, 2007; GU; GOETSCHALCKX; MCGINNIS, 2007), and layout design (CORMIER; GUNN, 1992; De Koster; LE-DUC; ROODBERGEN, 2007; GU; GOETSCHALCKX; MCGINNIS, 2010). Only the work of Gu, Goetschalckx and McGinnis (2010) addresses the subject, but does so in the sense of long-term decision making.

The next sections present the methodology used for selecting and analyzing papers with the results of content analysis.

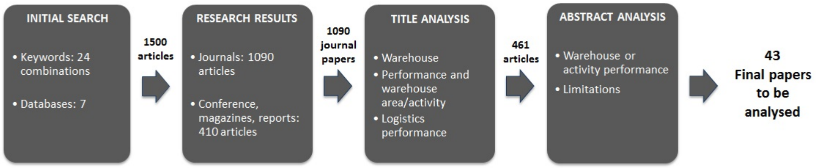


Figure 2.1: Bibliography research scheme.

2.2 Research methodology and delimitations

The process of collecting and selecting the papers is described in Figure 2.1. In the "Initial Search" phase, we defined a list of relevant keywords used for the database search, as demonstrated by the three parts of Table 2.1. The first subtable in the left side of Table 2.1 demonstrates the databases researched and the subtable in the right side shows the main keywords utilized. The third subtable of Table 2.1 (located below the first two subtables) presents all 24 possibilities of "Keywords Combinations" tested in all databases. The initial search did not limit publication year and document type; the only limitation was the results published in available English-language. This initial search resulted in 1500 articles, where 1090 were from journals and 410 from conferences, magazines and reports. We focus on journal publications, choosing just this kind of papers.

Analyzing the article's publication year, we found that the first publication about warehouse performance appears in 1970's with the work of Lynagh (1971). But the number of relevant papers available in databases up to 1990 is really rare. We can cite just the works of Khan (1984) and Svoronos and Zipkin (1988) as examples. To be sure that the literature review contains the majority of articles during a range of years, this study was restricted on publications from 1991 up to 2012. This range of years offers sufficient support to make conclusions from the results of descriptive analysis regarding their representativeness.

Following the steps presented in Figure 2.1, in the third phase, the journals articles are filtered by considering that their titles contain the keywords: (*i*) warehouse or similar (Distribution Center, Facility Logistics, Logistics Platforms, Cross Docking); (*ii*) the words "performance" or "management" or "evaluation" and the warehouse area / activity; (*iii*) logistics management and logistics performance measurement. During this selection, review papers in the warehouse area are also considered. From this stage, the database is narrowed down to 461

Table 2.1: Databases and Keywords used for papers research.

Databases	Keywords
Scopus (scopus.com)	Warehouse/ Distribution Center
Emerald (emeraldinsight.com)	Facility Logistics/ Logistics Platforms
EBSCO (ebscohost.com)	Performance/ Efficiency
Wiley (onlinelibrary.wiley.com)	Evaluation/ Measurement/ Assessment
Science Direct (sciencedirect.com)	Logistics/ Logistics audit
Web of Science (webofknowledge.com)	Operation Management
Compendex (engineeringvillage2.com)	Metrics/ index/ KPI

Keyword combinations
Performance Measur*/Assessment & warehouse/distribution center/logistics platform
Performance Measur* / Assessment & warehous* / DC & logist*
Performance Evaluation & distribution center / logistics platform
warehouse/ distribution center / logistics platforms & performance
warehouse operations management
warehouse / distribution center & logistics index
warehouse efficiency & measur*
performance & metric & warehouse
warehouse overall performance
warehouse management & logistics
warehouse & logistics KPI
logistics performance

papers.

Finally, the abstract of each article is analyzed. In this phase, the papers are filtered according to their relationship to warehouse performance. In case of doubt on the paper's content, the full text was also verified. Note that the final database (43 articles) does not include the works that are directly related to:

- Economical analysis about warehouse construction and/or investment;
- WMS (Warehouse Management System) evaluation (technical features) and implementation;
- Warehouse design;
- Warehouse location;
- Supply chain optimization (two or three echelons);
- Storage and picking policies evaluation;
- Distribution optimization.

The justification of not including the subjects cited above is that they treat strategical and tactical decision making (e.g. warehouse location, design) and not the operational performance management which is the main focus of our literature review (e.g. unloading time, labor productivity).

Only the works using decision making for operational warehouse management are taken into account. As the decision support tools are considered as means to manage the performance, the articles presenting decision support systems (DSS) to help warehouse manager's decisions (LAM; CHOY; CHUNG, 2011; LAO et al., 2011; LAO et al., 2012) and the articles treating the system influence on enterprise performance (AUTRY et al., 2005; KARAGIANNAKI; PAPAKIRIAKOPOULOS; BARDAKI, 2011) were included in this review as well.

The final database is used to make two different analysis as shown in Figure 2.2. First, we provide a descriptive analysis of all 43 papers in Section 2.3. That is, a quantitative evaluation of the general characteristics of the articles. The second analysis, presented in Section 2.4 and 2.5, focuses on the performance indicators used in warehouses. In the final database, only 35 articles present performance indicators. Among these 35 papers, 32 articles discuss the performance indicators which can be expressed by some simple equations, being "measured directly".

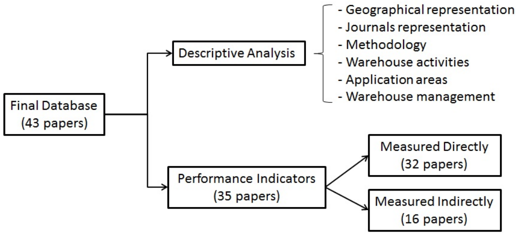


Figure 2.2: Analysis realized in this paper.

We qualify them as "direct indicators". We address this kind of papers in Section 2.4. There are 16 articles among 35 that assess performance indicators in an "indirect way". It means that these indicators represent more complex concepts which are difficult to measure by simple expressions like ratios. Therefore, more sophisticated statistical tools (e.g. regression analysis) are used to assess them. These performance indicators are named as "indirect indicators" and an analysis of them is provided in Section 2.5.

The papers of the final database are explored based on content analysis research method. Content analysis is an observational research method that is used to systematically evaluate the literature in terms of various categories, transforming original texts into analyzable representations (POKHAREL; MUTHA, 2009; KRIPPENDORFF, 2004).

Content analysis can be carried out in two steps: definition of variables analyzed and the unitization of them. The definition of the variables depends on research objectives. In this dissertation, the variables extracted from papers are: work methodology, mathematical tools utilized, warehouse activities and indicators used to assess performance. The second step to be performed is the unitization. Krippendorff (2004) defines unitizing as "the systematic distinguishing of segments of text that are of interest to an analysis". That is, in the final paper database we look for the variables and when they are not explicit in the text some predefined rules are used to classify the information acquired from the text. In order to maintain consistency in this procedure and to avoid biases, this step is conducted by the author of this thesis (this procedure is usually adopted when performing content analysis according to Krippendorff (2004)). This principal reader has filled the variables as presented in each study on a spreadsheet. This master listing of findings is then analyzed by the persons related to this research.

The results of the spreadsheet analysis are given in the next sections.

2.3 Results of Content Analysis

This section shows the content analysis by using tables which present some quantitative outcomes resulted from paper's classification. They present patterns identified from the data, allowing to categorize the warehouse performance literature. More specifically, Section 2.3.1 shows the number of publications per continent and per journal, Section 2.3.2 introduces paper methodologies, Section 2.3.3 shows their classification by application areas, Section 2.3.4 presents the warehouse activities most studied in the works and Section 2.3.5 summarizes the tools developed for helping managers on warehouse management.

2.3.1 Based on geographical and journal representation

Figure 2.3 shows one of the results from article analysis, the number of publications over years per continent. We note that the sum of the number of publications per continent/year could be more than the total curve value because some papers are co-authored by people from different continents and are counted more than once. From Figure 2.3 several inferences could be made. First, it is apparent that research on warehouse performance has increased in the last years, demonstrating the subject relevancy. Second, the representation of European papers has also increased substantially in the last years. The main European publishing countries are The Netherlands, Greece and Italy with four, three and three publications each, respectively. America, on the other hand, maintains almost the same number of publications over years with United States being the country with most publications (16 papers) of all continents. Third, the number of papers realized in international cooperation sums to 10 publications, almost one fourth of our database. Europe is the continent with the highest international co-authoring (7 papers), followed by America (6 papers).

In response to the question of where the warehouse performance management is most addressed, Table 2.2 demonstrates the journals that most publish in the area. The results show that publications are very widespread since the journals with one publication represent more than 60% of the selected articles. So, we can conclude that this area is very interdisciplinary. The "European Journal of Operational Research" has the highest concentration with five articles. It is interesting to highlight that four among these five publications are literature reviews showing the general interest on this subject area.

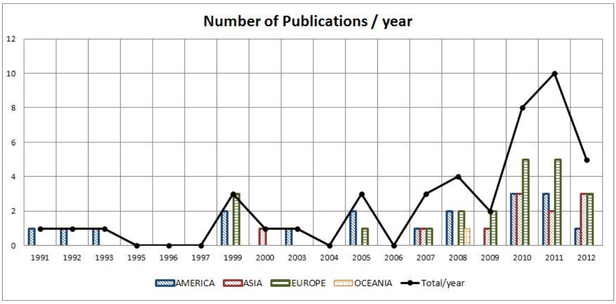


Figure 2.3: Number of publications over years / continent.

Table 2.2: Journals publications - of 43 total papers

Journal	NP [a]	%
European Journal of Operational Research	5	11.6
Journal of Business Logistics	3	7.0
Journal of Manufacturing Technology Management	3	7.0
International Journal of Production Research	2	4.7
International Journal of Production Economics	2	4.7
TOTAL	15	35

[a] Number of publications

2.3.2 Based on the work methodology

Other data points acquired by the descriptive analysis capture the articles' methodology. The articles are classified based on five research methodologies (see Seuring and Muller (2008)): mathematical, conceptual, case study, survey, and review papers. A paper is classified as quantitative/mathematical work if simple tools (e.g. mean, percentage and standard deviation, etc.) as well as more sophisticated tools (e.g. linear regression, analytical model, simulation) are used. To be classified as conceptual, the work needs to be presented as a theoretical concept; there is no kind of practical application or results implemented in practice. The case study is a work that develops a theory and verifies the results in practice; or it is a paper solving some specific problems verified in practice. Survey is a research paper carrying out a questionnaire to make conclusions about a subject. Each paper could be classified in more than one methodology, depending on its characteristics. The exception is the review papers, which were separated because of their relevance. The results of this classification are given in Table 2.3.

Table 2.3: Work Methodology - Total 43 articles

Review	Case Study	Survey	Conceptual	Mathematical	NP[a]	%	Articles
		✓		✓	17	39.5	Kiefer and Novack (1999), Ellinger, Ellinger and Keller (2003), Autry et al. (2005), De Koster and Warffemius (2005), Voss, Calantone and Keller (2005), Sohn, Han and Jeon (2007), De Koster and Balk (2008), Park (2008), O'Neill, Scavarda and Zhenhua (2008), Menachof, Bourlakis and Makios (2009), Forslund and Jonsson (2010), Lu and Yang (2010), De Marco and Giulio (2011), Johnson and McGinnis (2011), Markovits-Somogyi, Gecse and Bokor (2011), Banaszewska et al. (2012), Yang and Chen (2012)
	✓			✓	13	30.2	Wu and Hou (2009), Manikas and Terry (2010), Matopoulos and Bourlakis (2010), Wang, Chen and Xie (2010), Johnson, Chen and McGinnis (2010), Cagliano et al. (2011), Lam, Choy and Chung (2011), Goomas, Smith and Ludwig (2011), Karagiannaki, Papakiriakopoulos and Bardaki (2011), Lao et al. (2011), Sellitto et al. (2011), Lao et al. (2012), Ramaa, Subramanya and Rangaswamy (2012)
✓					5	11.6	Cormier and Gunn (1992), Berg and Zijm (1999), De Koster, Le-Duc and Roodbergen (2007), Gu, Goetschalckx and McGinnis (2007), Gu, Goetschalckx and McGinnis (2010)
	✓				3	7.0	Spencer (1993), Gunasekaran, Marri and Menci (1999), Gallmann and Belvedere (2011)
			✓		3	7.0	Mentzer and Konrad (1991), Rimiene (2008), Bisenieks and Ozols (2010)
			✓	✓	2	4.7	Yang (2000), Saetta et al. (2012)
			TOTAL		43	100.0	

[a] Number of publications

The quantitative works represent 74.4% of the total papers (i.e. survey/mathematical (39.5%), case study/mathematical (30.2%) and conceptual/mathematical (4.7%)). Due to their significance, we detailed the quantitative works according to the type of method used (see Table 2.4). The basic statistics are further detailed as ANOVA and F test; p value and σ; and Others. We note that some papers use more than one mathematical tool. In such papers, most of the time, the basic statistics are combined with other tools. For example, factor analysis or regression analysis are combined with the basic statistics to describe relations among warehouse activities (10 out of 32 papers). Another example is the use of statistics to compare the simulation results. The next subsections present which kind of industries and warehouse activities were most representative according to the database.

2.3.3 Application area of works

To verify the most relevant application areas, we classify the articles based on the position of the application point in the supply chain. Table 2.5 shows three major classes as: (1) manufacturing industries (with their respective Distribution Centers - DC). In this category, the articles are further classified as *one industry* and as *several industries* if the application is on a single or on several industries, respectively; (2) retailers, and (3) third party logistics. We classify as “Other” the works which are not related to any industrial activity, like Air Force (see Sohn, Han and Jeon (2007)) and as “Not Specified” if application areas are not mentioned. The main area appearing in papers is the Food industry, with a total of 8 works (5 are performed in Retailer companies and 3 in Manufacturing). The results presented in Table 2.5 show that 13 out of 19 articles related to a manufacturing domain cover several industries. This is not very surprising when we cross check with Table 2.3. We observe that there are a lot of survey papers (see Table 2.3) providing performance comparison among enterprises. Such articles analyze different industry segments at the same time.

We have also analyzed the kind of facility studied in the selected articles (warehouse or distribution center (DC)), but it is difficult to provide reliable statistics on this subject. Even though Manikas and Terry (2010) highlight that main differences exist between these two, defining “*a DC as a warehouse that emphasizes the rapid movement of goods*”, the same authors also state that “*a distribution center could be similar to a warehouse in terms of layout and operations management*”. In fact, in the related literature the terms DC and warehouse are often

Table 2.4: Mathematical tools

Math Tool	NP[a]	%
(1) Basic Statistics	20	40
(1.1) ANOVA and/or F test	8	16
(1.2) σ [b], *p value*	7	14
(1.3) Others	5	10
(2) Regression Analysis	6	12
(3) Factor Analysis	5	10
(4) DEA[c]	5	10
(5) Analytical Model	4	8
(6) Simulation	4	8
(7) Others	6	12
Total	50	100

[rma]Number of publications [b]standard deviation
[c]Data Envelopment Analysis

Table 2.5: Publications area

Area	NP[a]	%
(1) Manufacturer and its DC	19	44.2
(1.1) One industry	6	
(1.2) Several industries	13	
(2) Retailers	9	20.9
(3) Third Party Logistics	6	14.0
(4) Other	1	2.3
(5) Not Specified	8	18.6
Total	43	100

[a] Number of publications

used as synonyms (BERG; ZIJM, 1999; DOTOLI et al., 2009). Therefore, in this work, we consider all indicators and management practices realized in warehouse and distribution centers as equivalent.

2.3.4 Warehouse activities

Warehouses could have different activities according to product specification, customer requirements and service levels offered. For De Koster and Warffemius (2005), the complexity of the warehouse activities depend mainly on: (*i*) the number and variety of items to be handled; (*ii*) the amount of daily workload to be done; and (*iii*) the number, the nature and the variety of processes necessary to fulfill the needs and demands of the customers and suppliers.

Even though differences may exist among the warehouse activities, they were defined as: receiving, storage, order picking and shipping (BERG; ZIJM, 1999). In what follows we will use this generic classification. Some studies related to warehouse performance also mention the delivery process (5 articles are identified). In some cases, the delivery could be considered as a warehouse responsibility in the metrics sense. This is why, the delivery is also considered as a warehouse activity in our analysis.

However, we did not include other warehouse activities such as replenishment (transfer of products from the reserve storage to the picking area (MANIKAS; TERRY, 2010)) and sorting (if the picking is performed in batches, the products could be sorted before packing) in this analysis because the database papers do not present performance indicators for these activities.

As each of these five activities can be divided into several sub-activities, we consider the following definitions and boundaries to be used in our analysis:

- Receiving: operations that involve the assignment of trucks to docks, the scheduling and execution of unloading activities (GU; GOETSCHALCKX; MCGINNIS, 2007);

- Storing: material's movement from unloading area to its designated place in inventory (YANG; CHEN, 2012; MENTZER; KONRAD, 1991);

- Order Picking: process of obtaining a right amount of the right products for a set of customer orders (De Koster; LE-DUC; ROODBERGEN, 2007). This is the main and the most labor-intensive activity of warehouses (DOTOLI et al., 2009);

- Shipping: execution of packing and truck's loading after picking, involving also the assignment of trucks to docks (GU; GOETSCHALCKX; MCGINNIS, 2007);

- Delivery: the transit time for transportation from the warehouse to the customer.

Based on the above warehouse activities, the selected articles are analyzed and classified as in Table 2.6. This table helps identifying the major research areas by warehouse activities.

A major observation we make out of Table 2.6 is that almost 40% of the articles consider all major activities of the warehouse at the same time (rows 1 and 2 of Table 2.6). The articles mentioned in the second row (except Mentzer and Konrad (1991)) are on the employee performances. According to Berg and Zijm (1999) and Mentzer and Konrad (1991), the labor tasks impact all warehouse activities. Therefore, we choose to classify these papers as impacting all activities.

Another interesting insight is the fact that the majority of the articles include the picking activity in their studies. This is quite relevant with industrial observations and shows a certain maturity in the works undertaken. The order picking process is the most costly among all warehouse activities, because it tends to be either very labor intensive (manual picking) or very capital intensive (automatic picking). More than 60% of all operating costs in a typical warehouse can be attributed to order picking (BERG; ZIJM, 1999; GU; GOETSCHALCKX; MCGINNIS, 2007; MANIKAS; TERRY, 2010).

Table 2.6: Warehouse Activities studied

Receiving	Storage	Picking	Shipping	Delivery	NP [a]	%	Articles
✓	✓	✓	✓		12	27.9	Cormier and Gunn (1992), Berg and Zijm (1999), Gunasekaran, Marri and Menci (1999), Kiefer and Novack (1999), Gu, Goetschalckx and McGinnis (2007), Rimiene (2008), Karagiannaki, Papakiriakopoulos and Bardaki (2011), Cagliano et al. (2011), Gallmann and Belvedere (2011), Lao et al. (2012), Yang and Chen (2012), Ramaa, Subramanya and Rangaswamy (2012)
✓	✓	✓	✓	✓	5	11.6	Mentzer and Konrad (1991), Ellinger, Ellinger and Keller (2003), Wu and Hou (2009), Lu and Yang (2010), Sellitto et al. (2011)
		✓	✓		5	11.6	Spencer (1993), Autry et al. (2005), De Koster and Balk (2008), Johnson, Chen and McGinnis (2010), Johnson and McGinnis (2011)
	✓	✓	✓		3	7.0	De Koster and Warffemius (2005), O'Neill, Scavarda and Zhenhua (2008), Saetta et al. (2012)
		✓			3	7.0	De Koster, Le-Duc and Roodbergen (2007), Lam, Choy and Chung (2011), Goomas, Smith and Ludwig (2011)
	✓	✓			2	4.7	Bisenieks and Ozols (2010), Gu, Goetschalckx and McGinnis (2010)
✓	✓	✓			2	4.7	Manikas and Terry (2010), Wang, Chen and Xie (2010)
✓		✓	✓		2	4.7	Menachof, Bourlakis and Makios (2009), De Marco and Giulio (2011)
	✓				2	4.7	Sohn, Han and Jeon (2007), Park (2008)
✓			✓	✓	1	2.3	Matopoulos and Bourlakis (2010)
✓		✓			1	2.3	Voss, Calantone and Keller (2005)
				✓	1	2.3	Forslund and Jonsson (2010)
			✓		1	2.3	Markovits-Somogyi, Gecse and Bokor (2011)
		✓	✓	✓	1	2.3	Banaszewska et al. (2012)
	✓			✓	1	2.3	Yang (2000)
✓	✓				1	2.3	Lao et al. (2011)
			Total		43	100.0	

[a] Number of publications

In the final database, we find some works which explore warehouse management systems for decision aid and performance management. As these warehouse management tools are important supports for performance evaluation we give a descriptive analysis of them in the following subsection.

2.3.5 Warehouse Management tools

The early works on warehouse management are first focused on examining the processes and identifying areas where an efficient management could improve the performance of the warehouse. For example, Spencer (1993) presents a method based on value-added tax (V-A-T) analysis and Theory of Constraints (TOC) to identify such critical process points; Gunasekaran, Marri and Menci (1999) study the problems in Goods Inwards (GI) area and provide solutions to increase the performance of warehousing operations using Just in Time (JIT) and Total Quality Management (TQM). These early techniques do not necessarily need extensive Information Technology (IT) tools.

In the last decade, however, we observe an increasing complexity in the warehouse operations. This complexity is very well demonstrated by the implementation of sophisticated IT tools in warehouses and DCs. Since 2000, more complicated algorithms and simulations start to appear in publications on warehouse management as well. These articles follow the same trend and propose utilization or development of decision support systems for performance evaluation and performance improvement in warehouses. Information systems, such as Warehouse Management System (WMS), are recognized as useful means to manage resources in the warehouse (LAM; CHOY; CHUNG, 2011). Wang, Chen and Xie (2010) propose a Digital Warehouse Management System (DWMS) based on RFID (Radio Frequency Identification) to help managers achieve better inventory control, as well as to improve the operation efficiency. Cagliano et al. (2011) model the warehouse processes using System Dynamics and develop a dynamic decision support tool to assign employees to counting tasks. Lam, Choy and Chung (2011) develop a Decision Support System (DSS) to facilitate warehouse order fulfillment: when there is an incoming customer order, previous similar cases are retrieved as a reference solution to the new incoming order. Lao et al. (2011) develop a real-time inbound decision support system with three modules, which integrate the RFID technology, Case-Based Reasoning (CBR), and Fuzzy Reasoning (FR) techniques to help monitor food quality activities. Lao et al. (2012) propose a RFID based system to facilitate the food safety control activities in receiving area, by generating a proper safety plan.

To evaluate the technology investment, Autry et al. (2005) design a method to determine whether the investment in WMS-oriented operations results in desirable performance outcomes for the warehouses or not. More recently, Yang and Chen (2012) and Ramaa, Subramanya and Rangaswamy (2012) study the impact of information systems on warehouse performance. These studies conclude that the introduction of new technologies like RFID and WMS permits the integration of decision support tools in warehouse management and improves the manager's decisions.

In the next section, we present further analysis on the selected articles. But this time, the analysis is focused more specifically on the indicators used to assess the warehouse performance.

2.4 Direct Warehouse Performance Indicators

The traditional logistics performance measures include "hard" and "soft" metrics. The first one treats quantitative measures such as order cycle time, fill rates and costs; the second deals with qualitative measures like manager's perceptions of customer satisfaction and loyalty (CHOW; HEAVER; HENRIKSSON, 1994; FUGATE; MENTZER; STANK, 2010). The "hard" metrics are computable with some simple mathematical expressions while the soft metrics require more sophisticated tools of measurement (e.g. Regression analysis, fuzzy logic, Data Envelopment Analysis, etc.). This work will refer to the "hard" metrics as *direct* indicators and the soft ones as *indirect* indicators. The first group will be presented in this section, and the second one will be described in section 2.5.

For the purpose of the analysis, all direct indicators are extracted from papers and classified according to four performance evaluation dimensions, commonly used in industries. These are: *time* (MENTZER; KONRAD, 1991; SPENCER, 1993; NEELY; GREGORY; PLATTS, 1995; FRAZELLE, 2001; CHAN; QI, 2003; GUNASEKARAN; KOBU, 2007; GALLMANN; BELVEDERE, 2011), *quality* (NEELY; GREGORY; PLATTS, 1995; STAINER, 1997; FRAZELLE, 2001; GALLMANN; BELVEDERE, 2011), *cost* (NEELY; GREGORY; PLATTS, 1995; MENTZER; KONRAD, 1991; BEAMON, 1999; CHAN; QI, 2003; CAI et al., 2009; KEEBLER; PLANK, 2009), and *productivity* (STAINER,

1997; FRAZELLE, 2001; CHAN; QI, 2003; KEEBLER; PLANK, 2009; GALLMANN; BELVEDERE, 2011). We note that; some works prefer to use *flexibility* instead of *productivity* as the fourth dimension (NEELY; GREGORY; PLATTS, 1995; STAINER, 1997; BEAMON, 1999; GUNASEKARAN; KOBU, 2007), defining it as the "ability to respond to a changing environment"(BEAMON, 1999). However, Gunasekaran and Kobu (2007) state that flexibility may be intangible and difficult to measure in some cases. We present in Section 2.5 that flexibility is preferably measured indirectly rather than directly. Consequently, in this section productivity will be used as a dimension for direct warehouse performance indicators.

The following procedure is used for the classification. Initially, all the direct indicators found in the selected papers are listed. Once the list is completed, two types of aggregations are made: (i) similar indicators are regrouped; (ii) very specific metrics are included in more generic ones. One example of this second group is the work by Manikas and Terry (2010) mentioning the indicator "time of quality control in receiving". This can be considered as a portion of the "receiving operation time"; we include this indicator together with the class of indicators called the "receiving operation time". Finally, the indicators are organized according to what they measure (time, quality, cost or productivity). We note that, for the sake of uniformity throughout this work, the classifications presented here are based on our interpretation, instead of the original category proposed by the selected papers. For example, Banaszewska et al. (2012) consider the "number of consignment processed per warehouse employee" as a productivity indicator. Indeed, the measure is a productivity indicator. In this review we propose a sub-category, called the *labor productivity* and Banaszewska et al. (2012) appears in this (see Table 2.10). Another example is the article of Saetta et al. (2012), where the authors measure the customer satisfaction as "the percentage of orders on time" and we classify the article under a broader indicator which is the "on time delivery" (see Table 2.8). The classifications resulting from this analysis are given in Tables 2.7, 2.8, 2.9 and 2.10. We present a discussion on each class in the following sections.

2.4.1 Time related performance indicators

Table 2.7 shows the results for time related indicators. The most used metrics are order lead time, receiving operation time and order picking time, respectively. Surprisingly, order picking time is in the third position, even though Gu, Goetschalckx and McGinnis (2007) state that past research has focused strongly on order picking since this activity has large impact on the warehouse performance. One reason could be that in the literature, the order picking time is more specifically treated in optimization works, which are not considered in this review.

Analyzing the time spent by a product in the warehouse through all activities, the indicators found in Table 2.7 encompass almost all time components (receiving, putaway, picking, shipping and delivery). The exceptions are the replenishment and inventory time: there is no paper using an indicator like inventory coverage or replenishment time to measure it. Mentzer and Konrad (1991) presents indicators covering most of the activities in a descriptive way; however, no measurement is done. Another interesting point is that no author has measured the entire time spent by a product in the warehouse (since receiving up to delivery) using just one indicator.

Regarding the warehouse activities covered by indicators, for the inbound processes there are receiving and putaway times and for outbound processes picking, shipping and delivery times. Interestingly, these five indicators could be represented by just two: dock to stock time (for inbound process) and order lead time (for outbound process). In the case of order lead time, this indicator comprehends also administrative time beyond the activities presented (picking, shipping and delivery) since its definition expresses, according to Kiefer and Novack (1999), that order lead time starts to be measured at the time the customer makes an order.

2.4.2 Quality related performance indicators

Different from the time dimension, the quality embraces measures linked with customer satisfaction (external) and operations quality (internal).

The Table 2.8 illustrates the indicators used in the selected papers. We observe that the emphases are on "on-time delivery", "customer satisfaction" and "order fill rate". The result corroborate with the statement of Forslund and Jonsson (2010), that "*perfect order results supplier delivery performance in a more comprehensive way, but seems not to be as widely applied as on-time delivery*".

The inventory, the warehouse physical area in which the products remain until they are picked, is also considered as an important management part to achieve a high warehouse performance. Gallmann and

Table 2.7: Warehouse time indicators found in literature.

Authors	Order lead time	Receiving time	Order picking time	Putaway time	Delivery Lead Time	Queuing time	Loading time	Dock to stock time	Equipment downtime
Mentzer and Konrad (1991)	✓	✓	✓	✓	✓				✓
Kiefer and Novack (1999)	✓								
Yang (2000)	✓								
Gu, Goetschalckx and McGinnis (2007)	✓	✓	✓				✓		
O'Neill, Scavarda and Zhenhua (2008)	✓								
Rimiene (2008)	✓								
Menachof, Bourlakis and Makios (2009)	✓								
Manikas and Terry (2010)		✓							
Matopoulos and Bourlakis (2010)		✓			✓				
Wang, Chen and Xie (2010)							✓		
Cagliano et al. (2011)			✓	✓		✓			
Lam, Choy and Chung (2011)			✓						
Gallmann and Belvedere (2011)					✓				
Karagiannaki, Papakiriakopoulos and Bardaki (2011)						✓			
Lao et al. (2012)		✓							
Yang and Chen (2012)	✓			✓					
Ramaa, Subramanya and Rangaswamy (2012)	✓							✓	
Total/each indicator	9	5	4	3	3	2	2	1	1

Belvedere (2011) state that companies take into account inventory management as a key to reach excellent service levels. Although inventory is not an "activity", its indicators (represented in Table 2.8 by Physical inventory accuracy) were included in this work due to their importance in warehouse management.

2.4.3 Cost related performance indicators

The results for cost dimension are presented in Table 2.9. It is interesting to note that fewer works are recorded for cost indicators compared to the other dimensions. It could be explained by the affirmation of Gunasekaran and Kobu (2007) that the operational level performance evaluation is mostly based on non-financial indicators, but depends always on company's characteristics and choices. Despite the strategic importance in the supply chain, warehouses have most of their activities in the operational level.

Table 2.9 also shows that the majority of the works mentioning cost metrics use inventory cost indicator. From this data, it is apparent that what really interests managers regarding the warehouse management costs is the inventory. The inventory is a "cost generator" by nature: according to Kassali and Idowu (2007), inventory is a business that involves costs and risk. The risks may come from probable product losses (e.g. quality deterioration) or price uncertainty.

2.4.4 Productivity related performance indicators

Another important dimension for the warehouse management is the productivity. Productivity can be defined as the level of asset utilization (FRAZELLE, 2001), or how well resources are combined and used to accomplish specific, desirable results (NEELY; GREGORY; PLATTS, 1995).

It can be seen from Table 2.10 that labor productivity and throughput are the most employed metrics in warehouses. This result reinforces the fact that these are the main areas where the warehouses are pressured for outcomes.

2.5 Indirect Warehouse Performance Indicators

In the past, the distribution centers (DC) primarily served as warehouses with distribution functions. Nowadays, the DCs have interna-

Table 2.8: Warehouse quality indicators found in literature.

Authors	On-time delivery	Cust. satisfaction [a]	Order fill rate	Shipping accuracy	Delivery accuracy	Picking accuracy	Ord. ship. on time [b]	Cargo damage rate	Scrap rate	Perfect Orders	Storage accuracy	Physical inv. ac.[c]	Stock-out rate
Mentzer and Konrad (1991)	✓												
Gunasekaran, Marri and Menci (1999)	✓									✓			
Kiefer and Novack (1999)	✓	✓		✓								✓	✓
De Koster and Warffemius (2005)								✓					
Voss, Calantone and Keller (2005)	✓	✓					✓		✓		✓		
De Koster and Balk (2008)								✓					
Rimiene (2008)				✓		✓	✓						
Menachof, Bourlakis and Makios (2009)			✓										
Forslund and Jonsson (2010)	✓												
Lu and Yang (2010)	✓	✓											
Wang, Chen and Xie (2010)				✓									
De Marco and Giulio (2011)		✓											
Lam, Choy and Chung (2011)			✓										
Gallmann and Belvedere (2011)									✓				
Johnson and McGinnis (2011)			✓										
Lao et al. (2011)		✓	✓		✓								
Banaszewska et al. (2012)	✓	✓											
Lao et al. (2012)		✓	✓		✓								
Saetta et al. (2012)	✓					✓							
Yang and Chen (2012)	✓	✓	✓	✓	✓	✓					✓		
Ramaa, Subramanya and Rangaswamy (2012)	✓		✓	✓	✓					✓			
Total/each indicator	10	8	7	5	4	3	2	2	2	2	2	1	1

[a] Customer satisfaction [b] Orders shipped on time [c] Physical inventory accuracy

Table 2.9: Warehouse cost indicators found in literature.

Authors	Inventory cost	Order processing cost	Labor cost	Distribution cost	Cost as % of sales	Maintenance cost
Mentzer and Konrad (1991)					✓	
Kiefer and Novack (1999)		✓				
Yang (2000)	✓			✓		
Ellinger, Ellinger and Keller (2003)	✓					
Rimiene (2008)	✓	✓				
Johnson, Chen and McGinnis (2010)						✓
Lu and Yang (2010)	✓		✓	✓		
De Marco and Giulio (2011)						✓
Cagliano et al. (2011)	✓		✓			
Gallmann and Belvedere (2011)	✓					
Saetta et al. (2012)	✓					
Ramaa, Subramanya and Rangaswamy (2012)		✓			✓	
Total/each indicator	7	3	2	2	2	2

tional headquarters, call-centers, service centers or even manufacturing facilities as well (De Koster; WARFFEMIUS, 2005). This evolution is the outcome of a need to provide tailored services for the customers and to gain competitive advantage. These new services require additional indicators to measure the related performance. Oftentimes, the indicators are complex; either the equations are not available or they are too difficult to calculate. The warehouse capability (SOHN; HAN; JEON, 2007), the supervisory coaching behavior (ELLINGER; ELLINGER; KELLER, 2003), the relation between front-line employee performance and interdepartmental customer orientation (VOSS; CALANTONE; KELLER, 2005), etc. are some examples of these indicators. In this dissertation, we call such indicators, the *indirect* indicators. Instead of simple and straightforward equations, some structured mathematical tools are needed to calculate the value of these indicators. Normally, these mathematical tools evaluate different kinds of information and extract correlations and/or performances from databases. Some examples of such tools used in the literature are: SEM (Structural Equation Modeling), DEA (Data Envelopment Analysis), Regression Analysis, Canonical Matrix.

Table 2.10: Warehouse productivity indicators found in literature.

Authors	Labor productivity	Throughput	Shipping productivity	Transport utilization	Warehouse utilization	Picking productivity	Inventory space util.[a]	Outbound space util.[b]	Turnover	Receiving productivity
Mentzer and Konrad (1991)	✓	✓	✓							✓
Gunasekaran, Marri and Menci (1999)		✓								
Kiefer and Novack (1999)		✓	✓			✓				
De Koster and Warffemius (2005)			✓							
Voss, Calantone and Keller (2005)		✓								
Gu, Goetschalckx and McGinnis (2007)		✓								
De Koster and Balk (2008)	✓					✓				
O'Neill, Scavarda and Zhenhua (2008)				✓			✓	✓		
Rimiene (2008)	✓	✓			✓		✓	✓		
Johnson, Chen and McGinnis (2010)	✓	✓	✓					✓		
Manikas and Terry (2010)	✓	✓	✓							
Matopoulos and Bourlakis (2010)	✓			✓	✓					
Wang, Chen and Xie (2010)			✓		✓					
De Marco and Giulio (2011)		✓	✓	✓						
Cagliano et al. (2011)	✓									
Goomas, Smith and Ludwig (2011)	✓									
Johnson and McGinnis (2011)			✓		✓				✓	
Karagiannaki, Papakiriakopoulos and Bardaki (2011)	✓									
Markovits-Somogyi, Gecse and Bokor (2011)	✓									
Banaszewska et al. (2012)	✓	✓		✓						
Yang and Chen (2012)									✓	
Ramaa, Subramanya and Rangaswamy (2012)		✓				✓	✓			
Total/each indicator	11	11	8	4	4	3	3	3	2	1

[a] Inventory space utilization [b] Outbound space utilization

The papers presenting indirect indicators are listed in Table 2.11. We give next some details on these papers.

Table 2.11: Indirect indicators measured in papers.

Authors	Labor	VAL activity [b]	Inv. Man.[c]	War. Aut. [d]	Flexibility	Cust. Perc. [a]	Maintenance
Kiefer and Novack (1999)						✓	
Ellinger, Ellinger and Keller (2003)	✓						
Voss, Calantone and Keller (2005)	✓						
Sohn, Han and Jeon (2007)			✓	✓			✓
De Koster and Balk (2008)	✓	✓		✓	✓	✓	
Park (2008)	✓						
O'Neill, Scavarda and Zhenhua (2008)		✓					
Wu and Hou (2009)	✓						
Lu and Yang (2010)		✓		✓	✓	✓	
Wang, Chen and Xie (2010)			✓				
Gallmann and Belvedere (2011)			✓				
Goomas, Smith and Ludwig (2011)	✓						
Johnson and McGinnis (2011)		✓					
Banaszewska et al. (2012)	✓	✓		✓			
Yang and Chen (2012)			✓		✓		
Total	7	4	4	4	3	3	1

[a] Customer Perception [b] VAL - Value Added Logistics [c] Inventory Management
[d] Warehouse Automation

- **Maintenance:** Sohn, Han and Jeon (2007) have performed a survey based on warehouse characteristics in order to assess the capability of each warehouse taking part in the study. The facility management is determined by the authors as: (i) maintenance and repair of warehouse facilities, (ii) cooperation with facilities-related departments, (iii) new construction of modern warehouses, and (iv) full equipment for protecting facilities against fire. As a result of the study, Sohn, Han and Jeon (2007) conclude that facility management is the second highest impact on warehouse capability, after manpower management.

- **Flexibility:** we can verify that the flexibility measures are usually associated with other performance components such as time, volume, delivery. For example, Lu and Yang (2010) measure flexibility in terms of operation flexibility, rapid response to customer requests, delivery time flexibility and volume flexibility. Yang and Chen (2012) consider flexibility as urgent order handling and De Koster and Balk (2008) consider flexibility as the capacity to cope with the internal and external changes.

- **Labor:** the results in Table 2.11 demonstrate the importance of employee performance in warehouses with numerous articles in the area. Ellinger, Ellinger and Keller (2003) integrate the perception of supervisors to examine the employee performance (seen by the supervisors). Voss, Calantone and Keller (2005) show that the front-line employee performance and interdepartmental customer orientation have a positive effect on DC services. In their study, the authors consider the following variables to measure the employee performance: proper data recording, efficient trailer loading, storing products in proper locations, effective distribution operations, minimal product loss, minimal product damage, high productivity, high performance. Wu and Hou (2009) propose a model for the analysis of employee performance trends. This model is intended to determine the employees to reward or to train. Goomas, Smith and Ludwig (2011) evaluate the order selectors' performance after the implementation of an overhead scoreboard that informs the number of completed tasks, the number of tasks in queue and the team performance against the engineered labor standards. Park (2008) study the relationship between the store-level performance and the composition of the workforce. Workforce composition is expressed as the full-time and the part-time employees.

- **Customer Perception:** customer relationship and customer satisfaction are considered as the most satisfactory performance variables by managers Lu and Yang (2010). Accordingly, Kiefer and Novack (1999) state that understand the influence of some measures in customer's reaction is far more important than any internal measure alone.

  De Koster and Balk (2008) measure customer perception by using DEA. The authors verify the contribution of some activities (like cross-docking, cycle counting, return handling) to the increase of customer perception.

  Lu and Yang (2010) consider customer response as attributes of logistics service capabilities. Customer response encompasses pre-sale customer service, post-sale customer service and responsiveness to customer. As a result, the companies that are customer-response-oriented have the best performance among DC's in Taiwan.

- **Value Adding Logistic (VAL) Activities:** can be measured by the number of VAL activities offered by the company and performed in warehouses. De Koster and Balk (2008) divide VAL activities in low and high levels. The activities adding low value to the product include labeling, putting manuals, kitting; whereas high VAL activities consist of sterilization, final product assembly, product installation etc.

  For Gu, Goetschalckx and McGinnis (2007), the roles of VAL activities also include: buffering the material flow along the supply chain to accommodate variability caused by factors such as product seasonality and/or batching in production and transportation; consolidation of products from various suppliers for combined delivery to customers. The survey of O'Neill, Scavarda and Zhenhua (2008) confirm that VAL activities have become common activities in warehouses. However, on the average only 5 per cent of floor area is dedicated to these activities, indicating that VAL activities are minor in nature.

- **Inventory Management:** is an area where the automation support for activities has increased. The relations between inventory management and warehouse automation are getting closer to each other. Wang, Chen and Xie (2010) propose a digital warehouse management system (DWMS) based on RFID to help managers to achieve better inventory control. Yang and Chen (2012) examine the impact of information systems on DC's performance. Among the results, they found a positive correlation between *warehousing and inventory management* and *emergent order handling*. In Sohn, Han and Jeon (2007), the issues related to the inventory management and the accuracy of logistics information (considered in Table 2.11 as warehouse automation) are also discussed.

- **Warehouse Automation:** De Koster and Balk (2008) measure the degree of warehouse automation according to the level of technology used (use of a computer or WMS are low levels; RFID and barcoding or robots are high levels). Banaszewska et al. (2012) assess information technology in warehouses by the number of available information systems.

The impact of the use of warehouse automation on its performance has also been addressed. Yang and Chen (2012) conclude that high levels of information systems utilization in the order selection activity should have positive influences on delivery.

2.6 Classification of the Warehouse Performance Indicators

Throughout the classification process of direct indicators, we have observed that it is neither easy to draw straight forward frontiers for them, nor are the measurements clearly defined. For example, we could see two indicators with different names but measured the same way. Conversely, some metrics have the same name but measured differently. Moreover, while in some papers the measurements are explicit, in some others only the indicator names are given.

In order to provide well defined boundaries for the direct warehouse indicators, the results presented previously in this chapter are analyzed using an activity-based framework. The indicators that are classified in Section 2.4 according to quality, cost, time and productivity dimensions, are now also classified in terms of warehouse activities described in Section 2.3.4. The result of this new classification is illustrated by Table 2.12.

In order to classify the direct indicators with respect to the warehouse activities, we defined three types of direct indicators:

- Specific Indicators: are defined specifically for an activity.
- Transversal Indicators: are defined for a process rather than a unique activity. Therefore, their boundaries are also defined for a group of activities.
- Resource related Indicators: Some indicators are related to the resources used in the warehouses. We divide them into two distinct categories: Labor and equipment/building.

Table 2.12: Direct indicators classified according to dimensions and activities boundaries.

Dimensions	**Activity - Specific Indicators**					
	Receiving	**Storing**	**Inventory**	**Picking**	**Shipping**	**Delivery**
Time	receiving time	putaway time		order picking time	shipping time	delivery lead time
Quality		storage accuracy	physical inventory accuracy; stock-out rate	picking accuracy	shipping accuracy; orders shipped on time	delivery accuracy; on-time delivery; cargo damage rate
Cost			inventory cost			distribution cost
Productivity	receiving productivity		inventory space utilization; turnover	picking productivity	shipping productivity	transport utilization
Dimensions	**Process - Transversal Indicators**					
	Inbound Processes			**Outbound Processes**		
Time	Dock to stock time			Order lead time		
	Global= Queuing time					
Quality				Order fill rate, Perfect orders		
	Global= Customer satisfaction, Scrap rate					
Cost				Order processing cost		
	Global= Cost as a % of sales					
Productivity				Outbound space utilization		
	Global= Throughput					

2.6.1 Specific and Transversal Indicators

In Table 2.12 we propose a mapping for both the specific (on the upper half of the table) and transversal indicators (on the lower half) over the warehouse activities. The activities are given on the columns. Although inventory is not a warehouse activity, we choose to include it in Table 2.12 due to its importance in warehouse management. Gallmann and Belvedere (2011) state that companies consider inventory management as a key to achieve excellent service levels. We also observe numerous metrics treating the subject (see Section 2.4). On the rows of Table 2.12, it is possible to observe the previous classification dimensions (time, quality, cost and productivity). Each direct indicator is then placed in the related cell in the table. For example, "order picking time" is a time indicator which is specific to the picking activity.

In the lower half of Table 2.12, we illustrate the direct transversal indicators. Chan and Qi (2003) have defined that the inbound logistics concern both the materials transportation and storage, while outbound logistics involve the outbound warehousing tasks, transportation and distribution. Based on this idea, the inbound process covers both Receiving and Storage activities and are named as "Inbound Processes" in Table 2.12 while Picking, Shipping and Delivery activities are regrouped under "Outbound Processes". Inventory is considered as internal process in this case linking inbound to outbound processes. The indicators are then placed according to the extent of their boundaries. For example, the transversal indicator "Dock to stock time" is classified as an inbound indicator encompassing receiving and storing activities. "Order lead time" is an outbound indicator, covering picking, shipping and delivery activities. Moreover, there are the global transversal indicators that cannot be assigned to specific activities. That is the case, for example, of "Cost as a % of sales", defined as global to all warehouse activities since its measure represents a sum of warehouse activity efforts. Second, the throughput indicator was classified as a global measure inside the warehouse, since it assesses the quantity of products that are produced by the warehouse in items per hour (VOSS; CALANTONE; KELLER, 2005), not including the delivery.

We note that the boundaries of indicators as described in Table 2.12 depend on warehouse production processes. Table 2.12 is created following a make-to-stock environment. A warehouse which operates on a no storage strategy (eg. crossdocking) may define the boundaries of the indicators differently. The operating strategies impact mainly the transversal indicators. One example is the order lead time. If a make-to-order system is considered, the customer order would start upstream (in the supply process), not at the picking activity.

Some remarks can be made on Table 2.12 based on the shown empty fields. First of all, it is important to note that the empty cells in Table 2.12 do not mean that there is no indicators to measure the activity/process. It signifies that in the literature review, no paper analyzed has used an indicator related to the activity/process. In Table 2.12, it could be seen that the receiving and storage activities are less covered than the outbound areas. This shows that the statement of Gu, Goetschalckx and McGinnis (2007) that "the research on receiving is limited", is still valid. The number of outbound indicators is higher than the number of indicators for the inbound processes. This is not very surprising as the warehouse activities are getting more and more customer oriented. So, it is possible to conclude that the outbound processes are considered as more critical than the inbound ones and hence are subject to more control. The same discussion is also true for the inventory.

2.6.2 Resource Related Indicators

Some indicators are directly related to resources used in the warehouse. Such indicators impact all warehouse activities. Therefore, instead of presenting them in Table 2.12, we choose to classify them as "resource related indicators". There are 2 major resources: labor and equipment. The facilities are considered in the same group as equipment. The related indicators are given in Table 2.13.

Table 2.13: Indicators categorized according to dimensions and support areas.

Dimensions	**Resource Related Indicators**	
	Labor	Equipment and Building
Time		Equipment downtime
Quality		
Cost	Labor cost	Maintenance cost
Productivity	Labor productivity	Warehouse utilization

Analyzing Table 2.13 we note some empty cells for time and quality dimensions. The first empty cell is labor time, which is usually utilized as a data instead of an indicator. The labor time is used to measure several productivity indicators, thus, it is not utilized in warehouses for performance indicator purposes. For the cell quality *versus* labor, it is expected because the quality of work is usually measured for each activity separately (e.g, accuracy in picking, shipping; see Table 2.12) instead of a general way. The cell equipment *versus* quality is already represented by the indicator “Equipment Downtime”.

2.7 Conclusions

Some conclusions can be made from the reported results.

Warehouse performance evaluation has been explored in different ways by researchers. In general, the works diversify a lot in terms of performance area evaluated and the measurement tool used for it. The warehouse area means the evaluation of one/various types of warehouse with focus on one/several warehouse activities. The papers’ results are usually very specific for one kind of situation. For example, works related to tobacco industry warehouse (WANG; CHEN; XIE, 2010), a DC of fresh products (MANIKAS; TERRY, 2010) or an air force warehouse (SOHN; HAN; JEON, 2007) have used different mathematical tools and indicators to evaluate performance. Other differences are in the type of warehouse studied (e.g. distribution center (DC), industrial warehouse, warehouse dedicated to cross-docking operations, third-party warehouses), requiring specific configurations by means of their product particularities, what demand different tools to solve problems.

According to Section 2.3.2 the majority of our database has performed surveys to treat warehouse performance subject. This shows a new tendency of studies in two directions: to find relationships among different warehouse performance areas (e.g. degree of automation influencing warehouse productivity (De Koster; BALK, 2008)); and the evaluation of concepts not usually expressed as ratios and, therefore, not measured yet (e.g. VAL activities (De Koster; WARFFEMIUS, 2005)).

From these papers, it can be concluded that a high degree of automation has a positive impact on the delivery accuracy and the total cost (incl. depreciation and maintenance). This result was expected; otherwise, it would be more efficient to work with people and low automation. About the use of metrics to manage the information systems (WMS, RFID) we could see that they are not applied in warehouses. The indicators about information systems are usually designated to evaluate systems on the implementation phase (based on time/resources savings). After that, the managers generally use the indexes provided by the system to evaluate all other warehouse areas. For VAL activities, the studies evaluate their growing importance in warehouse operations and determine the low value and high-end activities.

The human resources management in warehouses is an area that has attracted increasing attention in the literature. Several papers of our database treat the operational labor performance. Measured directly or indirectly, it is an important area to achieve productivity goals and customer satisfaction. One reason for the importance of this subject is reported by Park (2008) who highlights that the front-line distribution center personnel could be responsible for any task in moving products inside the distribution center. Any service failure or inefficient performance directly increases customer order cycle time and negatively impacts the level of service as perceived by the customers. It can be seen from papers' application area that the majority of researches have considered manufacturing companies, which usually employ people to execute the warehouse activities since automation is a high investment for enterprises that do not have their focus on logistics.

Even if there is a tendency for "indirect measures", they are not used for daily management since they require a great quantity of data sometimes difficult to obtain. So, direct indicators continue to be the basis for warehouse performance measurement.

The total direct indicators sum 38 measures, from which 9 of time, 13 of quality, 6 of cost and 10 of productivity. There are indicators related to one activity/area (e.g. shipping productivity) or several (e.g. dock to stock time, cost as a % of sales). Analyzing the application area of indicators (i.e. the activity measured by the indicator) we can conclude that half of them are related to outbound activities (i.e. picking, shipping and delivery). This reveals that the outbound processes/activities are considered more critical than the inbound ones and hence they are subjected to more control.

An activity-based framework is proposed to help clarifying the boundaries of the indicators. In this framework we classify indicators not only according to quality, cost, time and productivity dimensions, but also in terms of warehouse activities (receiving, storage, picking, shipping and delivery). The result of this classification shows that the number of outbound indicators is much higher than the number of inbound indicators. This is not very surprising as the warehouse activities are getting more and more customer oriented.

An important evidence we can highlight is that literature about the performance analysis and management of the Distribution Center (DC) operations is not as abundant as for the location and cooperation problems (DOTOLI et al., 2009). Indeed, we have not found literature reviews focusing specifically on warehouse performance management and its indicators.

The low attention given for warehouse performance subject leaves several gaps that should be further investigated. A complete list of them is reported in conclusions, Chapter 8. In what is related to this dissertation goal, to develop a methodology for an integrated performance evaluation, there is no work concerning the aggregation of warehouse performance measures or developing an integrated performance measurement model for warehouses. Only some works evaluating the influence of indicators on the warehouse performance (e.g. Voss, Calantone and Keller (2005), De Koster and Balk (2008)) can be reported. The next chapter details these works regarding indicator or process relationships since this dissertation also measures indicator relations. Additionally, works about performance aggregation are presented to verify the main developments made in this theme and the mathematical tools used to attain this goal.

Chapter 3

Literature on Performance Integration and Tools

On n'a jamais fait de grande découverte sans hypothèse audacieuse.

Isaac Newton

Abstract

We first present the results of the literature review about indicator relationships and performance integration. The gaps are identified as well as the mathematical tools used to associate indicators. The general characteristics of the main techniques are presented to provide theoretical basis for the methodology development.

3.1 Introduction

The objective of this Chapter is twofold: to describe works related to indicator relationships and/or performance integration and to present the mathematical tools used in these papers.

To reach the first objective, a non exhaustive literature search is performed on online databases. The keywords used are related to performance integration, performance aggregation, performance relationships and indicator relationships. Moreover, all kinds of publications (journal articles, conference proceedings, etc.) are included in the database search. Due to the great variation of objectives and applications in the papers found, we only present the most related work to this dissertation in the next sections.

The second goal of this chapter is to present the mathematical tools used in the earlier works to relate indicators or aggregate performance measures. From the articles analyzed, it is possible to identify some groups of tools utilized with distinct objectives. Therefore, a general presentation of these groups is made, with a special attention on the statistical tools used for dimension reduction, which allow the indicators aggregation.

3.2 Literature Review

3.2.1 Literature on indicator relationships and indicators aggregation

Papers that define indicator relationships are not new. It is possible to identify two main development periods on this theme. First, the papers try to identify if there are indicator relationships; then, these relationships are measured. This measurement is made qualitatively (using decision making tools such as AHP (Analytic Hierarchy Process)) or quantitatively. An example of the first period is the work of Bititci (1995), which uses a QFD matrix (Quality Function Deployment) to display how measures of different levels (strategical, tactical, operational) are influencing each other according to manager's perception. In the same work the author models the process for each strategic measure defining a Cause-and-Effect diagram to control the interactions between operations and performance results.

In the relationships measurement period, the work of Suwignjo, Bititci and Carrie (2000) develops the Quantitative Model for Performance Measurement System (QMPMS) to quantify the effects of factors on performance through the AHP utilization, which is based on manager's opinion. The three main steps of QMPMS are: (i) identifying factors that affect performance and their relationships, (ii) structuring the factors hierarchically, (iii) quantifying the effect of the factors on performance. The authors discuss that even the methodology seems intuitive; one of the problems to measure relationships quantitatively is the qualitative nature of some measures, for example, management commitment (SUWIGNJO; BITITCI; CARRIE, 2000).

An approach to overcome this issue started to be extensively used in the performance management literature some years later. This approach is the statistical techniques of measurement, which allow the

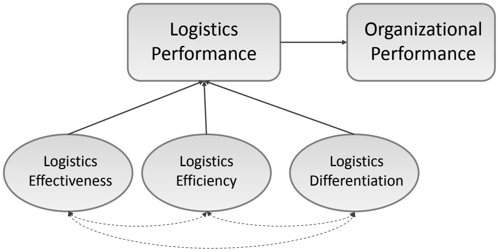


Figure 3.1: Relationships among logistics variables. Source: Fugate, Mentzer and Stank (2010)

quantitative evaluation of relationships between qualitative measures. For example, the work of Fugate, Mentzer and Stank (2010) investigates the influence of logistics performance in the organizational performance using Structural Equation Modeling (SEM) (Figure 3.1). The logistics performance is decomposed in efficiency, effectiveness and differentiation and the authors assume that all three are related. A questionnaire is performed with industry managers to obtain the necessary database for the tool application. At the end, the results suggest that the overall performance of the logistics function should produce high levels of logistics effectiveness, efficiency, and differentiation, affecting positively the organizational performance.

Another example is Cai et al. (2009), proposing a framework to analyze and to select the right key performance indicators (KPI) to improve supply chain performance. The framework assigns priorities to different KPIs and uses PCTM (KPI cost transformation matrix) to verify the cost incurred for the KPI accomplishment, considering also the extra cost caused in all other dependent KPIs. The authors interview managers and employees identifying 20 different KPIs and defining their coupled relationships. Then, the cost of each KPI accomplishment with its relationships is estimated from interviews with managers. The relationships between two dependent KPIs accomplishment costs are measured quantitatively by the following classification: weak (0,05), neutral (0,25), and strong (0,5).

Coskun and Bayyurt (2008) determine the effects of the indicator measurement frequency on managers' satisfaction of corporate performance. A questionnaire with 500 enterprises is performed to acquire opinions about indicator measurement frequency and overall corporate performance. An Exploratory Factor Analysis (EFA) aggregates performance indicators into groups according to Balanced Scorecard dimensions (Financial Measures, Customer Measures, Process Measures, Learning and Growth Measures). The relations between the measurement frequency of performance indicators and the corporate performance satisfaction is analyzed by using canonical correlation analysis.

At this moment, some researchers start to measure indicator relationships without human judgment. That is the case of Rodriguez, Saiz and Bas (2009) proposing a methodology to identify KPI relationships and projecting them on strategic objectives, to know whether the upstream objectives are being reached or not. Principal Component Analysis (PCA) is performed to quantify indicator relationships and group them according to these relations. Finally, a framework of these relationships with respect to their strategic objectives is outlined.

Patel, Chaussalet and Millard (2008) develop a methodology to demonstrate the cause and effect relationships between the components of the performance rating system. Using Structural Equation Modeling, a causal-loop diagram showing the cause and effect relationships between the 16 common performance indicators is constructed based on a data set of two years. These relationships are used to draw scenarios regarding an organization's future performance.

Johnson, Chen and McGinnis (2010) identify the operational policies, design characteristics, and attributes of warehouses that are correlated with greater technical efficiency, i.e. those factors that impact warehouse performance. The variables correlated with high efficiency are identified using a regression model and solve it using ordinary least squares. Another work using regression model to assess performance is by Kassali and Idowu (2007), which defines the factors determining the operational efficiency of onion storage and uses statistical inference to conclude the relationships among factors.

Regarding the nature of indicator relationships, it is important to highlight some classifications. Bititci (1995) defines that indicators may have simple or complex relationships; in other words, if one indicator changes this may alter one or more data items elsewhere in the information system. Suwignjo, Bititci and Carrie (2000) improve the classification of indicator relations as direct (vertical) effect (an indicator influences another of a higher level), indirect (horizontal) effect (an indicator influences another indicator of the same level), self-interaction effect (the indicator influences itself). Cai et al. (2009) classify the relationships into three categories: parallel, sequential and coupled. In a parallel relationship, two KPIs are independent of each other, i.e. the efforts of accomplishing these two KPIs are not related. A sequential relationship usually implies a simple cause-effect relationship, but the reverse dependence does not always hold. Finally, the coupled relationship means that both KPIs are dependent on each other.

3.2.2 Literature on Performance Integration

To the best of our knowledge, the term performance integration is interpreted in two different manners in the literature. Some researchers consider integrated performance as an indicator system framework which links the measures to strategy. One such example, as formulated by Chenhall and Langfield-Smith (2007), considers a pyramidal analysis with different aspects of an organization's performance (e.g. the *Tableau de Bord*) that feeds the three levels of management (strategy, management and operations). This aggregation usually deals with the translation of all the elementary performance expressions associated with the various heterogeneous criteria into a common reference (cost or degree of satisfaction) (CLIVILLÉ; BERRAH; MAURIS, 2007). In these works, usually the number of indicators from higher levels is reduced to allow managers to control just the key parameters, i.e. the key performance indicators. The literature about this kind of performance integration is significant, with several methods proposing the establishment of a performance indicator group (e.g. SCOR model - Supply Chain Operations Reference-model) or defining how the indicators should be chosen regarding company's strategy.

The second kind of performance integration, which is studied in this dissertation, refers to the performance measurement in a global view, not excluding indicators but aggregating them to find out the total performance of an area or enterprise. Franceschini et al. (2008) refer to the performance integration as the association of informations from one or more "sub-indicators" in just one aggregated and synthesized indicator. The number of papers studying performance integration according to this perception is less significant in the literature when compared to the first interpretation. The following papers are related to this second definition.

Chan and Qi (2003) develop a process-based model to measure the holistic performance of complex supply chains. They consider productivity, efficiency and utilization as composite measures since they relate inputs and outputs. A group representing various management areas of the supply chain is formed and the expert opinions are incorporated in a fuzzy model as relative weights to assess the aggregated performance.

Lohman, Fortuin and Wouters (2004) present a prototype system that basically is a balanced scorecard tailored to the needs of the company studied. After the performance indicator system determination, they suggest indicator's aggregation in one number. As each individual metric has a different dimension, the authors suggest a method for normalizing metrics linearly.

In Sohn, Han and Jeon (2007), the authors developed an Air Force Warehouse Logistics Index (WLI) to evaluate the logistics support capability of ROKAF (Republic of Korea Air Force) warehouses. Even if the main goal is not performance measurement, the constructed index takes into account relationships among various influential factors for warehouse capability. The dataset is obtained by interviews with warehouse employees and the answers are related to latent variables using Structural Equation Modeling (SEM). The six latent variables s_j, with $j = 1 \ldots 6$ influence WLI, which contributes to logistics support capability and warehouse modernization. The relationship between the overall logistics index η_i and the six observed variables y_{ij}, with i referring to each respondent is (Equation 3.1):

$$\eta_i = s_1 \times y_{i1} + s_2 \times y_{i2} + s_3 \times y_{i3} + s_4 \times y_{i4} + s_5 \times y_{i5} + s_6 \times y_{i6} \quad (3.1)$$

Luo, Liu and Shu-quan (2010) propose a hierarchical model of performance factors to assess the general logistics performance of an agricultural products distribution center. First, FAHP (Fuzzy Analytic Hierarchy Process) is used to calculate index weight, then fuzzy comprehensive evaluation method is used to get total logistics performance.

The work of Jiang, Chen and Zhang (2009) develops a theoretical indicator system of logistics performance with the objective to analyze the interactions among these performance measures and to optimize them. The dimensions of logistics performance measurement are time, quality, cost, flexibility (see Figure 3.2) and each dimension includes several indicators.

The DEMATEL method (DEcision-MAking Trial and Evaluation Laboratory method) is the utilized tool to optimize the index system and delete the indexes with small relational grade. Finally, DEMATEL is also applied to evaluate the weight of each index and the total performance of the enterprises (JIANG; CHEN; ZHANG, 2009).

Clivillé, Berrah and Mauris (2007) use the MACBETH (Measuring Attractiveness by a Categorical-Based Evaluation TecHnique) methodology as a global framework to define multi-criteria industrial performance expressions. The MACBETH procedure allows to express com-

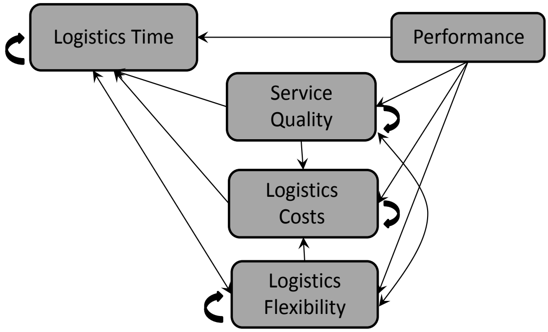


Figure 3.2: Framework to evaluate logistics performance in supply chains. Source: Jiang, Chen and Zhang (2009)

mensurate elementary performances and the relative weights of the performance measures from decision-maker's knowledge, and then to aggregate the elementary performances. Clivillé, Berrah and Mauris (2007) use MACBETH with Choquet integral operators to take into account the interactions among performances when defining the aggregated performance.

Some works try to achieve an aggregated performance measurement for benchmarking purposes. Benchmarking is essentially the process of identifying the highest standards of excellence for products, services, or processes, and then making the improvements necessary to reach those standards, commonly called best practices (De Koster; BALK, 2008). Regarding the warehouses, benchmarking is seen as the process of systematically assessing the performance of a warehouse, identifying inefficiencies, and proposing improvements (GU; GOETSCHALCKX; MCGINNIS, 2010). In these cases, DEA (Data Envelopment Analysis) is probably the most widely used mathematical approach for benchmarking of organizational units (JHA; YORINO; ZOKA, 2008).

Data Envelopment Analysis (DEA) is regarded as an appropriate tool for this task because of its capability to capture simultaneously all the relevant inputs (resources) and outputs (performances) using one single performance factor, to construct the best performance frontier, and to reveal the relative shortcomings of inefficient warehouses (GU; GOETSCHALCKX; MCGINNIS, 2010).

Some examples of this kind of works are by Schefczyk (1993), Ross and Droge (2002) and Johnson, Chen and McGinnis (2010). The recent work of Andrejić, Bojović and Kilibarda (2013) proposes to benchmark

DCs using PCA (Principal Component Analysis) before the DEA. The PCA is applied for inputs and outputs separately to reduce the number of variables for the DEA model.

It is important to highlight two main characteristics of the papers presented in this literature review. First, the majority of works develop a methodology for performance aggregation using statistical tools; however, the indicators aggregation is not included as a step before attaining the global performance. Only the work of Jiang, Chen and Zhang (2009) achieves global performance through indicator relationships. However, these relations are defined based on expert judgments. This situation demonstrates the second characteristic: the works proposing aggregated indicators to represent the global performance usually utilize methods based on expert judgments. One exception is the work of Rodriguez, Saiz and Bas (2009), which has already aggregated performance indicators in factors without human judgment. However, these factors are not yet transformed in a global performance. Hence, this dissertation comes to fulfill this gap, providing a global warehouse performance through the indicators' aggregation.

In the next sections, we present an overview on the mathematical tools used in the most relevant papers. A special attention is given to statistical tools which allow performance indicators' aggregation.

3.3 Overview on mathematical tools used for performance integration

The goal of this section is twofold: (i) to identify the most appropriate mathematical tools to attain indicators aggregation without human judgment; (ii) to provide a basic overview of these chosen mathematical tools, focusing on the requirements for their application and the interpretation of their results.

3.3.1 The choice of the dimension-reduction statistical tool

From the papers presented in the above section, we note that different kinds of mathematical tools are used to assess performance. It is possible to divide the tools in different groups: decision making tools, DEA techniques, dimension-reduction statistical tools.

There is a vast literature and numerous tools to help decision makers. Several papers treat the relationship among indicators using decision support systems. The majority of these tools interpret the manager's opinion about indicator relationships and weights in a quantitative measure. According to Rodriguez, Saiz and Bas (2009), the weakness of decision-aid methods as AHP is that they have judgments as inputs, which can be incongruent with the managerial cognitive limitations. Moreover, the objective of this dissertation is to find out relationships from the indicator equations and their data collected periodically, without manager judgment. Thus, methods which incorporate manager's opinions like AHP, FAHP (Fuzzy Analytic Hierarchy Process), DEMATEL (Decision-Making Trial and Evaluation Laboratory method), MACBETH (Measuring Attractiveness by a Categorical-Based Evaluation TecHnique) and Fuzzy are not considered in our analysis.

DEA technique is a non-parametric linear programming which enables the comparison of different DMUs (Decision Making Units), based on multiple inputs and outputs. In DEA approach, essential input and output data are selected and the set of observed data is used to approximate the Production Possibility Set (PPS). The PPS represents all input and output combinations that actually can be achieved. The boundary of the PPS is called the efficient frontier and characterizes how the most efficient warehouses trade off inputs and outputs (JOHNSON; CHEN; MCGINNIS, 2010). The efficiency is relative and relates to the set of units within the analysis, i.e. the warehouses are efficient among the other units (ANDREJIĆ; BOJOVIĆ; KILIBARDA, 2013).

Even if it is possible to use DEA to analyze just one DMU over time (another application besides the benchmarking), it does not satisfy our objectives in some aspects. Firstly, we want to define the indicator relationships to provide the managers additional information about the impacts of the decisions that are going to be taken based on performance results. DEA does not give information about input and output relationships. Secondly, the dataset (inputs and outputs of the model) used for efficiency analysis are operational data, and not the indicator results as we intend to use in this work. Therefore, DEA is also not utilized in this dissertation.

Looking at the statistical literature, the multivariate analysis has got the potential to identify relationships between variables over time, clustering them according to these relationships. Additionally, these tools can aggregate variables determining their weights and reducing the dimension of the analysis to help managers in decision-making situations.

Some techniques presented in next sections are: Principal Component Analysis, Factor Analysis, Canonical Correlation Analysis, Structural Equation Modeling and Dynamic Factor Analysis. Among these tools, only Dynamic Factor Analysis is specially designed for time series data, whereas the others have better results with other kinds of data. As an example, Hoyle (2012) cites that standard SEM approaches use variables measured on a continuous or quasi-continuous scale (e.g. 5- or 7-point response scales), or sometimes categorical data (e.g. true-false). However, the use of these tools with time series data is not forbidden, but in some cases adaptations need to be made for their application.

As these dimension-reduction tools are associated with this dissertation's proposal, they will be analyzed further in the next sections.

3.3.2 Principal Component Analysis - PCA

3.3.2.1 Objective

Principal Component Analysis (PCA) is one of the most common types of multivariate methods to identify association patterns between variables (KATCHOVA, 2013). A PCA often uncovers unsuspected relationships, allowing you to interpret the data in a new way (Minitab Inc., 2009). The main purpose is to reduce the information of many observed variables into a little group of artificial variables named components (MANLY, 2004). In PCA, the components empirically aggregate the variables without a presumed theory (WAINER, 2010).

3.3.2.2 Data characteristics

There is no specificity about the kind of data that should be used to perform PCA. The normality of data (usually required in statistical applications) is not a strict requirement specially when PCA is used for data reduction or exploratory purposes. However, some authors suggest that the PCA can provide better results if data follow a normal distribution.

The sample (dataset) is a matrix $n \times p$ with n number of observations for each p variable. Usually, the inputs come from questionnaires (each observation is a different person), but nothing prohibits the use of other types of data as, for example, time series.

There are some conditions that the dataset should satisfy (MANLY, 2004):

- the sample must be bigger than the number of variables included;
- the sample must have more than 30 observations;

- there must exist correlation among variables.

If the number of variables is greater than the number of observations, as some practical cases within the performance management context, the application of classic PCA presents problems. The solution could be to apply the NIPALS (Nonlinear Iterative Partial Least Squares) algorithm to estimate the different principal components Rodriguez-Rodriguez et al. (2010).

Besides the sample size, PCA is sensitive to great numerical differences among variables. Therefore, after the acquisition of the minimum number of observations required, it is often convenient to standardize each observation (ZUUR et al., 2003). The standardization is detailed in Chapter 4.

3.3.2.3 Basic principles

The principal components are defined in order to capture the greatest variance of the dataset. They are calculated by finding the variable eigenvalues and eigenvectors of the covariance matrix for the p variables. The eigenvalues are a numeric estimation of the variable variation explained by each component (WAINER, 2010). In the case of PCA, all variance of the observed variables is analyzed (shared, unique and error variances) (MANLY, 2004). Moreover, PCA considers that the variables comprise only linear relationships.

The PCA method essentially defines the same number of components as the quantity of variables. Since each component is perpendicular to the others, it creates a n-dimensional plot. As explained in the sequence, the number of components explaining the total dataset variance can be less than the total number of variables depending on the data characteristics.

Let us consider that Figure 3.3 demonstrates the scatter plot of indicators measured monthly. The X axis represents the time and Y axis the indicator values. The points in the graphic are the observations (indicator values) in all periods of time. In Figure 3.3, the first and second principal components are u and v, representing the first and the second greatest variance of the dataset, respectively. The u and v components are orthogonal demonstrating that they are uncorrelated to each other. It happens to all components (WAINER, 2010).

3.3.2.4 Main outcomes

From the p variables $X_1, X_2, \ldots, X_p$, each principal components $C_1, C_2, \ldots, C_p$ describes a "dimension" of data variation (MANLY, 2004).

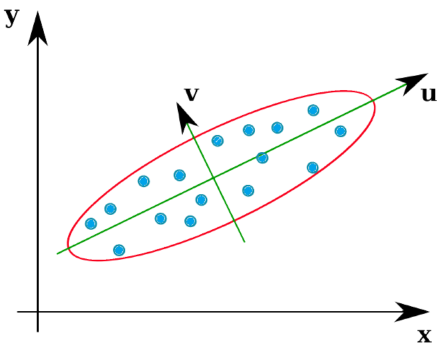


Figure 3.3: Scatter plot of the dataset with the first and second principal components.

Since each component is a linear combination of the observed variables, the principal components (C_i), combining the variables $X_1, X_2, \ldots, X_p$ have the form (Equation 3.2) (MANLY, 2004):

$$C_i = \sum_{i=1}^{p} \sum_{j=1}^{p} a_{ij} \times X_j \tag{3.2}$$

The outcome of PCA is principal components like Equation 3.2, since the maximum number of components extracted always equals the number of variables (Minitab Inc., 2009).

It is important to note, in Equation 3.2, that not all variables are included in every principal component. Just the original variables that account for the data variance explained by C_i are included in equation.

Principal components resulted from PCA are ranked in a descending order of importance, such that $Var(C_1) \geq Var(C_2) \geq \ldots \geq Var(C_p)$, where $Var(C_i)$ denotes the variance of C_i (MANLY, 2004).

The a_{ij} in Equation 3.2 are the coefficients of the variables with $i = 1, 2, \ldots, p$ and $j = 1, 2, \ldots, p$. These coefficients mean the correlation between the original variables and the component. It could be also interpreted as the relative weight of each variable in the component C_i. Thus, the bigger the absolute value of the coefficient, the more important the corresponding variable is in constructing the component (Minitab Inc., 2009). These loadings (notation used in this thesis) are optimally defined in PCA analysis to produce the best set of components which explain the maximum variation of the observed variables.

The loadings have the constraint presented in Equation 3.3. The squared loadings indicate the percentage of variance of an original variable explained by a component.

$$\sum_{i=1}^{p}\sum_{j=1}^{p} a_{ij}^2 = 1 \quad and \quad a_{ij} \in \Re \tag{3.3}$$

In summary, the procedure to implement PCA is:

- Data acquisition and standardization;
- Enter data (in the form of covariance or correlation data matrix) in a software which performs PCA (e.g. Minitab, AMOS, R (free software));
- Run the model to obtain the components;
- Interpretation of results.

3.3.2.5 Interpretation of the results

An important part of PCA is the interpretation of the results and its main task is to determine the number of principal components that will be retained to represent data. There is a need to retain an appropriate number of components based on the trade-off between simplicity (retaining as few as possible) and completeness (explaining most of the data variation) (KATCHOVA, 2013). Usually, the first few principal components are chosen to represent of the original data (GENTLE, 2007).

One of the PCA objectives is to explain the maximum amount of variables variance in a small number of components. If a component variance is low, it is possible to neglect this component. However, the results are not always easily interpretable. To help with this decision, there is the Kaiser's criterion. Kaiser's rule determines that principal components with eigenvalues bigger than 1 ($\lambda > 1$) should be retained. The eigenvalues of the correlation matrix are equal to the variances of the principal components, thus, eigenvalues measure the amount of variation represented by each component.

The scree plot can also help in PCA interpretation. This graphic shows the variance of the data (y axis) explained by each component (x axis) (see Figure 3.4 for an example). The principal components are sorted in decreasing order of variance, so the most important principal component is always listed first. The objective is to help analysts to visualize the relative importance of the components, identifying easily the sharp drop in the plot as a signal that subsequent components should be ignorable. Thus, in the example of Figure 3.4, components 1 up to 4 have a significant contribution in the explanation of data variance.

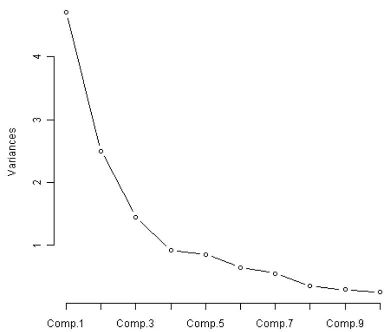


Figure 3.4: Scree Plot example.

It is also possible to decide on the number of principal components based on the amount of explained variance. For example, you may retain components that cumulatively explain 90% of the variance.

Finally, the decision on the number of principal components retained can be based on any of the two techniques presented above or even on a combination of them.

Even if the presented techniques provide a useful basis to choose the number of components, the analyst should know that all components must be interpretable (RODRIGUEZ-RODRIGUEZ et al., 2010). Since the components are synthetic variables which do not have a specific unit of measurement, it is important to find their meaning in the analysis carried out.

3.3.3 Factor Analysis - FA

3.3.3.1 Objective

Factor Analysis (FA) is widely used to analyze data because users find the results useful for gaining insight into the structure of multivariate data (MANLY, 2004). Factor analysis has aims that are similar to those of Principal Component Analysis, i.e. describe data in a far smaller number of dimensions compared to the original number of variables. Essentially, both Factor Analysis and Principal Component

Analysis summarize variables considering linear relationships between them.

The main difference between PCA and FA is that PCA is not based on any particular statistical model whereas FA is based on a model (MANLY, 2004). It means that Factor Analysis assumes the existence of a few common factors driving the data variation and Principal Component Analysis does not make such assumptions (KATCHOVA, 2013). Moreover, PCA uses all types of variance to estimate components whereas FA utilizes only the shared variance to define the factors.

There are two most common factor analysis methods: EFA (Exploratory Factor Analysis) and CFA (Confirmatory Factor Analysis). The EFA is used to search possible underlying structures in the variables while CFA's goal is to confirm with the data a predefined structure based on theoretical hypotheses.

An extension of the FA is the multiple factor analysis, which analyzes several data tables at the same time. These tables measure sets of variables collected on the same observation or the same variables are measured on different set of observations (for details, see Abdi, Williams and Valentin (2013)).

3.3.3.2 Data characteristics

There are some conditions to perform CFA:

- sample bigger than 150 observations for each variable, or the sample size should have 5 times the number of variables;
- no missing value (observation);
- data distribution may be normal;
- the observations (in a same variable) may be independent.

The last condition limits the utilization of time series as inputs in the model.

3.3.3.3 Basic principles

The FA model postulates that the observable random variable vector $\mathbf{X}$ (with p observations) is linearly dependent upon a few unobservable random factors $F_1, F_2 \ldots, F_m$ and p additional sources of variation $\varepsilon_1, \varepsilon_2 \ldots, \varepsilon_p$ called errors or specific factors (JOHNSON; WICHERN, 2002).

The dimensions (or factors) are formed by the combination of observed variables highly correlated. The objective is to identify the latent dimensions contained in data; i.e. to group the variables in dimensions that represent them. The explanation degree of each variable in each dimension is determined by the factor loadings.

3.3.3.4 Main outcomes

The representation of the factors is given by Equation 3.4 (JOHNSON; WICHERN, 2002).

$$X_i = b_{i1} \times F_1 + b_{i2} \times F_2 + \ldots + b_{im} \times F_m + \varepsilon_i \tag{3.4}$$

where F_j is the common factor and $j = 1, 2, \ldots, m$; b_{ij} are the factor loadings of the ith variable on the jth factor; X_i are the variables with $i = 1, 2, \ldots, p$; ε_i is the variation of X_i that is not explained by the factors F_j.

The factor loadings are measured by the FA model, representing how much a factor explains a variable. High loadings (positive or negative) indicate that the factor strongly influences the variable whereas low loadings (positive or negative) indicate a weak influence. It is necessary to examine the loading pattern to determine on which factor each variable loads. Some variables may load on multiple factors (Minitab Inc., 2009).

The communality (represented by h_i^2 in Equation 3.5) is the proportion of variance in $\mathbf{X}$ attributable to the common factors (KATCHOVA, 2013), i.e. it assesses the quality of the measurement model for each variable (KRIZMAN; OGORELC, 2010). Communality is measured by the sum of squares of the loadings of the ith variable on the m common factors (Equation 3.5)(JOHNSON; WICHERN, 2002):

$$h_i^2 = b_{i1}^2 + b_{i2}^2 + \ldots + b_{im}^2 \tag{3.5}$$

The higher the communality value, the more the variable is explained by common factors. This parameter is also used in the analysis of FA results as well as loadings. For example, Krizman and Ogorelc (2010) define in their paper that variables with a loading of less than 0.75 and communality less than 0.40 were discarded.

Some steps to perform Factor Analysis are, according to Costa (2006), as follows:

- Data Inputs (should be standardized).

- Calculates the correlation matrix of variables.

- Perform first a PCA and verify the number of factors that should be used (analyzing what kind of data each factor represent), when one does not know the variables' behavior.

- Rotation of factor loading. This procedure (using e.g. Varimax rotation) rotates the factor to get the higher number of factor loadings as possible. It helps to interpret the results, clarifying which variables should be part of each factor.

3.3.3.5 Interpretation of the results

A common tool used to provide visual information about the factors is the scree, or eigenvalue, plot (graph of factors versus the corresponding eigenvalues). From this plot, you can determine how well the chosen number of components fit the data.

Furthermore, if there is a subgroup of variables already known (e.g. individual, products, enterprises) the factor analysis can be measured separately for each group; it can avoid the designation of variables from different natures in the same factor.

Finally, the difficulty to interpret the variable clusters of the unrotated factor loadings can be overcome with their rotation, which simplifies the loading structure, allowing the analyst to more easily interpret the results. The goal of factors rotation is to find clusters of variables that, to a large extent, define only one factor (KATCHOVA, 2013).

There are two kinds of rotation: orthogonal and oblique. The orthogonal rotation preserves the perpendicularity of the axes (rotated factors remain uncorrelated). The oblique rotation allows the correlation between the rotated factors, and the main method is the Promax rotation (KATCHOVA, 2013). It corresponds to a nonrigid rotation of coordinate axes leading to new axes that are not perpendicular (JOHNSON; WICHERN, 2002).

There are four methods to orthogonally rotate the initial factor loadings (Minitab Inc., 2009):

- Equimax - maximizes variance of squared loadings within both variables and factors.

- Varimax - maximizes variance of squared loadings within factors (i.e. simplifies the columns of the loading matrix); the most widely used rotation method. This method attempts to make the loadings either large or small to ease interpretation.

- Quartimax - maximizes variance of squared loadings within variables (i.e. simplifies the rows of the loading matrix).

- Orthomax - rotation that comprises the above three depending on the value of the parameter gamma (0-1).

Nevertheless, Johnson and Wichern (2002) affirm that the choice of the type of rotation is a less crucial decision. For them, the most satisfactory factor analysis are those in which rotations are tried with more than one method and all the results substantially confirm the same factor structure.

3.3.4 Canonical correlation analysis - CCA

3.3.4.1 Objective

Canonical Correlation Analysis (CCA) is a method for exploring the relationships between two multivariate sets of variables. CCA is similar to multiple regression in assessing variable relationships. The main difference is that multiple regression allows only a single dependent variable whereas CCA analyzes multidimensional relations between multiple dependent and independent variables (COSKUN; BAYYURT, 2008). Therefore, CCA has, as main objective, to measure the relationships within each variable set, independent and dependent, and also between both (VOSS; CALANTONE; KELLER, 2005). For the purposes of this thesis, we are interested in the measurement of relationships between variable set.

3.3.4.2 Data characteristics

Canonical correlation analysis is not recommended for small samples. Moreover, multivariate normal distribution assumptions are required for both sets of variables (UCLA, 2012). Unlike Principal Components Analysis, standardizing the data has no impact on the canonical correlations.

3.3.4.3 Basic principles

The aim of CCA is to find a linear combination of the independent (or predictor) variables such that the outcomes has the maximum correlation with the dependent (or criterion) variable (JOHNSON; WICHERN, 2002).

To demonstrate how this result is attained, let us consider two set of variables X and Y, with p variables in X and q variables in Y. As in Principal Component Analysis, the objective is to look at linear combinations of the data, named U and V. U corresponds to the linear combinations of the first set of variables, X (Equation 3.6), and V corresponds to the second set of variables, Y (Equation 3.7) (PENNSTATE, 2015b). For computational convenience, it is defined that the number of variables in each set is $p \leqslant q$.

$$\begin{aligned} U_1 =& a_{11} \times X_1 + a_{12} \times X_2 + \ldots + a_{1p} \times X_p \\ U_2 =& a_{21} \times X_1 + a_{22} \times X_2 + \ldots + a_{2p} \times X_p \\ &\vdots \\ U_p =& a_{p1} \times X_1 + a_{p2} \times X_2 + \ldots + a_{pp} \times X_p \end{aligned} \tag{3.6}$$

$$\begin{aligned} V_1 =& b_{11} \times Y_1 + b_{12} \times Y_2 + \ldots + b_{1q} \times Y_q \\ V_2 =& b_{21} \times Y_1 + b_{22} \times Y_2 + \ldots + b_{2q} \times Y_q \\ &\vdots \\ V_q =& a_{q1} \times Y_1 + b_{q2} \times Y_2 + \ldots + b_{qq} \times Y_q \end{aligned} \tag{3.7}$$

Each member of U will be paired with a member of V, forming the canonical variates. Canonical dimensions, also known as canonical variates, are latent variables that are analogous to factors obtained in factor analysis. In general, the number of canonical dimensions is equal to the number of variables in the smaller set; however, the number of significant dimensions may be even smaller (UCLA, 2012).

For example, (U_1, V_1) is the first canonical variate and the objective is to find the coefficients $(a_{i1}, a_{i2}, \ldots, a_{ip}$ and $b_{i1}, b_{i2}, \ldots, b_{iq})$ of the linear combinations that maximize the correlations between the members of each canonical variate pair (PENNSTATE, 2015b). The canonical correlation (R_c) for the i_{th} canonical variate pair is given by the covariance (cov) of the canonical variate pair per the square root of variances (var) of U_i and V_i (Equation 3.8):

$$R_c = \frac{cov(U_i, V_i)}{\sqrt{var(U_i)var(V_i)}} \tag{3.8}$$

3.3.4.4 Main outcomes

The output of canonical correlation consists of two parts, canonical functions and canonical variates. Each canonical function is composed of two canonical variates, one independent and one dependent. The independent and the dependent canonical variates represent, each one, the optimal, linear and weighted combination of the variables that correlate highly (VOSS; CALANTONE; KELLER, 2005).

The correlation between the independent and dependent variates in each function is assessed by the canonical correlation coefficient (R_c) and the shared variance between the functions is assessed by the squared canonical correlation coefficient (R_c^2). Multiple canonical functions are then derived that maximize the correlation between the independent and dependent canonical variates, such that each function is orthogonal to all others (VOSS; CALANTONE; KELLER, 2005).

3.3.4.5 Interpretation of the results

Two main analytical findings can be secured from CCA results: (i) the evaluation of how many dimensions (canonical variables) are necessary to understand the association between the two sets of variables; (ii) to explore the associations among dimensions and how much variance is shared between them (PENNSTATE, 2015b).

To interpret each component, we must compute the coefficients (also named loadings) between each observed variable and the corresponding canonical variate (UCLA, 2012). The magnitudes of the loadings give the contributions of the individual variables to the corresponding canonical variable.

3.3.5 Structural Equation Modeling - SEM

3.3.5.1 Objective

Structural Equation Modeling (SEM) is a growing family of statistical methods for modeling the relations between variables. The method is also known as Covariance Structural Equation Modeling (CSEM), Analysis of Covariance Structures, or Covariance Structure Analysis (HOYLE, 2012).

SEM is appropriate for complex, multivariate data and testing hypotheses regarding relationships among observed and latent variables, the two broad classes of variables in SEM (KLINE, 2011).

3.3.5.2 Data characteristics

To perform SEM, it is necessary to be aware that the sample size and number of parameters to be estimated can make SEM unadvisable. Several estimation issues arise in SEM when the number of variables measurement occasions, T, exceeds the number of participants, N and some alternatives have been developed to handle this kind of data (CHOW et al., 2010). There is no firm decision rule for the minimum sample size for SEM, but several authors suggest that at lower sample sizes, typically below 150, structural models with latent variables become unreliable. Furthermore, there are similar advices against the use of SEM in cases where the ratio of sample size to estimated parameters is less than 10 (AUTRY et al., 2005). In cases where there is a relatively small sample size, the threshold values for factor loadings and communalities are, sometimes, increased, and Partial Least Squares Regression (PLS) is usually employed to assess the measurement model (KRIZMAN; OGORELC, 2010).

Some dataset requirements to apply SEM are (BENTLER; CHOU, 1987):

- Independence of observations - if not, there is serial correlation among the responses;
- Identical distribution of observations;
- Simple random sampling - each of the units or cases have the same probability to be included in the sample to be studied;
- Functional form - all the relations among variables are linear.

According to these requirements, estimating a structural equation model using time series data raises the issue of autocorrelated errors. There are methods for accommodating autocorrelated errors in structural equation models, but they are complex and will not make part of the scope of this dissertation.

3.3.5.3 Basic principles

SEM comprises the ability to construct latent variables: variables which are not measured directly, but are estimated in the model from several measured variables. SEM requires a theoretical model specification before its application. Thus, as the Confirmatory Factor Analysis (CFA), an accurate estimation of the latent variables depends on the quality of the theoretical model constructed. The test of the structural model constitutes a confirmatory assessment of the hypothesized causal relationships among the constructs (KRIZMAN; OGORELC, 2010).

The theoretical model of SEM can have numerous configurations. Initially, the model can have variables that are dependent and independent in the same model. For instance, a set of observed variables might be used to predict a pair of constructs (or latent variable) that are correlated, uncorrelated, or related in such a way that one forms the other. In the latter case, one of the dependent variables is also an independent variable since it is used to predict another dependent variable (HOYLE, 2012).

Another configuration of theoretical models regards the construct specification (i.e. the aggregation method used to define the latent variables) which can be classified as reflective or formative measurement model (JUNG, 2013). A formative construct refers to an index of a weighted sum of variables, i.e. the measured variables cause the construct. In the reflective construct, the latent variable causes the measured variables.

Figure 3.5 shows the reflective construct model represented by the path diagram, which is a graphical representation of direct and indirect effects of observed and latent variables. In this model, Y and X are the latent variables operationally defined by the measured variables y_1, y_2, y_3 and x_1, x_2, x_3, x_4, respectively. The parameters to be estimated are denoted by asterisks (HOYLE, 2012).

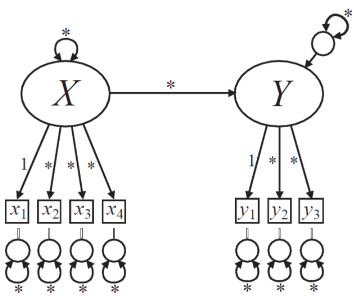


Figure 3.5: SEM model example (HOYLE, 2012).

3.3.5.4 Main outcomes

The path analysis, essentially:(i) helps in the understanding of correlations patterns among the variables; (ii) explains as much of the variable variation as possible with the model specified. In summary, after the definition of the theoretical model, it is tested using the dataset of the observed variables and the results will infer about whole hypothesized model: if it should be rejected, modified, or accepted (CHEN, 2011).

There are two general causal modeling approaches to model measurement: the covariance-based method and the partial least squares (PLS). Covariance-based methods are more appropriate for confirming theory and parameter estimation, and require large samples sizes with normal distribution. PLS, in contrast, is more appropriate when theory is lacking regarding the nature of relationships among constructs, dimensions and their indicators for prediction purposes (FUGATE; MENTZER; STANK, 2010).

3.3.5.5 Interpretation of the results

The interpretation of path coefficients cannot be done straightforward (KLINE, 2011). The higher the correlation among multiple indicators of a given construct, the more consistent i.e., reliable, the measures. However, they are not correlation coefficients. Suppose we have a network with a path connecting from region A to region B. The meaning of the path coefficient theta (e.g., -0.16) is this: if region A increases by one standard deviation from its mean, region B would be expected to decrease by 0.16 its own standard deviations from its own mean while holding all other relevant regional connections constant.

3.3.6 Dynamic Factor Analysis - DFA

3.3.6.1 Objective

Dynamic factor analysis is a special case of MARSS Model (Multivariate Autoregressive State Space Model). State-Space modeling techniques are originally developed as single-subject time series estimation tools (CHOW et al., 2010), studying linear stochastic dynamics systems (HOLMES; WARD; SCHEUERELL, 2014).

DFA can be looked at as a “super” regression model especially designed for time-series data with outcomes of dimension-reduction techniques (ZUUR; TUCK; BAILEY, 2003). Instead of examining correlates of a single summary metric (i.e. an output), DFA can provide information on correlation (explanatory variables) of patterns that emerge over time (HASSON; HEFFERNAN, 2011). Thus, DFA explains temporal variation of a set of n observed time series (variables) using linear combinations of m hidden trends (or common trends), where $m << n$ (HOLMES; WARD; SCHEUERELL, 2014).

3.3.6.2 Data characteristics

Although DFA has potential as a useful analysis technique, it often takes an unusually long time to converge (often exceeds several hours as larger the dataset and the number of common trends). The results also tend to become inconsistent with such large data sets (HOLMES; WARD; SCHEUERELL, 2014). Therefore, DFA brings good results when n (number of observed variables) is big and the number of time observations is small.

Besides the short dataset, DFA also accepts non-stationary time series with missing values (ZUUR; TUCK; BAILEY, 2003).

3.3.6.3 Basic principles

Dynamic Factor analysis manages to combine, from a descriptive point of view (not probabilistic), the cross-section analysis through Principal Component Analysis (PCA) and the time series dimension of data through linear regression model (FEDERICI; MAZZITELLI, 2005). DFA models observations in terms of a trend, seasonal effects, a cycle, explanatory variables and noise (ZUUR et al., 2003).

A limitation of DFA is that the common trends are combined in a linear fashion, and the explanatory variable regressions are linear as well. Therefore, nonlinear interactions between the components of the model are ignored (HASSON; HEFFERNAN, 2011).

3.3.6.4 Main outcomes

A DFA model has the following structure (HOLMES; WARD; SCHEUERELL, 2014):

$$\begin{aligned} \mathbf{x}_t &= \mathbf{x}_{t-1} + \mathbf{w}_t \quad \text{where} \quad \mathbf{w}_t \sim MVN(0, \mathbf{Q}) \\ \mathbf{y}_t &= \mathbf{Z}\mathbf{x}_t + \mathbf{a} + \mathbf{v}_t \quad \text{where} \quad \mathbf{v}_t \sim MVN(0, \mathbf{R}) \\ & \qquad\qquad\qquad\qquad x_0 \sim MVN(\pi, \Lambda) \end{aligned} \tag{3.9}$$

The general idea presented in Equation 3.9 is that the observed variables (y) are modeled as a linear combination of hidden trends (x). Then, the data entered into the model (y) is explained by some common trends (x). The factor loadings (Z) are used, as in PCA, to determine the variables that will be aggregated in each common trend. Other terms in Equation 3.9 are matrices with the following definitions (see Holmes, Ward and Scheuerell (2014) for a detailed explanation):

$\mathbf{w}$ is a $m \times T$ matrix of the process errors. The process errors at time t are multivariate normal (MVN) with mean 0 and covariance matrix $\mathbf{Q}$.
$\mathbf{v}$ is a $n \times T$ column vector of the non-process errors. The observation errors at time t are multivariate normal (MVN) with mean 0 and covariance matrix $\mathbf{R}$.
$\mathbf{a}$ are parameters and are $n \times 1$ column vectors.
$\mathbf{Q}$ and $\mathbf{R}$ are parameters and are $m \times m$ and $n \times n$ variance-covariance matrices.
π is either a parameter or a fixed prior. It is a $m \times 1$ matrix.
Λ is either a parameter or a fixed prior. It is a $m \times m$ variance-covariance matrix.

There are three ways of estimating factor loadings in DFA: (i) use Maximum Likelihood Function (MLE) and the Kalman Filter (KF); (ii) use Principal Components Extraction; (iii) combination of the two first. According to Montgomery and Runger (2003), MLE is one of the best methods of obtaining a point estimator of a parameter. The estimator will be the value of the parameter that maximizes the likelihood function.

The Kalman filter is an algorithm for calculating the expected means and covariances of the observed values for a whole time series in the presence of observation and process error. In its original form it works only for models that are linear (exponential increase or decrease or expected constant population size over time) with multivariate normal error; the extended Kalman filter uses an approximation that works for nonlinear population dynamics (BOLKER, 2007).

3.3.6.5 Interpretation of the results

Finally, interpretation of DFA results may not be straightforward. The DFA model uses hypothetical latent variables (the common trends) that are deemed to be responsible for the observed patterns; however, no information is provided as to what these variables are. Adding explanatory variables to the model could help with interpretation, but this increases complexity and does not always improve the model. In general, one must keep in mind that when using advanced techniques such as DFA, extra care may be needed when interpreting results (HASSON; HEFFERNAN, 2011).

3.4 Conclusions

This chapter is divided in two: the presentation of the literature about indicator relationships and aggregated performance; the explanation of mathematical tools to aggregate indicators.

From the literature, the main conclusions we can take from papers are: the works carrying out indicators aggregation does not use their results to achieve the global performance; and, papers usually aggregate performance using tools which incorporate human judgments. Furthermore, we have seen a tendency in papers to combine different mathematical tools to reach their objectives.

These conclusions demonstrate a clear gap in the literature and this dissertation seeks to fulfill it, providing an integrated warehouse performance measurement through indicators' aggregation.

To achieve our goal, it is necessary to investigate the statistical tools that are used for dimension reduction. They are introduced in a summarized manner, since the objective of the explanations is to allow the reader to recognize the characteristics and the requirements to apply each technique. In Chapter 4, these methods are then evaluated according to the requirements of the proposed methodology, determining the ones that can be used in our studied problem.

The knowledge basis constructed in this chapter is used to develop our proposal methodology, which is presented in the next chapter.

Chapter 4

Methodology to define an Integrated Warehouse Performance

Science is not about making predictions or performing experiments. Science is about explaining.

Bill Gaede

Abstract

This chapter presents the methodology to assess an integrated warehouse performance. The methodology is divided in four main areas (conceptualization, modeling, model solving, implementation and update), which are introduced in this chapter.

4.1 Introduction - General methodology presentation

According to Suwignjo, Bititci and Carrie (2000), with the large number of multidimensional factors affecting performance it is impossible to manage a scale system for each different dimension of measurement. So, integrating those multidimensional effects into a single unit can facilitate the trade-off between different measures.

The proposed methodology, presented throughout this chapter, presents an integrated performance model to overcome issues related to the interpretation of a large quantity of indicators measured in warehouses for performance management. Initially, the methodology is introduced from a general point of view, being deeply detailed throughout the sections.

In Chapter 1, the dissertation's methodology is classified as quantitative modeling research. For this kind of research, Mitroff et al. (1974) propose the work development in four phases: conceptualization, modeling, model solution and implementation. We use the same four phases to present our developed methodology (Figure 4.1).

It is apparent in Figure 4.1 that the proposed methodology is dynamic. The "implementation and update" phase can be seen, at a first glance, as the end of the methodology application. However, if a situation changes in the warehouse, the proposed model needs to be reviewed, and the methodology starts again by the conceptualization phase, closing the loop.

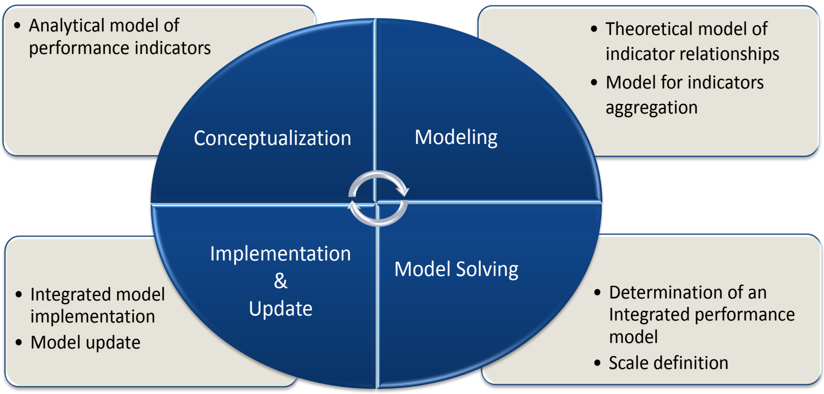


Figure 4.1: The proposed methodology phases with their main steps. Source: Adapted from Mitroff et al. (1974).

Figure 4.1 demonstrates the main outcomes inside of each phase in order to achieve and implement the integrated performance model. The Conceptualization phase results in an analytical model of performance indicators for the warehouse. Once the analytical model is defined, the Modeling phase defines the relationships among indicators and how they can be aggregated using different mathematical tools. Then, the Model Solving phase analyzes the results obtained in the previous phase, proposing an integrated performance model with a scale to evaluate and interpret the results. The last phase, Implementation and Update, describes the integrated model implementation in a company as well as how to update it.

To perform the proposed methodology, Figure 4.2 shows the process flow, detailing the steps carried out in each methodology phase (the dotted rectangles of Figure 4.2). Each step is explained in the next sections.

In summary, the first phase, Conceptualization, comprehends the determination of the methodology application boundaries, i.e. in which warehouse areas the performance will be measured and the indicators used for that. It means that, to perform the methodology, it is necessary to define the areas where the performance will be assessed and the indicator set used by the company to achieve it. These indicators need to be known in terms of their equations, since the analytical model is formed basically by this group of equations.

Once the analytical model is developed (last step of conceptualization in Figure 4.2), it is necessary to acquire data from indicators. This data is the time series of indicator results, which are measured periodically in the enterprise. From this step, two analyses can be carried out in parallel: the determination of indicator relationships theoretically and the use of historical data to perform indicators' aggregation. The theoretical model is defined from the Jacobian matrix measurement, which is detailed in Section 4.3.2 and the indicators' aggregation are achieved from dimension-reduction statistical tools (Section 4.3.3).

From the results of the mathematical tools application, a quantitative model of indicator relationships is constructed. It is denominated the aggregated performance model, which provides as outcome the global warehouse performance. Because the performance values obtained from these aggregated indicators cannot be interpreted straightforwardly, it is necessary to create a scale for them. Finally, the implementation step demonstrates the model utilization for periodic warehouse management and the update defines when the methodology needs to be revised.

The following sections describe how to perform each step detailedly.

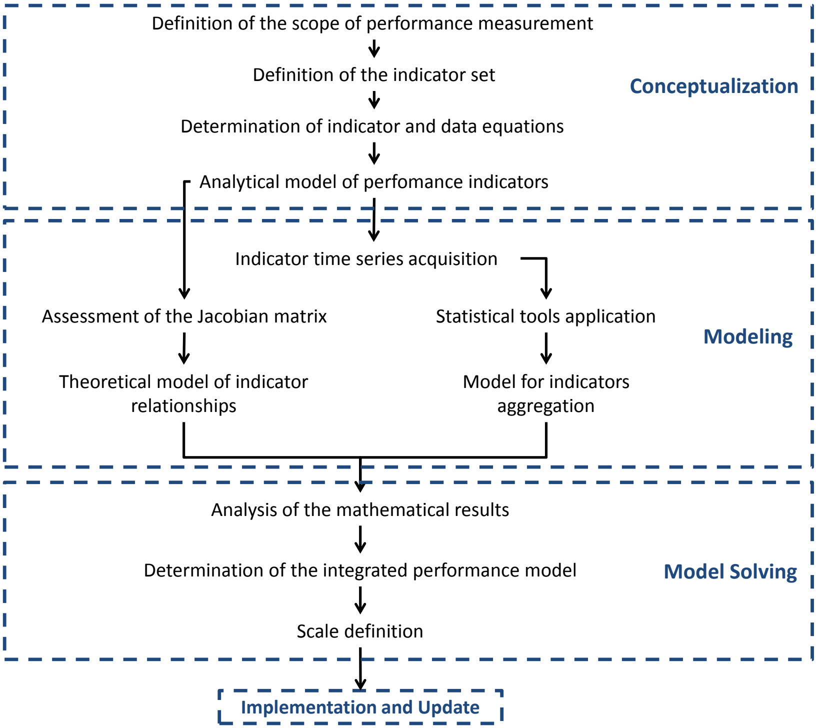


Figure 4.2: Methodology steps flow.

4.2 Conceptualization - The analytical model of performance indicators

The conceptualization phase involves the definition of the performance measurement system. For this methodology purposes, it is necessary to perform three steps: the scope of measurement, the definition of a metric set and, the determination of indicator equations, which creates the analytical model (see Figure 4.2).

It is really difficult to determine an evaluation model for distinct objectives, since each enterprise (and, consequently, its warehouse) has specificities linked to different processes/ activities. Moreover, the performance measurement has become a strategic tool for corporations to observe their weaknesses and act in a way to minimize them; so, it needs to be designed and evaluated in a consistent way to be effectively managed (RODRIGUEZ; SAIZ; BAS, 2009). Regarding the warehouse objectives, they are usually defined to improve the whole supply chain performance, and this make the choice of an evaluation model crucial in a networked organization. In fact, Fabbe-Costes (2002) states that all actors should create value for chain partners; however, sometimes this is difficult to achieve because the actors use different performance evaluation systems that are almost impossible to reconcile.

Besides the different warehouse objectives and processes, the performance measurement systems should also satisfy some conditions such as (MANIKAS; TERRY, 2010): inclusiveness (measurement of all related aspects), universality (allow for comparison under various operating conditions), measurability (data required are measurable) and consistency (measures consistent with organization goals).

There are methodologies in the literature enabling to define a set of performance indicators based on strategic goals (FERNANDES, 2006). Since the literature on this subject is vast and the amount of indicators utilized in the process shall be carefully determined, the definition of the indicators forming the warehouse metric system is out of this dissertation's scope. In order to keep a large spectrum of applications for our methodology, we consider that indicators utilized for warehouse management are derived from enterprise's strategy, being sufficient to perform the methodology.

Regarding the steps of the conceptualization phase, we describe the approach as follows:

Step 1: The scope of measurement is related to the warehouse activities/areas where the performance will be measured. Kiefer and Novack (1999) state that the complexity of the measurement systems increases as the number of activities performed by the warehouse increases. The proposed methodology considers that all warehouse activities can be included in the measurement scope. However, the manager could have no interest in the evaluation of some specific activities in an aggregated manner, denoting the importance of manager's participation in the definition of the measurement scope.

Step 2: After the definition of the methodology application boundaries, it is necessary to determine the indicators set used for performance measurement. According to Melnyk, Stewart and Swink (2004), the term "metric" is often used to refer to one of three different constructs: (i) the individual metric; (ii) the metric set; and (iii) the overall performance measurement systems. For the methodology application, the metric set is the group of indicators already used by the warehouse to manage its activities.

Steps 3 & 4: Even if some indicators from higher levels are generally related to the ones of lower levels (BÖHM; LEONE; HENNING, 2007), in this thesis we aggregate only the operational metric set (i.e. the set of individual operational indicators). As our objective is to find a good statistical representation of indicator relationships based on internal warehouse data, it is important to consider indicators mostly influenced by other internal indicators. The same does not happen to tactical and strategical indicators, which are usually related to financial, market tendencies and customer demand.

There is no limit on the number of performance indicators considered for aggregation, but some constraints must be satisfied: the indicators need to be measured in a quantitative way, i.e. there are equations to describe them; historical data of measurement is necessary to consider the indicator in the methodology, since this data will be used to model indicators' aggregation.

Example: Although this methodology is generic, it is better explained through an example. Let us consider that a warehouse measures six indicators $I_1, I_2, I_3, I_4, I_5, I_6$, which are defined quantitatively by the equations:

$$I_1 = A + B; \quad I_2 = C + D; \quad I_3 = E - F; \quad I_4 = G/A; \quad I_5 = C/B; \quad I_6 = J/H \tag{4.1}$$

where $A, B, C, D, E, F, G, H, J$ are quantitative data measured periodically in the warehouse.

These quantitative indicators described in form of equations represent one part of the analytical model. The second part comes from data equations. It is necessary to define data equations because sometimes collected data are calculated from other subdata, and this information will be necessary to find theoretically the relationship between indicators. In our example, we consider that J data is calculated according to Equation 4.2, and all other data have no relation with each other.

$$J = A + G \tag{4.2}$$

Thus, the final analytical model for this example comprehends Equations 4.1 and 4.2.

The next section presents the modeling phase, which includes data acquisition, the definition of indicator relationships and their aggregation.

4.3 Modeling

4.3.1 Data acquisition

The required data to apply the proposed methodology are time series of indicators, i.e. indicator values measured periodically by the warehouse. We define time series data as a moderate number of measurements made on a single individual and on a repeated context (TOIT; BROWNE, 2007). Initially, the number of measurements collected for the same indicator (i.e. the dataset size) should be as long as possible and available in the company. For instance, for the example described in Section 4.2, indicator's time series are measured monthly in the warehouse as shown in Table 4.1, and the unit of each indicator is demonstrated in parenthesis.

Table 4.1: Examples of indicator time series

Month	I_1 (min)	I_2 (%)	I_3 (\$/order)	I_4 (order/h)	I_5 (%)	I_6 (\$/month)
1	10	98	10	5	2	100
2	12	97	9	6	1.5	120
3	14	99	9	8	1	130
4	12	97	11	6	2	110
5	15	98	12	7	1.5	100
6	13	99	10	8	2	120
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Since the indicators are very heterogeneous with regard to their measurement units (\$, time, %, etc.), Rodriguez, Saiz and Bas (2009) suggest three operations to be applied on raw data: filtering, homogenization and standardization. The filtering analyzes the abnormal behavior of the dataset; homogenization puts all data in the same temporal frequency (it is necessary when some indicators are measured in weeks and others in months, for instance); standardization provides an auto-scaled and dimensionless data. A usual technique utilized to standardize data is demonstrated in Equation 4.3 (GENTLE, 2007):

$$X_{new} = \frac{X_{actual} - X_{mean}}{\sigma_X} \tag{4.3}$$

where X_{new} is the new value of the variable, X_{actual} is the real variable value, X_{mean} is the time series mean of the variable dataset, σ_X is the standard deviation of the variable time series.

The final dataset form a matrix of data filtered, homogenized in frequency and standardized, and ready for application of the proper mathematical techniques for identifying relationships between indicators. The matrix is similar to Table 4.1, with the measurement date shown in rows and the indicators separated by columns.

Depending on the statistical tool utilized (Section 4.3.3), there may be some limitations on the dataset to perform the statistical tools.

For instance, some statistical tools may require the dataset to follow a normal distribution. To verify it, Newsom (2015) suggests to examine the skew and kurtosis of univariate distributions. Kurtosis is usually a greater concern than skewness, but the literature only recommends special analysis if skewness > 2 and kurtosis > 7. If the univariate distributions are non-normal, the multivariate distribution will also be non-normal. One reason for non-normality is the presence of outliers in the dataset. In this case, the reason of the outliers shall be examined, to eliminate the ones generated by typeset errors, for instance.

Another requirement of some statistical tools is the non-existence of missing values. In a first moment it is not recommended to fill in the missing values by other ones generated (for instance, there is a technique where the missing value is replaced by the time series mean). As there are softwares to perform the statistical methods, usually they take care automatically of this kind of issue, deleting the matrix line to eliminate the missing values.

Once the data is collected and treated, they are ready to be the inputs of mathematical techniques described in next sections.

4.3.2 Theoretical model of indicator relationships

The quantitative relationships among indicators are the results from different variations and effects of warehouse processes occurring at the same time. We could verify two main forms of relationships: the effects of chained processes and of data shared among indicators.

The effect of chained processes is the impact of one performance indicator on the other one that corresponds to the next activity in the process chain. For example, if an order is shipped with delay, probably the delivery indicators (like delivery on time) will be influenced by this problem. So, one intervention in the system can cause a delay chain for the rest of the process. However, the delay can be compensated by a great productivity of the next operations, and at the end the order is delivered on time. Due to the variability of the cases, this kind of relationship is not considered in the theoretical model construction.

The effect of data shared among indicators considers that two indicators are related through the number of data they have in common. The main idea of this effect is that if two indicators have in common one or more data, they have some kind of relationship because once the data change, both indicators will be impacted, changing in some way. This circumstance defines a relationship between two indicators. For example, labor productivity and scrap rate use the same data, products processed, in their measurement (Section 5.2 shows the indicator equations). If products processed change, both indicators will also change. It is important to note that the variation intensity is not necessarily the same in the concerned indicators. So, the data shared by indicators just suggest indicator relationships but not their intensity.

By the use of an analytical model, the data (and subdata) used in all indicator equations can be easily verified. Thus, the analytical model defined in Section 4.2, with indicator and data equations, is used as an input to assess indicator relations based on data sharing. To certify the indicators which share similar data we calculate the Jacobian Matrix.

The Jacobian is a matrix of partial derivatives that is used to determine the output/input relationship (MONTGOMERY; RUNGER, 2003). In other words, the Jacobian is a partial derivative matrix of the n outputs with respect to the m inputs. Each matrix cell gives the sensitivity of the output with respect to one input variation, maintaining the other inputs constant.

So, for a function $f : S \subset \mathbb{R}^m \rightarrow \mathbb{R}^n$ we define $\partial f/\partial x$ to be the $n \times m$ matrix (GENTLE, 2007). To meet the methodology's purpose, we derive all functions f (indicator equations) with respect to their data inputs x as shown in Equation 4.4.

$$J = \frac{\partial f}{\partial x} = \begin{array}{c} \\ \text{outputs} \end{array} \overbrace{\begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \cdots & \frac{\partial f_1}{\partial x_m} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \cdots & \frac{\partial f_2}{\partial x_m} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_n}{\partial x_1} & \frac{\partial f_n}{\partial x_2} & \cdots & \frac{\partial f_n}{\partial x_m} \end{bmatrix}}^{\text{inputs}} \tag{4.4}$$

Equation 4.4 results in a $n \times m$ matrix where n is the outputs (indicators) and m the number of inputs (independent data). The independent data refers to the non-combined data used to calculate indicators. In the example defined in Section 4.2, the independent data inputs used to assess the indicators (outputs) are A, B, C, D, E, F, G, H. The data J is out of this list because it is calculated from the sum of A

and G (Equation 4.2), resulting in an aggregate data. For this example, the final Jacobian Matrix is (after partial derivatives calculation of indicator equations I):

$$J = \frac{\partial I}{\partial data} = \begin{array}{c} \begin{array}{cccccccc} \mathbf{A} & \mathbf{B} & \mathbf{C} & \mathbf{D} & \mathbf{E} & \mathbf{F} & \mathbf{G} & \mathbf{H} \end{array} \\ \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 & 0 & 0 \\ -G/A^2 & 0 & 0 & 0 & 0 & 0 & 1/A & 0 \\ 0 & -C/B^2 & 1/B & 0 & 0 & 0 & 0 & 0 \\ 1/H & 0 & 0 & 0 & 0 & 0 & 1/H & -(A+G)/H^2 \end{bmatrix} \end{array} \begin{array}{c} \\ \mathbf{I_1} \\ \mathbf{I_2} \\ \mathbf{I_3} \\ \mathbf{I_4} \\ \mathbf{I_5} \\ \mathbf{I_6} \end{array} \tag{4.5}$$

In the Jacobian matrix detailed in Equation 4.5, the non-zero cells signifies that a change in the data (input) will impact the indicator(s) (output). Therefore, it is possible to identify the indicators which share data analyzing each matrix column. For example, the column A has three non-zero cells, a_{11}, a_{41} and a_{61}, representing that this data influence the indicators 1, 4 and 6, respectively. Since these three indicators share data A, we conclude that indicators 1, 4 and 6 have some kind of relationship.

Analyzing all data columns of the Jacobian matrix provide insights about indicator relationships in an innovative way, without considering human judgments nor possible dataset issues when used in statistical analysis of relationships (since the dataset can contain imperfections as outliers or bias). Chapter 6 demonstrates in detail with an application how to perform Jacobian matrix analysis.

From the methodology steps of Figure 4.2, the development of the theoretical analysis of indicator relations occurs in parallel with the model for indicators' aggregation. This last one is discussed in next section.

4.3.3 Statistical tools application

The objective of applying statistical tools is to group indicators based on their correlation and data variation. The statistical tools available to achieve the objective of dimension-reduction are the ones presented in Chapter 3.

Before the application of dimension-reduction methods, the correlation matrix of indicators is calculated from standardized time series data. The objective is twofold: correlation matrix is used as input of dimension-reduction tools and it gives a first impression on the strength of indicator relationships.

It is important to emphasize that the relationship between the variables are described as causal, meaning that it is explicitly recognized that a change of value in one variable will lead to a change in another variable (BERTRAND; FRANSOO, 2002). However, it is not possible to identify crossed relationships from correlation results, as this technique carries out pair-wise comparisons between pairs of indicators instead of analyzing all indicators at the same time (RODRIGUEZ; SAIZ; BAS, 2009).

After obtaining the correlation matrix, statistical tools are applied to reduce data dimensionality creating factors/components/trends (the denomination depends on the method used), which represent a group of indicators. As presented in Chapter 3, each statistical tool has some requirements to allow its utilization. To assign data characteristics with the mathematical tools requirements, Table 4.2 is built. It is divided in two parts: the right side lists the requirements demanded by each method to be applied, according to the data and sample characteristics presented on the left-side table. The objective of Table 4.2 is to evaluate the suitable tools to be applied in the methodology, as shown on the last column of the right-side table.

Table 4.2: Mathematical tools evaluation

Data Characteristics
1. Data is a time series
2. There are no missing values
3. Data is non-stationary
4. Normality of data
5. Big sample size ($\geqslant 150$)
6. Small sample size
7. Data is categorical
8. Standardized data
9. Independence of observations

Math Tool	Requisites to be applied	Could be used in the proposed methodology?
FA	Item 2, 4, 5, 7, 8, 9	NO
SEM	Item 4, 5, 7, 9	NO
CCA	Item 4, 5	NO
PCA	Item 2, 8	YES
DFA	Item 1, 3, 6	YES

The mathematical tools analyzed in Table 4.2 are Factor Analysis (FA), Structural Equation Modeling (SEM), Principal Component Analysis (PCA), Canonical Correlation Analysis (CCA) and Dynamic Factor Analysis (DFA).

FA and SEM demand a lot of data requirements, but the main issues impeding their utilization are the big sample size (Item 5) and the independence of observations (Item 9). Regarding the sample size, Rodriguez-Rodriguez et al. (2010) affirm that indicators are dynamic as well as the PMS (Performance Measurement System), and enterprises usually do not have large stores of data. They could keep financial registers from lots of years but it is not a normal practice for other PMS measures. The SEM method has a measurement model less restrictive regarding the sample size. Fugate, Mentzer and Stank (2010) state that PLS (Partial Least Squares Regression - SEM measurement model) is often applied for analyzing constructs because it accepts small sample sizes with no data distribution requirements, as normality. However, our methodology proposes the use of time series as model inputs, and this kind of data cannot fit the condition of observations' independence.

Moreover, to apply Factor Analysis and Structural Equation Modeling methods, it is also necessary to specify an initial model, i.e., to establish which are the observed variables, the error terms as well as their possible relationships (RODRIGUEZ; SAIZ; BAS, 2009).

Therefore, FA and SEM are not initially considered as options for our methodology. Even if there are some mathematical adjustments in FA and SEM model to overcome the independence of observations problem, allowing their utilization with time series data (for instance, see Choo (2004), Toit and Browne (2007), Wang and Fan (2011)), these applications are suggested for future researches.

In the case of CCA, the variables are initially classified in a specific group, and then, the correlation between variables and groups are calculated in order to obtain the highly correlated linear combinations of variables (WESTFALL, 2007). Even if it is possible to roughly affirm that the CCA results are quite similar of PCA and DFA (i.e. to group variables according to their similarities), we do not include the CCA as an option for our methodology since there is no idea about which variables (in our case the indicators) can be classified on the dependent and independent groups. Also, as big samples are required to apply CCA, its utilization in our methodology are limited for the same reasons presented for FA and SEM.

The techniques which can be used in our methodology are PCA and DFA. Both of them could be used to determine indicator groups even if the techniques display some differences. PCA is optimal to find linear combinations that represent the original set of variables as well as possible, capturing the maximum amount of variance from the original variables (WESTFALL, 2007). In the case of DFA, besides it is particularly designed for small and non-stationary time series, this technique models the time series (variables) in terms of a trend, seasonal effects, a cycle, explanatory variables and noise (ZUUR et al., 2003), and the variables with similarities in these aspects are grouped together (called common trend).

Getting back to the generic example started in Section 4.2, a possible result from the dimension-reduction tool application (PCA or DFA) is illustrated in Figure 4.3. Taking the indicators defined in Section 4.2, the dimension-reduction tool will separate them according to their correlations.

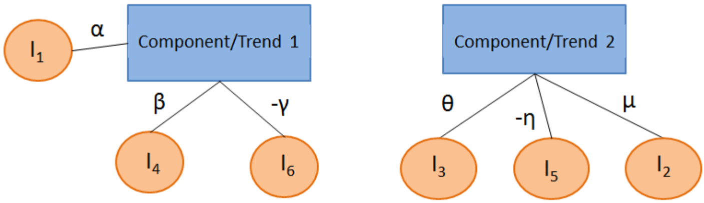


Figure 4.3: Hypothetical PCA or DFA result: indicators grouped in components/trends.

Figure 4.3 shows a hypothetical result whereas the indicators are aggregated in two different trends or components (the name will be in accordance to the tool applied). The coefficient of each indicator (α, β, γ, θ, η, μ) represents the relative weight between the original variable ($I_1, \ldots, I_6$) and the component/trend. The results from Figure 4.3 can be described in form of Equations 4.6.

$$\begin{aligned} Component/Trend_1 &= \alpha I_1 + \beta I_4 - \gamma I_6 \\ Component/Trend_2 &= \theta I_3 - \eta I_5 + \mu I_2 \end{aligned} \tag{4.6}$$

The analysis of this result is discussed in the next section.

4.4 Model Solution

4.4.1 Integrated Performance proposition

This step of the proposed methodology comprehends the analysis of all mathematical results achieving an integrated performance model at the end. The mathematical tools analyzed are: Jacobian matrix , correlation matrix and PCA or DFA result.

Initially, the main objective is to define which indicators should make part of the aggregated model and which ones should be discarded. The theoretical model of indicator relationships (the Jacobian matrix) and the correlation matrix may be evaluated together to verify indicators that should be excluded because they will not fit well the dimension-reduction statistical tool. For instance, if the Jacobian matrix demonstrates that an indicator does not share data with any other and, in the correlation matrix, the correlation coefficients "r" (named Person's r) are low (e.g. values lower than 0,3), we can conclude that the indicator should be excluded from the model. After the exclusion of one indicator, it is suggested to perform the PCA or DFA once again for the new indicator group.

In our theoretical example, the mathematical tools analyzed are the Jacobian matrix (Equation 4.5) and the PCA/DFA result (Equation 4.6). From the Jacobian matrix we conclude that indicator I_3 has no relation with the indicator group, since it does not share any data with other indicators. Moreover, let us consider that the correlation matrix presents as the maximum correlation coefficient (Person's r) for indicator I_3, $r = 0,3$. Therefore, both results (Jacobian and Correlation) recommend to discard this indicator because it does not make part of the indicator's group which relates among them.

The exclusion of I_3 requests a new application of PCA method (Figure 4.3 shows the first result), which hypothetically has the following new outcome (Figure 4.4 and Equation 4.7). The exclusion of I_3 has improved the result, since all the indicators are explained now by just one component/trend in the new outcome. Equation 4.7 shows the final result. It is important to note that the indicators' coefficients have also changed due to the modification of the dataset with the I_3 exclusion.

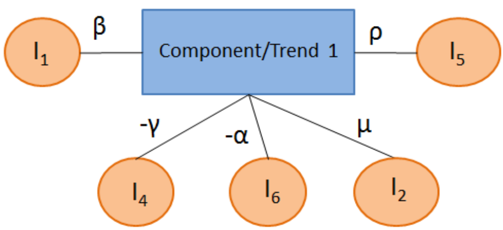


Figure 4.4: Hypothetical result after exclusion of indicator I_3.

$$Component/Trend_1 = \beta I_1 + \mu I_2 - \gamma I_4 + \rho I_5 - \alpha I_6 \tag{4.7}$$

Equation 4.7 represents the integrated performance model for the example carried out throughout this chapter. However, if the number of indicators is high, usually it is difficult to aggregate all measures in just one component. Generalizing the result of Equation 4.7, a generic model representing several components can be described by Equation 4.8, from Manly (2004).

$$C_i = \sum_{j=1}^{m} b_{ij} X_j \qquad \forall \ \ i = 1, \ldots, n \tag{4.8}$$

where:
C_i = principal components
$b_{11} \ldots b_{nm} \in \Re$ = relative weight of each variable ($X_1, \ldots, X_m$) in the corresponding component ($C_1, \ldots, C_n$)
$X_1 \ldots X_m$ = performance indicators.

The integrated performance model presented in Equation 4.8 can be implemented in the company and used for daily management. For that, each component needs a scale to allow the interpretation of results, since the inputs are normalized indicators, producing components without units. Analyzing the global performance of a warehouse using different components without physical units can be difficult for managers because of their subjectivity.

Therefore, we propose an aggregated expression for the component's equations. There are several methods to achieve this global expression. Lohman, Fortuin and Wouters (2004) state that aggregation can be done directly if the underlying metrics are expressed in the same units of measure, which can be achieved after a normalization, for example. Clivillé, Berrah and Mauris (2007) cite some examples of methods as the weighted mean, which is the more common aggregation operator; the weighted arithmetic mean; and the Choquet integral aggregation operator, which generalizes the weighted mean by taking mutual interactions between criteria into account.

Taking the components of Equation 4.8 and aggregating them using the weighted mean, the result is shown in Equation 4.9.

$$GP = a_1 \times C_1 + a_2 \times C_2 + a_3 \times C_3 + \ldots + a_n \times C_n \tag{4.9}$$

where:
GP = global performance (integrated indicator).
$a_1 \ldots a_n \in \Re$ = component weights.
$C_1 \ldots C_n$ = principal components which group X_1 up to X_m in linear combinations.

The determination of the component weights depends on several factors. Firstly, depends upon the aggregation formula. For example, the criteria in a weighted mean and in a weighted geometric mean would not be the same (CLIVILLÉ; BERRAH; MAURIS, 2007). Secondly, the relative importance of the indicators should be considered. Each warehouse will have different results of indicator aggregation which requires an analysis of the indicators grouped in each component to define their weights (some indicators could be more important than others). Lastly, the weights depend upon the warehouse strategy. Each warehouse has different objectives and can rank component's weight according to its priority.

The company can choose to stop the solution method in the component level (Equation 4.8) or build the integrated indicator (Equation 4.9). In both situations, the results of component's expressions or integrated indicator must be interpretable. One way to achieve it is creating a scale, which is presented in next section.

4.4.2 Scale definition

A scale determines the maximum and minimum values reached by a variable. It can be used to develop interview instruments in an organized way, verifying some hypothesis from the data. For example, Chen (2008) uses a six-item scale to measure the operational performance of a manufacturing plant after different levels of lean manufacturing practice. However, the scale is used in our work as a reference point to evaluate the results of given variables, which are the principal components (Equation 4.8) and the integrated indicator (Equation 4.9).

Jung (2013) states that the four main types of scale are: nominal scales (categorical: only attributes are named), ordinal scales (rankings: attributes can be ordered), interval scales (equal distances corresponding to equal quantities of the attribute), and ratio scales (equal distances corresponding to equal quantities of the attribute where the value of zero corresponds to none of the attributes). The scale developed for our purpose is the interval one, as there is not a fixed "zero" and ratios cannot be expressed.

Regarding the different measurement units of indicators (time, %, etc.), Rodriguez, Saiz and Bas (2009) propose the auto-scaled technique, which combines centering and standardization. The scale is built for each variable independently, using its mean and standard deviation to define the lower and an upper scale limits. One potential problem of the auto-scaled technique is that it does not allow the comparison among different variables, because each of them has a distinct scale.

The work of Lohman, Fortuin and Wouters (2004) proposes the normalization method to create the same scale range for different indicators. The authors determine a linear $0 - 10$ scale. Two steps need to be taken for normalizing the metric scores (LOHMAN; FORTUIN; WOUTERS, 2004): (1) the definition of the metric score range that corresponds to the $0 - 10$ scale; (2) the normalization of the scores to a $0 - 10$ scale, since the values $0 - 10$ should always have the same meaning, regardless the metric observed.

For the component expressions (Equation 4.8) it is not possible to use this kind of procedure since indicators may have opposite objectives (e.g. the productivity wants high values whereas time aims for the lower ones), complicating the target definition.

One possible solution is the use of optimization methods to define the best warehouse performance. It facilitates the inclusion of different indicator goals in the same model as well as all warehouse operation constraints.

The proposed scale using optimization seems a good option to evaluate the integrated indicator compared with an objective/goal. The development of this scale is presented in Chapter 7.

4.5 Implementation and Update

4.5.1 Integrated model implementation

The implementation consists of demonstrating the equations that may be maintained and refreshed for periodic management, and how the integrated results should be interpreted.

The expressions that will be used by the manager for warehouse performance measurement are Equations 4.8 and 4.9. Other equations from the analytical model are not used once the aggregated model is achieved. It is important to note that the coefficients 'a_i', 'b_{ij}' are real constants in Equations 4.8 and 4.9.

The objective of the integrated model is to be used as any other indicator system, being measured periodically and analyzed according to a given objective. To attain this, the integrated model should be refreshed as follows:

1. Calculate the indicator values in their original units of measure;
2. Standardize these indicator values according to Equation 4.3;
3. Replace these standardized indicators in component Equations 4.8, obtaining the component values;
4. These component results are used in Equation 4.9 to obtain the integrated indicator value.

These steps can be easily automatized on a spreadsheet to facilitate manager's work.

This procedure should be done periodically (preferably with the same periodicity of the performance indicator measurements) allowing to follow the evolution of the integrated indicator throughout time. As all operational performance indicators are also measured, it is possible to identify significant changes in indicators which alter the aggregated one. Moreover, the developed scale provides the warehouse performance limits; if the manager evaluates this integrated indicator periodically he is aware of the warehouse performance progress.

Before the implementation, it is important to confirm with the managers that the results from the aggregated model and the scale fit the warehouse reality. If it is confirmed, the analytical model and aggregated performance expressions are validated by the reality.

4.5.2 Model update

The aggregated model cannot be considered as a static entity: it must be maintained and updated to remain relevant and useful for the organization (LOHMAN; FORTUIN; WOUTERS, 2004). However, some authors cite that the literature has not yet satisfactorily addressed the issue of how performance measures should evolve over time (i.e. be flexible) in order to remain relevant with the constant evolution of organizations (KENNERLEY; NEELY, 2002; NEELY, 2005).

Regarding this situation, our methodology proposes a periodic reevaluation of the integrated performance model. This reevaluation encompasses mainly the selection of the metrics with their equations, the application of statistical tools (PCA, DFA) in a new dataset to compare the results, and the revision of component's weights in the integrated indicator equation.

The aggregated performance model, which emerges from the proposed methodology, has a life cycle and is only valid as long as the internal and external environment remains stable. For example, new business areas or new challenges require a revision of the model. A periodic revision of the model can help with this identification. It is important to recognize these changes as soon as possible to redefine the quantitative basis of the model. This practice is also used in other PMS proposed in the literature (e.g. Suwignjo, Bititci and Carrie (2000)). The model redefinition encompasses the comparison of desired performance indicators with existing measures (to identify which current measures are kept, which existing measures are no longer relevant, and which gaps exist so that new measures are needed) (LOHMAN; FORTUIN; WOUTERS, 2004).

4.6 Methodology implementation on this thesis

The methodology presented in this chapter explains the steps that should be done to attain an integrated performance model. In order to provide a general methodology, different alternatives of mathematical tools/ methods are presented without determining, in some cases, a specific one to be applied. That is the case of: indicator equations definition (each warehouse should define its indicator set); the dimension-reduction statistical tool (PCA or DFA); the final aggregated model (using just component equations or also the aggregated indicator), the criterion for scale optimization (the constraints depend on warehouse situation). Therefore, the methodology provides a customized integrated model for each warehouse, according to its choices.

Before starting the implementation of the methodology in next chapters, we present an overview of the methodology application on this thesis. Figure 4.5 depicts the activities performed (numbered from 1 up to 21) to achieve the aggregated model for the studied warehouse.

Figure 4.5 shows the phases of the methodology in green dotted rectangles (Conceptualization, Modeling, Model Solving, Implementation and Update). The blue rectangles highlight the main outcomes of each phase with their activities written in black.

The implementation of this methodology is performed in a theoretical manner, meaning that we define a standard warehouse (activity 1) as the object of the study, and the performance indicators are taken from the literature to manage the fictitious warehouse. The equations

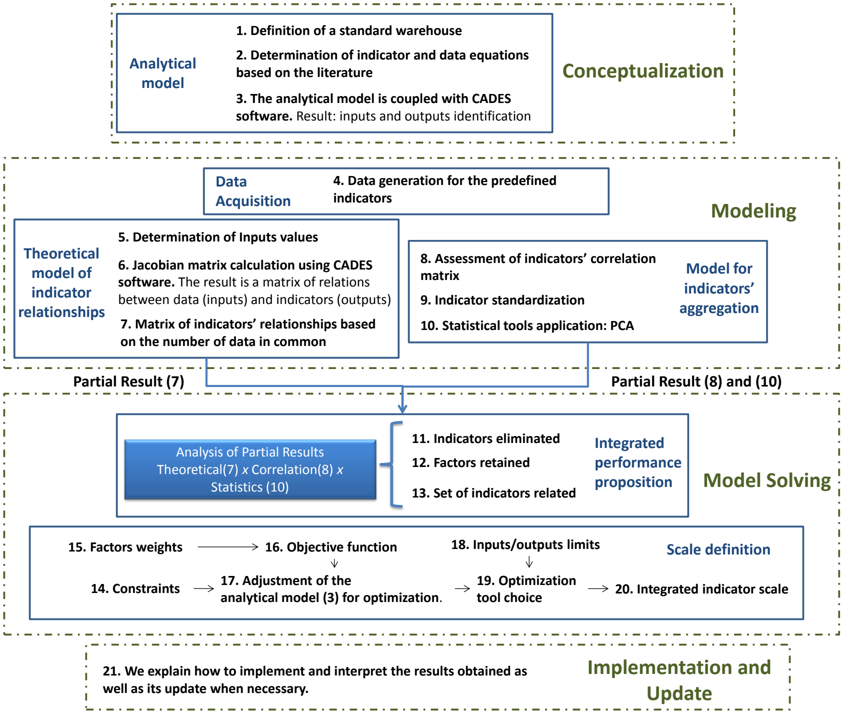


Figure 4.5: Methodology application in this dissertation.

for these indicators are a result of the literature interpretation, based on metric's definition (activity 2). The final group of equations form the analytical model, which is coupled with the software CADES® (Component Architecture for the Design of Engineering Systems). We use this software to analyze the analytical model, providing the independent inputs and outputs (activity 3) and calculating the Jacobian matrix (activity 6).

To apply the statistical tool, a dataset is necessary. We generate data to calculate indicators periodically reproducing the warehouse dynamics (activity 4). This data is used for the next steps: theoretical model of indicator relations and aggregated model. For the first one, just a sample is used to calculate the Jacobian matrix automatically using CADES® (activity 5). For the second one, the dataset created is standardized (activity 9) to be used as input of the dimension-reduction statistical tool.

Regarding the application of statistical tools, the correlation matrix is calculated (activity 8) as well as the PCA method (activity 10). Both results with the indicator relationships matrix (activity 7) are analyzed to provide insights about the behavior of the indicators. The PCA and DFA have been tested to aggregate indicators. For the DFA, results do not fit with the objective of this thesis. Further study needs to be developed and it is proposed as future research (for details about the first results obtained see Appendix F). In the case of PCA, good results are attained and it was the chosen method to determine indicator groups. Moreover, it is simple to apply and interpret, which are interesting characteristics for industrial applications.

The partial results (7, 8 and 10) are analyzed to define the integrated performance model with a global indicator (activities 11, 12, 13). The integrated indicator scale is defined using an optimization model (activities 14 up to 20). The application finishes with an explanation of the model utilization for periodic management and when its update is necessary (activity 21).

4.7 Conclusions

This chapter presents a methodology to define an integrated warehouse performance model. It consists of several steps to analyze indicator relationships from different points of view, using distinct mathematical tools to group these indicators according to their correlation and proposing an expression which aggregates them in a unique measure.

The proposed methodology encompasses different disciplines to achieve the aggregated model: the analytical model and the Jacobian matrix measurement to analyze indicator relationships; the statistical tools to propose indicator groups; the optimization method to develop the scale for the integrated indicator. This multidisciplinary approach permits a good model construction to manage warehouse performance.

The methodology is general; it gives several alternatives that one can choose when developing the integrated model. Each warehouse can present different objectives, processes, particularities, and the fact of not specifying the tools allows the adaptation of the methodology for specific situations.

The next chapters detail the methodology implementation.

Chapter 5

Conceptualization

The question is not what you look at, but what you see.

Henry David Thoreau

Abstract

This chapter performs the Conceptualization phase of the methodology. It begins by presenting the studied standard warehouse, with its characteristics and processes (i.e., the scope of the work). Thereafter, the metric system used to measure the warehouse performance is defined, based on the literature review. To determine the first part of the analytical model, formed by indicator equations, indicator definitions are interpreted in detail. Finally, the data of all indicators are expanded into new equations; then, the complete analytical model is constituted of indicators and data equations.

5.1 Introduction - the Standard Warehouse

This chapter is the starting point to implement the methodology presented in Chapter 4, establishing the basis of an integrated performance model. All steps needed to develop an analytical model of performance indicators are carried out: the definition of the performance measurement scope; the determination of the indicator set; the formulation of indicators and data equations.

Warehouses can have different configurations according to the product specification, customer requirements, service level offered, etc. The scope of this implementation is on a hypothetical warehouse, named standard warehouse (shown in Figure 5.1). The denomination "standard" is due to the processes carried out on it. We consider the main operational activities performed by the majority of warehouses, which are (Section 2.3.4 presents their definitions): receiving, storing, internal replenishment, order picking, shipping and delivery. Thus, the performance measurement is carried out on the warehouse shop floor, also including the delivery activity.

Figure 5.1 details not only the boundaries of the activities carried out in the standard warehouse but also its layout and the measurement unit limits of the performance indicators, both explained in the sections 5.1.1, 5.1.2.

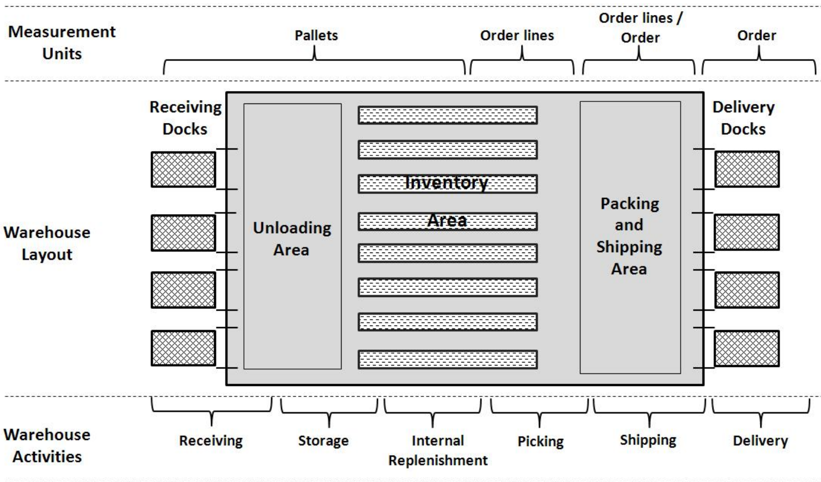


Figure 5.1: The standard warehouse.

5.1.1 Warehouse Layout

The layout of the standard warehouse is shown in the middle part of Figure 5.1 with the following regions: receiving docks for truck assignment, unloading area, inventory area, packing and shipping area, delivery docks.

Since the majority of warehouses have intensive handling activities in order picking (De Koster; LE-DUC; ROODBERGEN, 2007), this warehouse follows a manual system for storing and picking products. In the manual system, the order picker/forklift driver has to store products in a proper location (in case of storage activity) or localize and pick the searched products in racks (in case of order picking).

We consider that this facility supplies the market with a make-to-stock production. In a make-to-stock operation, the customer orders launch a process in the picking area, going up to the product delivery to the client.

The inventory area of Figure 5.1 comprehends the reserve storage area and the forward picking area. The reserve area contains the bulk stock and it is located in superior rack levels. The forward picking area is situated in the same racks of bulk stock, but in the inferior levels to facilitate order picking process. So, this configuration implies in regular internal replenishments from the reserve to the forward picking area.

The inbound area of the warehouse encompasses the receiving of trucks until the storage of products in inventory area, and the outbound area comprises the replenishment activity performed from the inventory area up to the delivery of the product to the client.

5.1.2 Measurement Units of Performance Indicators

The top of Figure 5.1 demonstrates the boundaries of measurement units used to calculate warehouse performance indicators in this dissertation. The units are: pallets, order lines and order.

A "customer order" or simply "order" (as described in this work) is an individual customer request to be fulfilled by the warehouse. It generally includes product specificities and the quantity of each one (JOHNSON; CHEN; MCGINNIS, 2010). "Order lines" are the number of different product types in a customer order. Each line designates a unique product or stock keeping unit (SKU) in a certain quantity (De Koster; LE-DUC; ROODBERGEN, 2007). A pallet refers to the products transported on it, with the quantity and kind of products varying from one pallet to another.

Each measurement unit described in the top of Figure 5.1 is related to the indicator units in one or more warehouse activities. For example, in receiving, storage and internal replenishment, the operations are measured in "pallets". Similarly, "order lines" is the unit for picking indicators and "order" is the standard measure for delivery indicators.

The exception is the shipping activity, where both "order lines" and "order" are used to measure shipping indicators. Packing and shipping are transition areas, in which some indicators are related to internal operations (e.g. labor performance in shipping activity) whereas others are customer-oriented (e.g. orders shipped on time).

As each part of the warehouse uses a specific unit of measure (for instance, pallets, orders), we also define a smaller unit related to a single item, named “product” or “SKU”(stock keeping unit). This distinct notation is used in more general indicators, measuring several activities (e.g., Stock out rate, Equation 5.40) or the whole warehouse (e.g., Labor productivity, Equation 5.9).

5.2 Analytical model of Indicator Equations

5.2.1 Definition of the metric set

After the definition of the warehouse characteristics, the metric system used for performance measurement needs to be defined. Keebler and Plank (2009) study the logistics measures most commonly used by the managers in the US industry. The results show some preference for the indicators such as the outbound freight cost, the inventory count accuracy, the finished goods inventory turn and the order fill. However, the authors conclude that there is not a consensus of a group of measures used to assess warehouse performance.

The methodology presented in Chapter 4 determines that the indicators used to develop the integrated model need to come from strategic goals of the enterprise. As our standard warehouse is theoretical, we consider that its operational metric system comes from the analysis of strategical goals.

Regarding the indicator requisites, the methodology defines that they need to be quantitatively measured, i.e. it is necessary to describe them in equations. Thus, the metric system is defined from the direct indicators resulting from the literature review, which are presented in Table 2.12 and Table 2.13, of Chapter 2.

Comparing Tables 2.12 and 2.13 with the warehouse characteristics, we can see that not all warehouse areas contain indicators (e.g. there are no indicators related to the replenishment). Moreover, some indicators related to specific activities are missing. That is the case of productivity indicators, for example. Table 2.12 shows productivity indicators related only to receiving, picking and shipping activities.

Therefore, we make some adjustments in the initial group of indicators taken from the literature which result in the indicators presented in Table 5.1. To maintain consistency among the warehouse activities, indicators related to internal replenishment, not verified in literature review but also important for warehouse management, are added to the metric set. Furthermore, quality and productivity indicators for receiving and storage activities are also considered in the final indicator group.

From the literature, we can infer that the cost indicators are not so frequently used for warehouse management as quality or productivity indicators. The cost indicators found in papers are more global and usually related to several activities, demonstrating that costs are analyzed in managerial levels. One reason for that could be that the operational objectives of the warehouse are usually related to process performance due to the intensive work-handling (e.g. lead time reduction, quality improvements) instead of cost measures. For these reasons, we have not included new cost indicators related to specific activities as we made in quality, time and productivity dimensions.

Table 5.1: Final warehouse performance indicators group.

Dimension	**Activity - Specific Indicators**						
	Receiving	**Storing**	**Inventory**	**Replenishr**	**Picking**	**Shipping**	**Delivery**
Time	$\mathbf{Rec_t}$	$\mathbf{Put_t}$		$\mathbf{Rep_t}$*	$\mathbf{Pick_t}$	$\mathbf{Ship_t}$	$\mathbf{Del_t}$
Quality	$\mathbf{Rec_q}$*	$\mathbf{Sto_q}$	$\mathbf{Inv_q}$, $\mathbf{StockOut_q}$	$\mathbf{Rep_q}$*	$\mathbf{Pick_q}$	$\mathbf{Ship_q}$, $\mathbf{OTShip_q}$	$\mathbf{Del_q}$, $\mathbf{OTDel_q}$
Cost			$\mathbf{Inv_c}$				$\mathbf{Tr_c}$
Productivity	$\mathbf{Rec_p}$	$\mathbf{Sto_p}$*	$\mathbf{InvUt_p}$, $\mathbf{TO_p}$	$\mathbf{Rep_p}$*	$\mathbf{Pick_p}$	$\mathbf{Ship_p}$	$\mathbf{Del_p}$*, $\mathbf{TrUt_p}$
Dimension	**Process - Transversal Indicators**						
	Inbound Process				**Outbound Process**		
Time	$\mathbf{DS_t}$				$\mathbf{OrdLT_t}$		
Quality					$\mathbf{OrdF_q}$, $\mathbf{PerfOrd_q}$		
	$\mathbf{CustSat_q}$, $\mathbf{Scrap_q}$						
Cost					$\mathbf{OrdProc_c}$		
	$\mathbf{CS_c}$, $\mathbf{Lab_c}$, $\mathbf{Maint_c}$						
Productivity							
	$\mathbf{Th_p}$, $\mathbf{Lab_p}$, $\mathbf{WarUt_p}$, $\mathbf{EqD_p}$						

* The symbol denotes indicators added after the literature review analysis.

In contrary of the indicator additions, some others listed in the metric system of Chapter 2 are not included in Table 5.1 since more general metrics encompass them. That is the case of "Queuing time" and "Outbound space utilization". For Queuing time, it is comprised in data equations of time indicators (Appendix A demonstrates this parameter inside the time indicator equations) and Outbound space utilization is considered in Warehouse utilization equation (Equation 5.19, Appendix A).

The final warehouse metric system analyzed in this thesis has 41 indicators. Table 5.1 shows these indicators using the same table format presented in Chapter 2. The only difference is that, besides the metrics added (highlighted with the symbol *), the resource related indicators (Labor cost '$\mathbf{Lab_c}$', Labor productivity '$\mathbf{Lab_p}$', Equipment downtime '$\mathbf{EqD_p}$', Maintenance cost '$\mathbf{Maint_c}$' and Warehouse utilization '$\mathbf{WarUt_p}$', presented in Table 2.13) are also included in Table 5.1, being classified as transversal indicators.

The notation used in Table 5.1 to describe indicators is a standard created in this thesis to represent indicator names. This notation is detailed in Section 5.2.3.

Finally, it is important to underline that this group of indicators does not provide an exhaustive analysis of warehouse performance. Thus, in real situations other indicators can be measured by the warehouses which are not included in Table 5.1.

5.2.2 Transformation of Indicator Definitions in Equations

After the determination of the final group of indicators, their definitions are used as a basis to establish indicator equations. While some definitions are easily transformed in equations, others do not have the same interpretation. The definitions come basically from the same paper database of the literature review. In the cases that the indicators are not defined in papers, we look for these definitions in a supplementary database. Tables 5.2, 5.4, 5.6, 5.8 present three kinds of indicators distinguished by the symbols ^{a}, ^{b} and ^{c}. The indicators symbolized as ^{a} need an interpretation of their definitions in order to transform them into equations. One example is receiving time indicator defined as unloading time (see Table 5.2). We determine its equation as the total unloading time divided by the number of pallets unloaded in a month (Equation 5.1). The indicators represented by the symbol ^{b} are the ones for which neither the definition nor the measurement are found in the literature. We define these indicators based on the best common sense that we could infer from the literature. The symbol ^{c} is attributed to maintenance cost indicator (Table 5.6), the only metric defined by the union of two distinct definitions (from De Marco and Giulio (2011) and Johnson, Chen and McGinnis (2010)). In the cases where there is more than one definition, they are demonstrated in the table (e.g. order lead time in Table 5.2) and the alternatives are discussed in the respective section.

All other indicators, described in Tables 5.2, 5.4, 5.6, 5.8 without symbols, have their measurement given directly by their definition (e.g. lead time to pick an order line, total of products stored per labor hour storing, etc.). Some of these definitions are just adjusted to the measurement unit used in this work. For example, picking accuracy is defined as "orders picked correctly per orders picked" but we changed the unit "order picked" to "order line picked".

5.2.3 Notation to describe Indicator Equations

The final metric system encompasses Equation 5.1 to Equation 5.41. To better illustrate the results, we show in parenthesis the equation outcomes, even if they are not units derived from International System of Units (SI). For example, we define "*pallet*" as a pseudo unit indicating the number of pallets. To define the data used in each indicator's equation, Tables 5.3, 5.5, 5.7, 5.9 describe the data meanings and their measurement units (in parenthesis). The time base used in this work is "month" and the measurement unit follows the description made in Section 5.1.2.

The indicator notations presented in this chapter are used all along the thesis. All indicator names are written in bold format (for instance, $\mathbf{Rec_t}$) and data used in indicator equation are in sans serif style (e.g. $\mathsf{Pal\ Unlo}$). Moreover, the indicators have also a letter at the end of the indicator name to designate their classification: **t** for time, **p** for productivity, **c** for cost and **q** for quality.

The next sections present the indicator equations separated in terms of time, productivity, cost and quality indicators.

5.2.4 Time Indicators

The time indicator equations are elaborated from the interpretation of the indicator definitions given in Table 5.2. The data used in these time indicators (Equation 5.1 up to Equation 5.8) are explained in Table 5.3.

Table 5.2 presents two indicators with more than one interpretation: order lead time and dock to stock time. Analyzing order lead time definition from customer's perspective, it should encompass from the time when the customer order is placed up to the time when the customer receives his order and not until the product is shipped by the warehouse. Thus, all parts of the supply chain involved to the accomplishment of this task should be included in this indicator. For dock to stock time, it is important to note that some definitions could be misleading. The definition of Ramaa, Subramanya and Rangaswamy (2012) could be interpreted as if the indicator comprehends the inventory and replenishment times (time from the storage up to the product is picked), but this is not the case. The authors consider that the product is available for order picking at the moment of storing. Therefore, dock to stock is the time from supply arrival up to the storage in the inventory floor.

Usually, the activities performed in a warehouse are sequential, i.e. the shipping starts after the picking is finished. As the time indicators are measured in terms of the mean time one activity takes, it is possible to depict all these measures in a timeline, as shown in Figure 5.2. Some events are pointed out in the timeline, to demonstrate exactly the beginning and the end of each measurement, according to the definitions described in Table 5.3. It is important to highlight that $\Delta t(\mathsf{Rec})$ encompasses also the inspection activity, which takes some time after the unloading finishes to enable the pallets to be stored.

Table 5.2: Warehouse time indicator definitions.

Notation	Indicator	Definition	Authors	Equation
$\mathbf{Rec_t}$	Receiving time	unloading time	Gu, Goetschalckx and McGinnis (2007), Matopoulos and Bourlakis (2010)	(5.1)[a]
$\mathbf{Put_t}$	Putaway time	lead time between the product(s) is unloaded and available to be storage until its effective storage in a designated place	Mentzer and Konrad (1991), De Koster, Le-Duc and Roodbergen (2007), Yang and Chen (2012)	(5.2)[a]
$\mathbf{DS_t}$	Dock to stock time	lead time from supply arrival until product is available for order picking	Ramaa, Subramanya and Rangaswamy (2012)	(5.3)[a]
		the amount of time it takes to get shipments from the dock to inventory floor without inspection	Yang and Chen (2012)	
$\mathbf{Rep_t}$	Replenishment time	lead time to transfer products from reserve storage area to forward pick area	Manikas and Terry (2010)	(5.4)
$\mathbf{Pick_t}$	Order picking time	lead time to pick an order line	Mentzer and Konrad (1991)	(5.5)
$\mathbf{Ship_t}$	Shipping time	lead time to load a truck per total orders loaded	Campos (2004)	(5.6)
$\mathbf{Del_t}$	Delivery lead time	total time of distributions per total orders distributed	Campos (2004)	(5.7)
$\mathbf{OrdLT_t}$	Order lead time	lead time from customer order to customer acceptance	Mentzer and Konrad (1991), Kiefer and Novack (1999), Rimiene (2008), Menachof, Bourlakis and Makios (2009), Yang and Chen (2012)	(5.8)[a]
		lead time from order placement to shipment	Yang (2000), Ramaa, Subramanya and Rangaswamy (2012)	

[a] Interpretation of the indicator definition

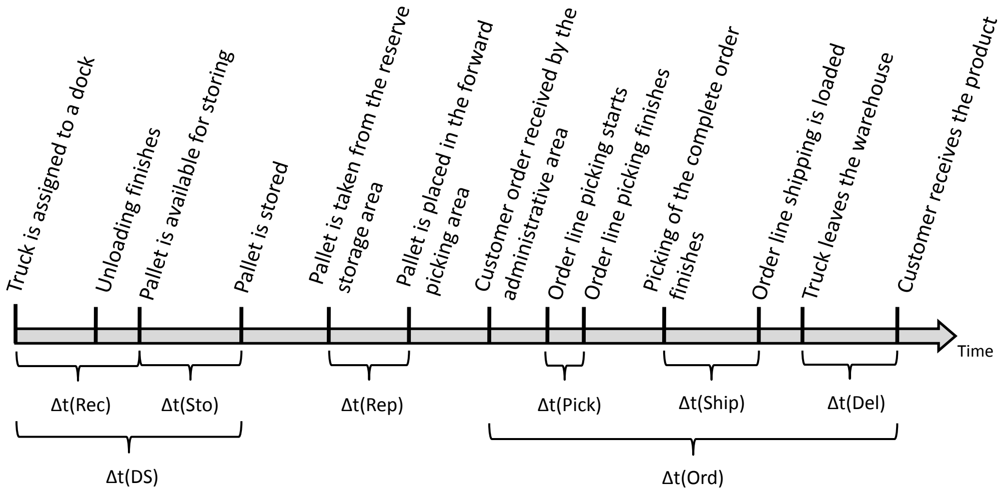


Figure 5.2: Time line for time indicators data .

The time indicators (Equation 5.1 up to Equation 5.8) are measured monthly, so the sum operator in all equations are related to the activities performed during a whole month. The indexes p, l and o in indicator equations correspond to pallets, order lines and orders, respectively.

Table 5.3: Explanation of Data used in Time indicators.

Notation	Definition
$\Delta t(\mathsf{Rec}) =$	Time between the truck assignment to a dock and the moment when the unloading finishes and the pallet is available to be stored ($hour/PalUnlo$)
$\Delta t(\mathsf{Sto}) =$	Time between the instant when the pallet is available to be stored and its effective storing ($hour/PalSto$)
$\Delta t(\mathsf{DS}) =$	Time between the truck assignment to a dock up to the storing of the pallet ($hour/PalUnlo$)
$\Delta t(\mathsf{Rep}) =$	Time to transfer a pallet from the reserve storage area to the forward picking area ($hour/PalMoved$)
$\Delta t(\mathsf{Pick}) =$	Time between the instants when operator starts to pick an order line and when the picking finishes ($hour/OrdLiPick$)
$\Delta t(\mathsf{Ship}) =$	Time between the instants when the order picking finishes and when the order line shipping is loaded in the truck ($hour/OrdLiShip$)
$\Delta t(\mathsf{Del}) =$	Time between the truck leaving the warehouse and the customer acceptance of the product ($hour/OrdDel$)
$\Delta t(\mathsf{Ord}) =$	Time between the customer ordering and the customer acceptance of the product ($hour/OrdDel$)
Pal Unlo =	number of pallets unloaded per month ($pallets/month$)
Pal Sto =	number of pallets stored per month ($pallets/month$)
Pal Moved =	number of pallets moved during replenishment operation per month ($pallets/month$)
OrdLi Pick =	number of order lines picked per month ($order\ lines/month$)
OrdLi Ship =	number of order lines shipped per month ($order\ lines/month$)
Ord Del =	number of orders delivered per month ($orders/month$)

$$\mathbf{Rec_t} = \frac{\sum_{p=1}^{PalUnlo} \Delta t(\mathsf{Rec})_p}{\mathsf{Pal\ Unlo}} \left(\frac{hour}{pallet}\right) \tag{5.1}$$

$$\mathbf{Put_t} = \frac{\sum_{p=1}^{PalSto} \Delta t(\mathsf{Sto})_p}{\mathsf{Pal\ Sto}} \left(\frac{hour}{pallet}\right) \tag{5.2}$$

$$\mathbf{DS_t} = \frac{\sum_{p=1}^{PalSto} \Delta t(\mathsf{DS})_p}{\mathsf{Pal\ Unlo}} \left(\frac{hour}{pallet}\right) \tag{5.3}$$

$$\mathbf{Rep_t} = \frac{\sum_{p=1}^{PalMoved} \Delta t(\mathsf{Rep})_p}{\mathsf{Pal\ Moved}} \left(\frac{hour}{pallet}\right) \tag{5.4}$$

$$\mathbf{Pick_t} = \frac{\sum_{l=1}^{OrdLiPick} \Delta t(\mathsf{Pick})_l}{\mathsf{OrdLi\ Pick}} \left(\frac{hour}{order\ line}\right) \tag{5.5}$$

$$\mathbf{Ship_t} = \frac{\sum_{l=1}^{OrdLiShip} \Delta t(\mathsf{Ship})_l}{\mathsf{OrdLi\ Ship}} \left(\frac{hour}{order\ line}\right) \tag{5.6}$$

$$\mathbf{Del_t} = \frac{\sum_{o=1}^{OrdDel} \Delta t(\mathsf{Del})_o}{\mathsf{Ord\ Del}} \left(\frac{hour}{order}\right) \tag{5.7}$$

$$\mathbf{OrdLT_t} = \frac{\sum_{o=1}^{OrdDel} \Delta t(\mathsf{Ord})_o}{\mathsf{Ord\ Del}} \left(\frac{hour}{order}\right) \tag{5.8}$$

5.2.5 Productivity Indicators

Productivity can be defined as the level of asset utilization (FRAZELLE, 2001), or how well resources are combined and used to accomplish specific, desirable results (NEELY; GREGORY; PLATTS, 1995). Productivity is a relationship, usually a ratio or an index between output of goods, work completed, and/or services produced and quantities of inputs or resources utilized to produce the output (BOWERSOX; CLOSS; COOPER, 2002).

One of the most commonly used productivity measure is the labor productivity. Indeed, warehouses usually have many handling-intensive activities. Bowersox, Closs and Cooper (2002) affirms that logistics executives are very concerned with labor performance. In fact, the number of papers found concerning this theme confirms his statement. There are several ways to measure labor productivity, and two definitions are presented in Table 5.4. The first labor productivity indicator (from De Marco and Giulio (2011)) measures the workers' efficiency, verifying the production during the real time used to execute the tasks. The second definition (from Frazelle (2001)) produces a measure based on the work done during the available time to work, e.g. measuring the number of items processed during a day. We use the last indicator in our work because it is the most commonly used in warehouses among the two presented.

It is interesting to make a remark about the interpretation of labor productivity. The definition in Table 5.4 and Equation 5.9 shows that this indicator does not measure directly the employee efficiency, it focuses on time usefulness. It means that all incoming flow (number of products processed per month, in our case) processed will be divided by the total number of hours available to work. If there are some periods where there is no product to process, this will reduce the indicator result even if the employees have worked well.

The indicator Equipment Downtime, $\mathbf{EqD_p}$ Equation 5.20, was initially identified in the work of Mentzer and Konrad (1991) and defined as a "period in which an equipment is not functional, downtime incurred for repairs". Since this is a time indicator, they were classified in this dimension in Section 2.4.1. However, the definition of Bowersox, Closs and Cooper (2002) presented in Table 5.4 produces an indicator with more information, relating the time in which the equipment is not functional in all available time. For this reason, Equipment Downtime is transformed and used as a productivity indicator in this thesis.

The productivity indicators are described in Equation 5.9 up to Equation 5.21. It is interesting to highlight that the pseudo unit *times*, in Equation 5.17, signifies the number of times that the inventory turns in a month.

$$\mathbf{Lab_p} = \frac{\textsf{Prod Proc}}{\textsf{WH}} \left(\frac{products}{hour}\right) \tag{5.9}$$

$$\mathbf{Rec_p} = \frac{\textsf{Pal Unlo}}{\textsf{WH Rec}} \left(\frac{pallets}{hour}\right) \tag{5.10}$$

$$\mathbf{Sto_p} = \frac{\textsf{Pal Sto}}{\textsf{WH Sto}} \left(\frac{pallets}{hour}\right) \tag{5.11}$$

Table 5.4: Warehouse productivity indicator definitions.

Notation	Indicator	Definition	Authors	Equation
$\mathbf{Lab_p}$	Labor productivity	ratio of the total number of items managed to the amount of item-handling working hours	De Marco and Giulio (2011)	(5.9)
		total produced per total man-hour	Frazelle (2001)	
$\mathbf{Rec_p}$	Receiving productivity	number of vehicles unloaded per labor hour	Mentzer and Konrad (1991)	(5.10)
$\mathbf{Sto_p}$	Storage productivity	total number of products stored per labor hour in storage activity	our definition	(5.11)[b]
$\mathbf{Rep_p}$	Replenishment productivity	total number of pallets moved per labor hour in replenishment activity	our definition	(5.12)[b]
$\mathbf{Pick_p}$	Picking productivity	total number of products picked per labor hours in picking activity	Kiefer and Novack (1999), Manikas and Terry (2010), Yang and Chen (2012)	(5.13)
$\mathbf{Ship_p}$	Shipping productivity	total number of products shipped per time period	Mentzer and Konrad (1991), Kiefer and Novack (1999), De Koster and Warffemius (2005)	(5.14)
$\mathbf{Del_p}$	Delivery Productivity	total number of orders delivered per labor hours in delivery activity	our definition	(5.15)[b]
$\mathbf{InvUt_p}$	Inventory utilization	rate of space occupied by storage	Ramaa, Subramanya and Rangaswamy (2012), Ilies, Turdean and Crisan (2009)	(5.16)
$\mathbf{TO_p}$	Turnover	ratio between the cost of goods sold and the average inventory	Johnson and McGinnis (2011), Yang and Chen (2012)	(5.17)
$\mathbf{TrUt_p}$	Transport utilization	vehicle fill rate	O'Neill, Scavarda and Zhenhua (2008), Matopoulos and Bourlakis (2010)	(5.18)
$\mathbf{WarUt_p}$	Warehouse utilization	rate of warehouse capacity used	Bowersox, Closs and Cooper (2002)	(5.19)
$\mathbf{EqD_p}$	Equipment downtime	percentage of hours that the equipment is not utilized	Bowersox, Closs and Cooper (2002)	(5.20)
$\mathbf{Th_p}$	Throughput	items / hour leaving the warehouse	Mentzer and Konrad (1991), Gunasekaran and Kobu (2007), Kiefer and Novack (1999), De Koster and Warffemius (2005), Voss, Calantone and Keller (2005), Gu, Goetschalckx and McGinnis (2007)	(5.21)

[b] This indicator is not explicitly defined in the literature and we consider the definition presented in this table for the purpose of this work.

Table 5.5: Explanation of Data used in Productivity indicators.

Notation	Definition
Ave Inv =	average warehouse inventory per month (\$/*month*)
CGoods =	cost of all products sold by the warehouse per month (\$/*month*)
Inv CapUsed =	average number of pallets in inventory per month (*pallets/month*)
Inv Cap =	total amount of pallet space (*pallets*)
Kg Tr =	total of kilograms transported per month (*kg/month*)
Kg Avail =	delivery capacity in kilograms per month (*kg/month*)
HEq Stop =	total number of hours during which equipments are stopped per month (*hour/month*)
HEq Avail =	total number of hours during which equipments are available to work per month (*hour/month*)
OrdLi Pick =	number of order lines picked per month (*order lines/month*)
OrdLi Ship =	number of order lines shipped per month (*order lines/month*)
Ord Del =	number of orders delivered per month (*orders/month*)
Pal Unlo =	number of pallets unloaded per month (*pallets/month*)
Pal Sto =	number of pallets stored per month (*pallets/month*)
Pal Moved =	number of pallets moved during replenishment operation per month (*pallets/month*)
Prod Ship =	number of products shipped per month (*nb/month*)
Prod Proc =	number of products processed by the warehouse per month. Products processed refers to the number of products shipped in the warehouse (*products/month*)
WH =	total item-handling working hours for all warehouse activities per month. In this thesis, WH is calculated by the sum of WH Rec, WH Sto, WH Rep, WH Pick, WH Ship (*hour/month*)
War CapUsed =	total warehouse floor area occupied by activities per month (m^2/*month*)
War Cap =	total warehouse capacity floor (m^2)
WH Rec =	total employee labor hours available for receiving activity per month (*hour/month*)
WH Sto =	total employee labor hours available for storing activity per month (*hour/month*)
WH Rep =	total employee labor hours available for replenishment activity per month (*hour/month*)
WH Pick =	total employee labor hours available for picking activity per month (*hour/month*)
WH Ship =	total employee labor hours available for shipping activity per month (*hour/month*)
WH Del =	total employee labor hours available for delivery activity per month (*hour/month*)
War WH =	total number of hours during which the warehouse is open per month (*hour/month*)

$$\mathbf{Rep_p} = \frac{\textsf{Pal Moved}}{\textsf{WH Rep}}\left(\frac{pallets}{hour}\right) \tag{5.12}$$

$$\mathbf{Pick_p} = \frac{\textsf{OrdLi Pick}}{\textsf{WH Pick}}\left(\frac{order\ line}{hour}\right) \tag{5.13}$$

$$\mathbf{Ship_p} = \frac{\textsf{OrdLi Ship}}{\textsf{WH Ship}}\left(\frac{order\ line}{hour}\right) \tag{5.14}$$

$$\mathbf{Del_p} = \frac{\textsf{Ord Del}}{\textsf{WH Del}}\left(\frac{order}{hour}\right) \tag{5.15}$$

$$\mathbf{InvUt_p} = \frac{\textsf{Inv CapUsed}}{\textsf{Inv Cap}} \times 100(\%) \tag{5.16}$$

$$\mathbf{TO_p} = \frac{\textsf{CGoods}}{\textsf{Ave Inv}}(times) \tag{5.17}$$

$$\mathbf{TrUt_p} = \frac{\textsf{Kg Tr}}{\textsf{Kg Avail}} \times 100(\%) \tag{5.18}$$

$$\mathbf{WarUt_p} = \frac{\textsf{War CapUsed}}{\textsf{War Cap}} \times 100(\%) \tag{5.19}$$

$$\mathbf{EqD_p} = \frac{\textsf{HEq Stop}}{\textsf{HEq Avail}} \times 100(\%) \tag{5.20}$$

$$\mathbf{Th_p} = \frac{\textsf{Prod Ship}}{\textsf{War WH}}\left(\frac{products}{hour}\right) \tag{5.21}$$

5.2.6 Cost Indicators

In Table 5.6 there are three different definitions for inventory costs. Analyzing the results of the literature review, inventory level assessed monetarily is the most employed metric in papers. It is true that some expenses like depreciation and insurance could be included in total warehouse costs and not necessarily in inventory costs. However, considering just inventory level seems to be an incomplete way of measurement since other expenses like holding cost and stock out penalty are also taken into account by other authors like Rimiene (2008) and Li, Sava and Xie (2009). So, the inventory cost definition used in this work follows Li, Sava and Xie (2009).

Table 5.6: Warehouse cost indicator definitions.

Notation	Indicator	Definition	Authors	Equation
$\mathbf{Inv_c}$	Inventory costs	the holding cost and the stock out penalty	Li, Sava and Xie (2009)	(5.22)[a]
		total storage costs / unit	Rimiene (2008)	
		inventory level (measured monetarily)	Cagliano et al. (2011), Gallmann and Belvedere (2011)	
$\mathbf{Tr_c}$	Transportation costs	amount of dollars spent per order delivered.	Bowersox, Closs and Cooper (2002)	(5.23)
$\mathbf{OrdProc_c}$	Order processing cost	total processing cost of all orders per number of orders	Campos (2004)	(5.24)
$\mathbf{CS_c}$	Cost as a % of sales	total warehousing cost as a percent of total company sales	Bowersox, Closs and Cooper (2002), Ilies, Turdean and Crisan (2009), Ramaa, Subramanya and Rangaswamy (2012)	(5.25)
$\mathbf{Lab_c}$	Labor cost	cost of personnel involved in warehouse operations	Cagliano et al. (2011)	(5.26)
$\mathbf{Maint_c}$	Maintenance cost	costs of building maintenance (1) and equipment maintenance (2)	(1)- De Marco and Giulio (2011) (2)- Johnson, Chen and McGinnis (2010)	(5.27)[c]

[a] Interpretation of the indicator definition or many indicators' aggregation [c] Union of two distinct definitions.

The final group of cost indicators are presented in Equation 5.22 up to Equation 5.27, with the meaning of data utilized in cost indicators described in Table 5.7.

$$\mathbf{Inv_c} = \mathsf{InvC} + \mathsf{LostC}(\$) \tag{5.22}$$

$$\mathbf{Tr_c} = \frac{\mathsf{TrC}}{\mathsf{Ord\ Del}}(\frac{\$}{order}) \tag{5.23}$$

$$\mathbf{OrdProc_c} = \frac{\mathsf{Ord\ ProcC}}{\mathsf{Cust\ Ord}}(\frac{\$}{order}) \tag{5.24}$$

$$\mathbf{CS_c} = \frac{\mathsf{WarC}}{\mathsf{Sales}} \times 100(\%) \tag{5.25}$$

$$\mathbf{Lab_c} = \mathsf{Salary} + \mathsf{Charges} + \mathsf{Others}(\frac{\$}{month}) \tag{5.26}$$

$$\mathbf{Maint_c} = \mathsf{BuildC} + \mathsf{EqMaintC} + \mathsf{Others}(\frac{\$}{month}) \tag{5.27}$$

5.2.7 Quality Indicators

The quality indicators are presented in Equation 5.28 up to Equation 5.41, derived from metric definitions (Table 5.8). These indicators measure characteristics of the products and the work performed in a quantitative way. The indicator data are described in Table 5.9.

The distinction between the indicators "on time delivery" and "orders shipped on time" (see Table 5.8) resides in what is considered as the final monitoring point. On time delivery is a measurement, which covers up to the product delivering to the customer. In other words, if the warehouse monitors the delivery activity, it will use the indicator "on time delivery". The indicator "orders shipped on time" does not include the delivery activity and if the warehouse measures their indicators up to the shipping activity (i.e. the moment when the products leave the warehouse), it will use the indicator orders shipped on time. In this work both measures are maintained in the metric system to evaluate their interaction with other indicators.

$$\mathbf{Rec_q} = \frac{\mathsf{Cor\ Unlo}}{\mathsf{Pal\ Unlo}} \times 100(\%) \tag{5.28}$$

$$\mathbf{Sto_q} = \frac{\mathsf{Cor\ Sto}}{\mathsf{Pal\ Sto}} \times 100(\%) \tag{5.29}$$

Table 5.7: Explanation of Data used in Cost indicators.

Notation	Definition
InvC =	financial cost to maintain inventory in warehouse per month($\$/month$)
LostC =	penalty measured by company as a cost when the customer makes an order and the product is not available per month ($\$/month$)
TrC =	total transportation cost, which is the sum of assets, oil, maintenance and labor costs per month ($\$/month$)
Ord Del =	number of orders delivered per month($nb/month$)
Ord ProcC =	sum of office and employee costs to process orders per month ($\$/month$)
Cust Ord =	number of customer orders per month ($nb/month$)
WarC =	sum of all activity costs that the warehouse has in charge per month ($\$/month$)
Sales =	total revenue from sales per month ($\$/month$)
Salary =	total salaries of all warehouse employees per month ($\$/month$)
Charges =	total charges paid over salary for all warehouse employees per month ($\$/month$)
BuildC =	total cost to maintain warehouse building per month($\$/month$)
EqMaintC =	total equipment maintenance costs per month ($\$/month$)
Others =	other costs not defined in the formulas per month ($\$/month$)

Table 5.8: Warehouse Quality indicator definitions.

Notation	Indicator	Definition	Authors	Equation
$\mathbf{Rec_q}$	Receiving accuracy	pallets unloaded without incidents	our definition	$(5.28)^b$
$\mathbf{Sto_q}$	Storage accuracy	storing products in proper locations	Voss, Calantone and Keller (2005), Rimiene (2008)	$(5.29)^a$
$\mathbf{Rep_q}$	Replenishment accuracy	movement of the right product from storage area to the right place in forward pick area, without damages	our definition	$(5.30)^b$
$\mathbf{Inv_q}$	Physical inventory accuracy	the physical counts of inventory agree with the inventory status reported in the database	Bowersox, Closs and Cooper (2002)	$(5.31)^a$
$\mathbf{Pick_q}$	Picking accuracy	number of orders picked correctly per orders picked	Bowersox, Closs and Cooper (2002)	$(5.32)^a$
$\mathbf{Ship_q}$	Orders shipped accuracy	number of errors free orders shipped	De Koster and Warffemius (2005), De Koster and Balk (2008)	$(5.33)^a$
$\mathbf{Del_q}$	Delivery accuracy	number of orders distributed without incidents	Campos (2004)	$(5.34)^a$
$\mathbf{OTDel_q}$	On time delivery	number of orders received on time or before committed date	Voss, Calantone and Keller (2005), Forslund and Jonsson (2010), Lu and Yang (2010), Yang and Chen (2012)	(5.35)
$\mathbf{OTShip_q}$	Orders shipped on time	number of orders shipped on time per total orders shipped	Kiefer and Novack (1999)	(5.36)
$\mathbf{OrdF_q}$	Order fill rate	number of orders filled completely on the first shipment	Ramaa, Subramanya and Rangaswamy (2012)	(5.37)
$\mathbf{PerfOrd_q}$	Perfect order	number of orders delivered on time, without damage and with accurate documentation	Kiefer and Novack (1999)	(5.38)
$\mathbf{CustSat_q}$	Customer satisfaction	number of customer complaints per number of orders	Lao et al. (2011), Voss, Calantone and Keller (2005), Lao et al. (2012)	(5.39)
$\mathbf{StockOut_q}$	Stockout rate	number of stock products out of order	Lao et al. (2011), Yang and Chen (2012), Lao et al. (2012)	$(5.40)^a$
$\mathbf{Scrap_q}$	Scrap rate	Rate of product loss and damage	Voss, Calantone and Keller (2005)	$(5.41)^a$

[a] Interpretation of the indicator definition [b] This indicator is not explicitly defined in the literature and we consider the definition presented in this table for the purpose of this work.

Table 5.9: Explanation of Data used in Quality indicators.

Notation	Definition
Complet 1st Ship=	number of orders delivered complete in one shipment per month (*orders/month*)
Cor Unlo =	number of pallets unloaded correctly per month (*pallets/month*)
Cor Sto =	number of pallets stored correctly per month (*pallets/month*)
Cor Rep =	number of pallets moved correctly from reserve storage to forward picking area per month (*pallets/month*)
Cor OrdLi Pick =	number of order lines picked correctly per month (*order lines/month*)
Cor OrdLi Ship =	number of order lines shipped correctly per month (*order lines/month*)
Cor Del =	number of orders delivered correctly per month (*orders/month*)
Cust Complain=	number of orders with customer complaints regarding on logistics aspects per month (*orders/month*)
Prod noAvail=	number of products per month that are not available in stock when the customer makes an order (*product/month*)
Nb Scrap=	number of scraps occurred in warehouse operations per month (*product/month*)
OrdLi Pick =	number of order lines picked per month (*order lines/month*)
OrdLi Ship =	number of order lines shipped per month (*order lines/month*)
Ord Ship =	number of orders shipped per month (*orders/month*)
Ord Del =	number of orders delivered per month (*orders/month*)
Ord Del OT=	number of orders received by customer on or before deadline per month (*orders/month*)
Ord Ship OT=	number of orders shipped on or before the deadline per month (*orders/month*)
Ord OT, ND, CD=	number of orders received by customer on time (OT), with no damages (ND) and correct documentation (CD) per month (*orders/month*)
Prob data =	number of pallets with inaccuracies between the physical inventory and the system per month (*pallets/month*)
Prod Out =	number of products taken out of the inventory per month (*product/month*)
Pal Unlo =	number of pallets unloaded per month (*pallets/month*)
Pal Sto =	number of pallets stored per month (*pallets/month*)
Pal Moved =	number of pallets moved during replenishment operation per month (*pallets/month*)

$$\mathbf{Rep_q} = \frac{\text{Cor Rep}}{\text{Pal Moved}} \times 100(\%) \tag{5.30}$$

$$\mathbf{Inv_q} = \frac{\text{Pal Unlo + Pal Sto + Pal Moved - Prob data}}{\text{Pal Unlo + Pal Sto + Pal Moved}} \times 100(\%) \tag{5.31}$$

$$\mathbf{Pick_q} = \frac{\text{Cor OrdLi Pick}}{\text{OrdLi Pick}} \times 100(\%) \tag{5.32}$$

$$\mathbf{Ship_q} = \frac{\text{Cor OrdLi Ship}}{\text{OrdLi Ship}} \times 100(\%) \tag{5.33}$$

$$\mathbf{Del_q} = \frac{\text{Cor Del}}{\text{Ord Del}} \times 100(\%) \tag{5.34}$$

$$\mathbf{OTDel_q} = \frac{\text{Ord Del OT}}{\text{Ord Del}} \times 100(\%) \tag{5.35}$$

$$\mathbf{OTShip_q} = \frac{\text{Ord Ship OT}}{\text{Ord Ship}} \times 100(\%) \tag{5.36}$$

$$\mathbf{OrdF_q} = \frac{\text{Complet 1st Ship}}{\text{Ord Ship}} \times 100(\%) \tag{5.37}$$

$$\mathbf{PerfOrd_q} = \frac{\text{(Ord OT, ND, CD)}}{\text{Ord Del}} \times 100(\%) \tag{5.38}$$

$$\mathbf{CustSat_q} = \frac{\text{Ord Del - Cust Complain}}{\text{Ord Del}} \times 100(\%) \tag{5.39}$$

$$\mathbf{StockOut_q} = \frac{\text{Prod noAvail}}{\text{Prod Out}} \times 100(\%) \tag{5.40}$$

$$\mathbf{Scrap_q} = \frac{\text{Nb Scrap}}{\text{Prod Proc}} \times 100(\%) \tag{5.41}$$

5.3 Complete Analytical Model of Performance Indicators and Data

5.3.1 The Construction of Data Equations

The first part of the analytical model encompasses the indicator equations presented in the previous sections. To achieve the complete analytical model, we elaborate quantitative expressions for indicator data to find theoretically the indicator relationships (performed in Section 6.3). The purpose of creating data equations is to verify their relationships, identifying the independent and combined data. The combined data is measure from other data, e.g. data J in Equation 4.2, Chapter 4, is a combined data since it is calculated from the sum of A and G data. The independent data are the real inputs of the system, i.e. they are not calculated from any other data (e.g. A and G in Equation 4.2 are independents).

The complete analytical model, presented in Appendix A, has one more data format besides the ones already presented (indicator's name are in bold, as $\mathbf{Rec_t}$, and data used in indicator equations are in sans serif style, e.g. Pal Unlo): the components inside data equation are in *slanted* style like *Prob Rep*. In the cases where the same component is used in indicator equation and in data equation, we choose to format it in the higher "level". For instance, the term OrdLi Ship is used as indicator data in Equation 5.14 and also as data in Equation 5.42; so, it is formated in sans serif style.

To illustrate the construction of data equations and the identification of independent and combined data, let us analyze some indicators already defined:

$$\mathbf{Lab_p} = \frac{\mathsf{Prod\ Proc}}{\mathsf{WH}}\left(\frac{products}{hour}\right) \tag{5.9}$$

$$\mathbf{Ship_p} = \frac{\mathsf{OrdLi\ Ship}}{\mathsf{WH\ Ship}}\left(\frac{order\ line}{hour}\right) \tag{5.14}$$

$$\mathbf{Lab_c} = \mathsf{Salary} + \mathsf{Charges} + \mathsf{Others}\left(\frac{\$}{month}\right) \tag{5.26}$$

Initially, analyzing these equations, one could infer that all these 7 different data are independents because it is not possible to calculate one in terms of another. However, there are just two independent data: OrdLi Ship and Others. The term Others is independent and has no relationship with any data presented. The other six data form two different groups: Prod Proc is calculated from OrdLi Ship, and WH, WH Ship, Salary and Charges have relationships. The relationships among data (and consequently among indicators) are developed from the data equations, presented in Equations 5.42, 5.43, 5.44, 5.45, 5.46.

Equation 5.42 is developed from the data definition described in Table 5.5, where Prod Proc is calculated as the number of products shipped Prod Ship.

$$\mathsf{Prod\ Proc} = \mathsf{Prod\ Ship} = \mathsf{OrdLi\ Ship} \times \textit{Prod Line} \tag{5.42}$$

where Prod Proc is the number of products processed in the warehouse, represented by the shipped products, OrdLi Ship are order lines shipped, Prod Ship is the number of products shipped and *Prod Line* is the average number of products in a shipping order line. From this equation we conclude that OrdLi Ship and *Prod Line* are independent data.

Analyzing the data equations of the other four data (WH, WH Ship, Salary and Charges) we have:

$$\mathsf{WH} = \mathsf{WH\ Rec} + \mathsf{WH\ Sto} + \mathsf{WH\ Rep} + \mathsf{WH\ Pick} + \mathsf{WH\ Ship} + \mathsf{WH\ Others} \tag{5.43}$$

where WH is the total available working hours for all warehouse activities (WH Rec, WH Sto, WH Rep, WH Pick, WH Ship, WH Others). The available working hours for a specific activity (e.g. WH Ship, used in indicator Equation 5.14) is calculated as the average number of employees working in storing (*nb of employees*) times the total number of hours the warehouse is open in a month (*WarWH*) (see Equation 5.44).

$$\mathsf{WH\ Ship} = \textit{nb of employees} \times \textit{WarWH} \tag{5.44}$$

$$\begin{aligned} \mathsf{Salary} = \$/h_{rec} \times \mathsf{WH\ Rec} + \$/h_{sto} \times \mathsf{WH\ Sto} + \$/h_{rep} \times \mathsf{WH\ Rep} \\ + \$/h_{pick} \times \mathsf{WH\ Pick} + \$/h_{ship} \times \mathsf{WH\ Ship} + \$/h_{admin} \times (1-\beta_{ord}) \times \textit{WH Admin} \\ + \$/h_{other} \times \textit{WH Others} \end{aligned} \tag{5.45}$$

$$\mathsf{Charges} = \alpha \times \mathsf{Salary} \quad \text{and} \quad 0 < \alpha < 1 \tag{5.46}$$

where Salary encompasses the total amount payed for all shop floor employees of each activity. $\$/h$ is the remuneration value per hour for each activity ($\$/h_{rec}$, $\$/h_{sto}$, $\$/h_{rep}$, $\$/h_{pick}$, $\$/h_{ship}$). β_{ord} is an index to represent the percentage of the total available labor hours the employees are dedicated to customer orders administration. These customer orders working hours are included in $\mathbf{OrdProc_c}$ indicator (Equation 5.24), and the working hours left is considered in Salary equation. α is an index to represent the partial quantity over the Salary payed as Charges.

It is possible to see from Equations 5.43 - 5.46 that WH, WH Ship, Salary and Charges are combined data since they are computed from other informations. The real inputs from these equations are: $\$/h$ of all activities, *nb of employees* of each activity, *WarWH*, β_{ord} and α.

Therefore, Equation 5.9, 5.14 and 5.26 have as real inputs to be calculated (independent data): OrdLi Ship, *Prod Line*, $\$/h$ of all activities, *nb of employees* of each activity, *WarWH*, β_{ord} and α, Others.

As demonstrated here through an example, we have elaborated expressions for data of the 41 indicators. The complete analytical model derived from data and indicator equations is exhibited in Appendix A.

5.3.2 Analytical model assumptions

The analytical model should be developed according to the context of the studied warehouse, since the specificities of each warehouse result in different equations. Therefore, the developed analytical model refers to the standard warehouse presented throughout this chapter.

Even if it is not possible to generalize the analytical model, the proposed equations can help with the development of analytical models in other warehouse contexts. For this reason, the term "others" is included in some equations to allow their adjustments if necessary.

The main assumptions made which impact equation definitions are as follows:

- The picking process is performed manually;
- The inventory cost is not a part of the total warehouse costs. The reason is that inventory costs are usually a charge of the enterprise as a whole, and the warehouse just manages it;
- The distribution cost (Equation 5.23) does not make part of total warehouse costs (Equation A.48) even if delivery is considered as part of the warehouse management. As the costs incurred for delivery activity usually have no relation with the internal warehouse activities, managers prefer to treat these costs separately;

- Trucks used for delivery are enterprise's assets. Therefore, distribution costs includes truck maintenance. If the company has an outsourced distribution, all these components are changed by the monthly value paid for the third party logistics company which carries out the delivery activity;

- Warehouse building is an enterprise asset, impacting mainly the assessment of warehouse costs;

- The quality data is defined as a sum of a process made correctly and with problems, and this division allows the identification of quality problems through the process. Assume the delivery accuracy (Equation 5.34), which is measured by orders delivered correctly per total orders delivered. In the total orders delivered, a portion of it may be delivered correctly while the other part may not. This other part is named orders delivered with problems, *Prob Del*. But it does not mean that the order could not be delivered, it just means that this order is recorded with quality issues. For example, the number of orders not delivered on time are counted in *Prob Del* even if they arrive to the client;

- Two data are differentiated even if their results can occasionally be the same. For example, the number of orders delivered, Ord Del, is not considered as equal to customer orders Cust Ord. Even if these numbers will be close to each other, usually there are orders in process inside the warehouse at the end of the month, when the data is collected to measure indicators. Some orders have already been processed by the administration but not delivered yet. Thus, to calculate the order processing cost indicator, $\mathbf{OrdProc_c}$, the total customer orders are taken into account while for the order lead time indicator, $\mathbf{OrdLT_t}$, orders delivered are considered. Other similar examples are explained in Appendix A.

5.4 Conclusions

The main objective of this chapter is to develop an analytical model of performance indicators and data.

This chapter starts with the presentation of the theoretical warehouse studied (named Standard Warehouse) with its layout and activities. After, the metric system to assess warehouse performance is defined, firstly based on the literature review. A total of 41 indicators compose the metric system, representing all activities that the standard warehouse has in charge.

In order to create the analytical model, the indicator definitions are first interpreted in order to build indicator equations. From these results, data equations are developed, expanding indicator equations and providing information about the kind of inputs used in the analytical model. The complete analytical model demonstrates all relations among data and in the next chapter it will be used to determine indicator relationships theoretically.

Chapter 6

Modeling

Measurement is complex, frustrating, difficult, challenging, important, abused and misused.

Sink, 1991.

Abstract

In this chapter, a scenario representing the flow of products between processes for the standard warehouse is designed. This scenario is used to generate shop-floor monthly data, which are utilized to measure performance indicators. The dataset formed by performance indicators measured monthly are the inputs of the mathematical tools used to model indicator relationships. Firstly, the Jacobian matrix is assessed and the results give some insights about the relationships between indicators based on their equations. Secondly, statistical tools are applied to propose a model for indicators' aggregation. The first results suggest that the relationships between indicators are mainly based on their measurement domain, i.e. the indicators are aggregated according to warehouse activities.

6.1 Introduction

This chapter performs the modeling phase of the methodology. The main objectives of this phase are to provide the theoretical model of indicator relationships and to apply the statistical tool, obtaining the first insights about the indicators' aggregation.

To reach these objectives, a dataset is necessary. In a real context, data from the warehouse shop floor exists in databases or can be collected. However, as our studied warehouse is theoretical, we generate data for the standard warehouse, representing its flow of products between processes. This initial dataset is used to calculate performance indicators monthly, creating indicator time series that are coupled with the mathematical tools.

Following the data generation, we demonstrate a method to find indicator relationships, from the assessment of the Jacobian matrix. Finally, some statistical tools are performed (normality tests, correlation measurement and principal component analysis) to analyze data characteristics and their possible aggregation.

6.2 Data generation for the Standard Warehouse

6.2.1 Assumptions in data generation

The main scenario created for data generation occurs in the shop-floor of the standard warehouse presented in Figure 5.1. Instead of developing indicator measures directly, we preferred to generate the data used to calculate indicators, which are the ones presented in the analytical model of Chapter 5. The reason for this choice is that there is great quantity of relationships among all data which directly impact indicator results (for instance, the same data can be used to calculate another data and some indicators, see the example in Section 5.3.1). If the indicator results are generated directly, these relationships may be lost (e.g. it may not be possible to see the impact of a data change in the indicator results). Thus, it could become more difficult to group indicators according to their relationships.

There are a lot of methods for data generation. In this work, a spreadsheet in *Excel*® software is developed. The *Excel*® spreadsheet is elaborated to create data following normal and random functions and to represent the effect of chained processes (as discussed in Chapter 4, Section 4.3.2). Due to the difficulty of representing reality, some assumptions are made for data generation:

- The queuing time is zero for all activities;
- All terms described as 'Others' in equations of Chapter 5 are considered equal to zero;

- The supplier orders have always the same quantity, a truck of 10 tons with 25 pallets;
- The number of employees is constant over time;
- An order can not present two different errors within the same month;
- The warehouse processes only one product and it is possible to put 40 products in a pallet;
- There is no inspection during the shipping activity; thus, $Insp_2 = 0$;
- The indicators Perfect order, $\mathbf{PerfOrd_q}$, and Delivery quality, $\mathbf{Del_q}$, (Equations 5.38 and 5.34, Section 5.2.7) consider that an order is perfect (and, consequently, correct) if it is on time, with no damages, with the right quantity and the right documents. Due to this consideration, the number of correct orders delivered ($\mathsf{Cor\ Del}$) and the number of perfect orders ($\mathsf{Ord\ OT,\ ND,\ CD}$) are equal, resulting that both indicators remain the same equation. Thus, delivery quality is eliminated from the metric set, and the final group encompasses 40 indicators.

It is important to discuss the assumption that the warehouse manages and delivers just one product. Even if it seems a restrictive assumption, the data created with one or several products does not change substantially indicator results, which are calculated with the data generated. The two following examples demonstrate the impacts of this decision in indicators from inbound and outbound areas.

The inbound operations usually use the unit 'pallet' to measure indicators. In some cases (e.g. the indicator Labor productivity, $\mathbf{Lab_p}$), it is also necessary to know the number of products that are in the pallets. Even if there are different products in a pallet, the interest is in the total number of products received in pallets, which will not change for one or several kinds of products. Consequently, the scenario considering one product does not modify the final indicator results for the inbound operations.

For the outbound operations, the assumption that an order has just one kind of product results in 'number of orders' and 'number of order lines' with the same quantity, since all orders have just one line. However, this situation impacts only the productivity and time indicators for picking and shipping activities (total of 4 indicators) from the 40 indicators included in the metric set.

Therefore, we consider that these data can be used to represent a warehouse operation and to validate the methodology application performed in this dissertation.

6.2.2 The global warehouse scenario

Figure 6.1 shows the global scenario of the standard warehouse. The main informations present characteristics related to physical inventory and products processing capacity. We assume that the warehouse has 5.000 m^2 of area, operates eight hours per day and can store 1000 pallets. The information about the proportion of pallets capacity in a warehouse area of 5.000 m^2 is acquired from specialized websites about warehouse construction (e.g. www.spartanwarehouse.com/warehouse-space-calculator).

From these characteristics, the quantity of products entering and leaving the warehouse every month is, on average, 28000 units. Figure 6.1 depicts products arriving in trucks of 10 tons (with 25 pallets per truck and 40 products per pallet) and orders leaving the warehouse in 5 tons trucks (capacity of 12 pallets) three times per day.

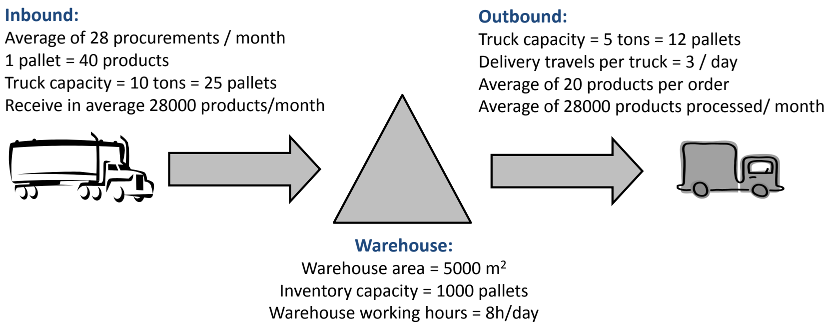


Figure 6.1: Main informations about warehouse, inbound and outbound activities.

The objective of creating this scenario is to measure the warehouse performance for all activities, i.e. from the product arrival at the dock to be unloaded up to order delivery to the client. For indicators' measurement, we assume that this warehouse collects data once a month, commonly in the last working day, and these data signify all efforts made during the month to process supplier and customer orders. Hence, the data generated represents a summary of all that has been processed by the warehouse during the month.

6.2.3 The internal warehouse scenario

The detailed warehouse scenario is shown in Figure 6.2, representing a "picture" of the warehouse activities at the end of the last working day of the month. This figure represents the product and information flows occurred during the month; these data are obtained to assess indicators. There are three kinds of symbols in Figure 6.2: $\dashrightarrow$ illustrates the flow of products inside the warehouse with their associated information; $\cdots>$ shows the information flow in an activity or between warehouse areas; $\cdots\bullet$is the internal data inputs (IntInput) and outputs (IntOutput) used to measure indicators related to a specific activity. The notation used in the inputs and outputs of activities is the same as the ones presented by the complete analytical model in Appendix A.

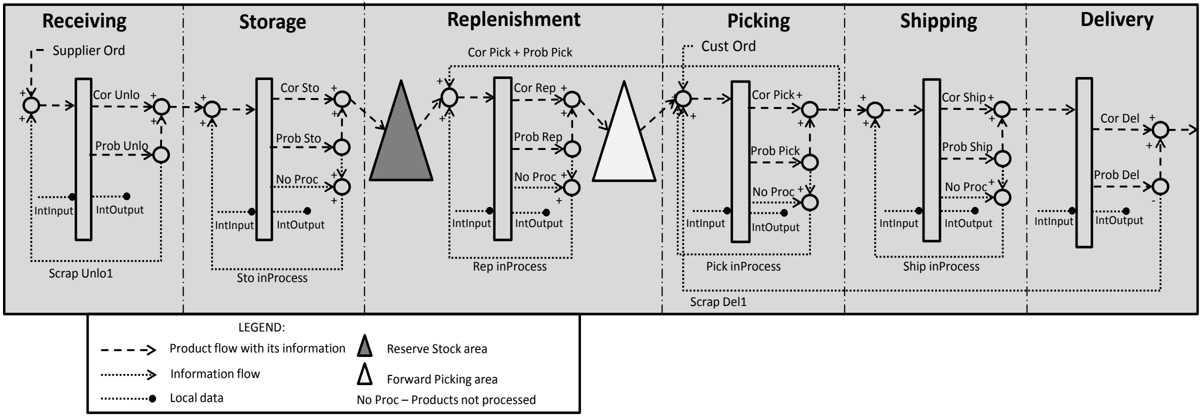


Figure 6.2: Flow of products and information throughout the warehouse activities.

In Figure 6.2, the product flows throughout warehouse areas are demonstrated by the inputs and outputs of each activity.

The inputs vary among activities. The storage, shipping and delivery have as main inputs the products processed by the previous activity, and the receiving depends on the number of supplier orders requested in the month. For replenishment, the products are taken out from the reserve stock area according to the total number of orders picked (Cor Pick + Prob Pick), since the forward picking area needs to have space to receive the replenishment. Finally, the picking activity takes products out of the forward picking area according to the number of customer orders received (Cust Ord).

The outputs for all activities are the total of products processed correctly and with problem (for instance, in storage activity, the outputs are correct pallets stored,Cor Sto, and pallets stored with problems, Prob Sto). The outputs with "problems" are divided into two categories: the problems totally solved during the month, allowing the products to advance to the next process (as demonstrated by the arrow added to correct products); and the problems that have not been solved yet, which are added in the next month to the number of products that should be processed (information arrow added to 'No Proc'). Therefore, the 'problems not solved' impacts the product flows (e.g. scrap) while the others (considered as solved) are just registered for indicators' measurement but they do not impede product flows (e.g. data information error). As the solved problems make part of products processed, the two outputs (activity performed correctly and with solved problems) become the input of the next activity.

Some activities have, at the end of the month, products that are not processed yet (defined as 'No Proc' in Figure 6.2). It means that not all supplier and customer orders received in the month have already been completely processed. The sum of products with problems not solved (defined above) and products not processed result in the products "in Process" (e.g. Sto inProcess, Figure 6.2). These products in Process are not considered in performance measures but they are included as inputs to the activity of the next month.

For simplification, the receiving and delivery activities do not have 'No Proc' products. As demonstrated in Figure 6.2, these activities do not have products not processed, which means that there are no more trucks to unload (in receiving) and all pallets loaded during the day were delivered (in delivery). For both activities, just the products with non solved scrap problems are aggregated on the production of the following month.

From this scenario, data is built for each warehouse activity, as shown in Appendix B. The next section summarizes the different kinds of data generated and presents some examples.

6.2.4 Data characteristics

As stated earlier, a spreadsheet is designed to represent the activities described in Figure 6.2. Due to the complexity of the warehouse scenario, different categories of data are necessary to better represent process variabilities. They are distinguished as fixed, uniform, and normal data.

The fixed data are established values that will not change over time, e.g. warehouse space, number of equipments, warehouse opening hours per day, number of employees.

The 'uniform data' is a random number generated from a uniform distribution of probabilities with pre-defined limits (function '*randbetween*' in *Excel*®). These limits can be fixed (for instance, the number of days per month that the warehouse operates varies between 20 and 25) or variable (if the limits are determined by other variables). As an example of this last case, the number of products stored correctly can not be higher than the total number of products processed in receiving activity. Hence, the number of products stored will have its limits defined by the outputs of the receiving process. These kinds of limits are applied for all the warehouse activities, representing the effect of chained processes.

Finally, the normal function calculates a certain probability using the normal distribution according to a given mean and standard deviation (function 'norminv' in *Excel*®). This function is utilized in different situations along the warehouse data generation. For instance, the range of products received and delivered in a month follows a normal distribution, with mean of 28000 products and standard deviation of 2000 products. Moreover, the number of products per order uses the same function with mean of 20 products and standard deviation of 2.

The complete list is presented in Appendix B, where all equations used to generate data are described separately for each warehouse activity.

Once we have the dataset available, it is possible to calculate indicators representing the products processed in the warehouse during a whole month. These indicators assessed monthly are used as inputs of the mathematical tools to find indicator relationships. In the next section, the theoretical model introduced in Chapter 4, Section 4.3.2 is implemented for the 40 indicators set.

6.3 Theoretical model of Indicator relationships

The complete analytical model defined in Chapter 5 demonstrates that the relations among data are complex, making the global performance hard to evaluate taking into account the data dependency. So, it is crucial to understand these relationships to better evaluate the warehouse performance.

Section 4.3.2 has presented how to verify indicator relationships analyzing indicator equations. In this section we perform this analysis for the complete analytical model of 40 indicators with their data equations. Initially, we have carried out a manual procedure to define indicator relationships, which is presented in Appendix C. However, the results achieved are not exhaustive; not all data relationships are taken into account. Thus, we demonstrate in this section an exhaustive procedure, composed of two main steps:

1. Evaluation of data associations;

2. Determination of the number of data shared by indicators;

First of all, the data equations from the complete analytical model (see Appendix A) are studied to differentiate the independent data from the combined data (as defined in Section 5.3.1, the combined data is measured from other data, whereas the independent ones are the real inputs of the system). Once the independent data are identified, we verify the total number of indicators related by one or more data inputs. For that we use the partial derivative matrix of indicator equations. Finally, the indicator relationships are discussed.

To get the results of this exhaustive procedure, we utilize the software CADES® (Component Architecture for the Design of Engineering Systems) [1]. CADES has three main modules dedicated to simulation and optimization of systems.

The first module, CADES Generator, allows to code the analytical model of equations in *sml* language (System Modeling Language) (ENCIU; WURTZ; GERBAUD, 2010). The model equations that can be implemented in sml are analytical and/or semi-analytical. When CADES compiles a model written in sml, it calculates automatically

[1] http://www.vesta-system.fr/fr/produits/cades/

its gradient by using derivation techniques and the result is an "icar" component containing the model output functions in terms of the inputs (STAUDT, 2015). The Jacobian matrix of the system is calculated in CADES Calculator, the second module, using the exact derivatives obtained in CADES Generator. Finally, the third module, CADES Optimizer, allows to couple the icar component directly to optimization algorithms (more details of this module are presented in Section 7.4.3).

6.3.1 The data associations

In Section 5.3.1, an example was carried out to demonstrate how data are highly connected, with some data making part of more general ones. Regarding this situation, Figure 6.3 depicts the combined data with their main elements for the majority of the indicator set. The rectangle colors do not have a special meaning; Figure 6.3 demonstrates data in the external rectangles comprehending the data from the internal ones. For example, Equation A.3 shows that unloaded pallets can be divided into pallets unloaded correctly and with problems. The first rectangle in the upper left side of Figure 6.3 represents this equation. The blue rectangle concerns all pallets unloaded (sum of data) and inside it there are two other rectangles corresponding to the pallets unloaded correctly "Cor Unlo" and the pallets unloaded with problems "*Prob Unlo*". Yet, "*Prob Unlo*" have two other data represented by the rectangles "1" and "2", signifying, respectively, the scraps and data system errors during the unloading.

Figure 6.3 is divided in four areas: inbound, outbound, resource and general. The inbound and outbound contain data regarding the activities executed in this warehouse areas. The resource data is related to capacity and the general data concern several warehouse activities; that is the reason why they are separated from the other data.

We can infer from Figure 6.3 that it is hard to identify the independent data with so many relations among them. Thus, next section determines the independent data using the CADES® software.

6.3.2 Determination of the independent data

After the identification of data association, we want to obtain a list of the independent data necessary to assess the 40 indicator set. Due to the big quantity of information to evaluate (all equations of the complete analytical model in Appendix A), it is difficult to make manually the same analysis performed in Section 5.3.1, in order to define the

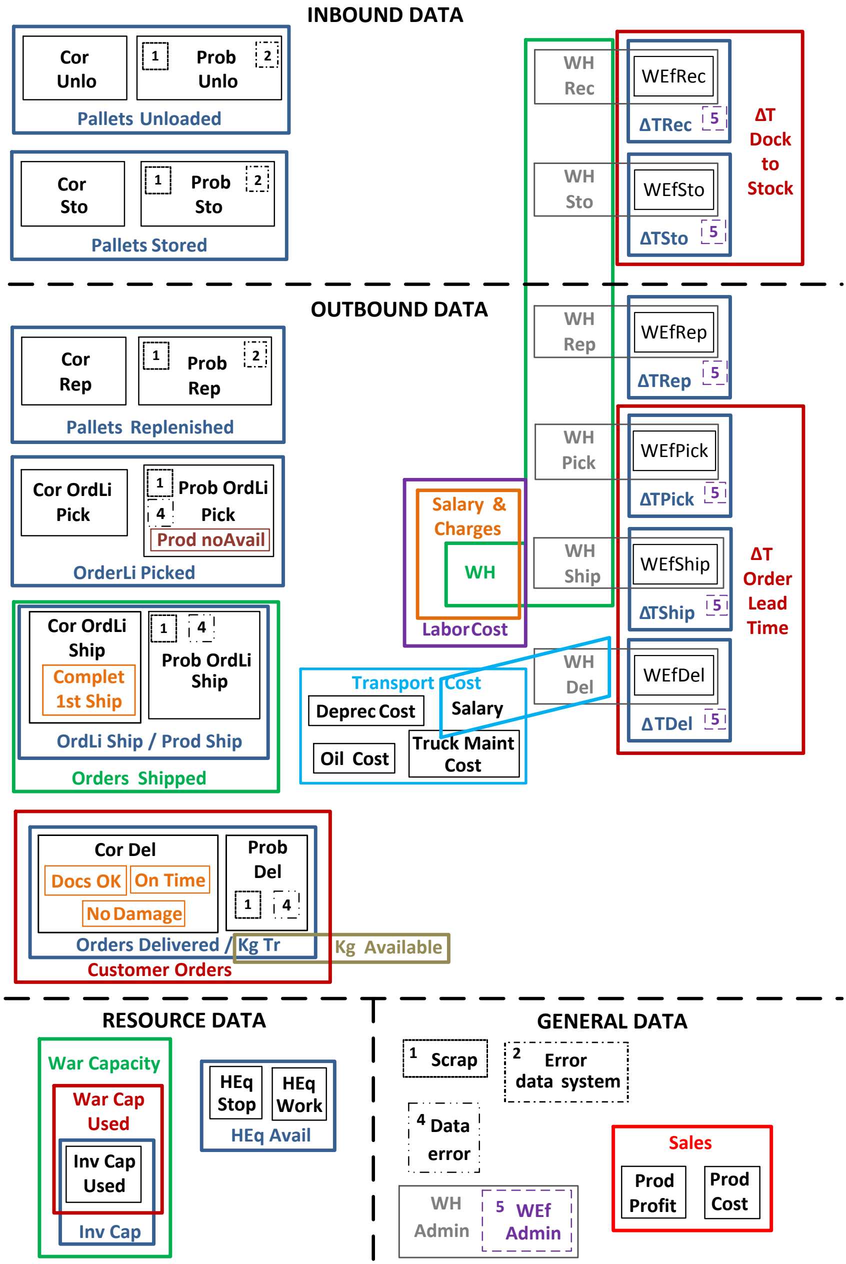


Figure 6.3: Data relationships.

independent and combined inputs of the system. Therefore, the complete analytical model (without the data components named "Others") is coupled with the software CADES Generator to obtain all the inputs (independent data) and outputs (indicators) of the equations.

The compilation provides as outputs the 40 indicators studied in this work and the input's list contains 81 independent data, as shown in Table 6.1. The meaning of each data input is found in Appendix A.

Table 6.1: Analytical model data inputs

Data Inputs			
α	deprec$_2$	kg Prod	Profit
β_del	empl Admin	l_used	Rate
β_ord	empl Del	mean_Insp	Remain_Inv
β_pick	empl Pick	nbMachine	scrap$_1$
β_rec	empl Rec	nb_travel	scrap$_2$
β_rep	empl Rep	NoComplet Ord Ship	scrap$_3$
β_ship	empl Ship	Ord Del OT	scrap$_4$
β_sto	empl Sto	Ord Ship OT	scrap$_5$
BuildC	EqMaintC	pal_truck	scrap$_6$
cap	error data system$_1$	pallet_area	Truck Maint C
Cor OrdLi Pick	error data system$_2$	Prob OrdLi Pick	War Cap
Cor OrdLi Ship	error data system$_3$	Prob OrdLi Ship	war used area
Cor Del	HAdmin$_{del}$	Prob Del	War WH
Cor Rep	HAdmin$_{pick}$	Prob Rep	\$/h$_{admin}$
Cor Sto	HAdmin$_{rec}$	Prob Sto	\$/h$_{del}$
Cor Unlo	HAdmin$_{rep}$	Prob Unlo	\$/h$_{pick}$
Cust Ord	HAdmin$_{ship}$	Prod Ord	\$/h$_{rec}$
Cust Complain	HAdmin$_{sto}$	Prod pal	\$/h$_{rep}$
ΔT(Insp)$_2$	HEq Stop	Prod noAvail	\$/h$_{ship}$
deprec$_1$	Inv Cap	Prod Cost	\$/h$_{sto}$
			\$ oil

After the determination of this final data list, we proceed with the verification of the indicator relationships.

6.3.3 Data *versus* indicator relationships

To check all indicators that have relations by the use of the same data we use the Jacobian Matrix, defined in Section 4.3.2.

In our case, we derive all functions f (indicator equations, from Equation 5.1 to Equation 5.41, excepting $\mathbf{Del_q}$) with respect to their data inputs x (presented above, Table 6.1). So, the final partial derivative matrix has the size 40×81 ($n \times m$), where n are the indicators and m the data inputs.

Due to the substantial size of the partial derivative matrix, we also automatize the Jacobian generation using the software module CADES Calculator.

Before getting the results of the Jacobian matrix, it is necessary to provide initial values to the inputs. The assigned values correspond to the first month of the data generated for our warehouse scenario, presented in the beginning of this chapter (see Appendix D for the complete list of initial input values). Afterwards, CADES® computes and gives the numerical results of the Jacobian matrix for the supplied input data set. Figure 6.4 shows the software interface with the inputs, outputs, and the Jacobian matrix result.

The calculated Jacobian matrix is initially analyzed with respect to its columns. We observe that there are two main kinds of inputs (columns of the matrix): the ones related to only one output (see Table 6.2) and the others linked to several outputs (see Table 6.3). For illustration purposes, only some parts of the matrix are shown in Tables 6.2 and 6.3. Each cell, in both tables, contains the partial derivative values of the output with respect to the corresponding input data. The partial derivative value can be interpreted as the variation of the output when the corresponding input varies, maintaining other inputs constant.

Table 6.2: Partial area of Jacobian matrix with inputs related to just one output.

	Cust_Ord	CustComplain	ErrorDataSystem3	nbMachine	NoComplet_OrdShip	OTDel_ord	OTShip_ord	palSpace
CSc	0	0	0	0	0	0	0	0
CustSatq	0	-0,07496	0	0	0	0	0	0
Delp	0	0	0	0	0	0	0	0
Delt	0	0	0	0	0	0	0	0
DSt	0	0	0	0	0	0	0	0
EqDp	0	0	0	-2,1	0	0	0	0
Invc	0	0	0	0	0	0	0	0
Invq	0	0	-0,05006	0	0	0	0	0
InvUtp	0	0	0	0	0	0	0	-0,07192
Labc	0	0	0	0	0	0	0	0
Labp	0	0	0	0	0	0	0	0
Maintc	0	0	0	0	0	0	0	0
OrdFq	0	0	0	0	-0,07402	0	0	0
OrdLTt	0	0	0	0	0	0	0	0
OrdProcc	-0,00155	0	0	0	0	0	0	0
OTDelq	0	0	0	0	0	0,07496	0	0
OTShipq	0	0	0	0	0	0	0,07402	0
PerfOrdq	0	0	0	0	0	0	0	0

From the 81 data inputs, 27 are associated with one output and

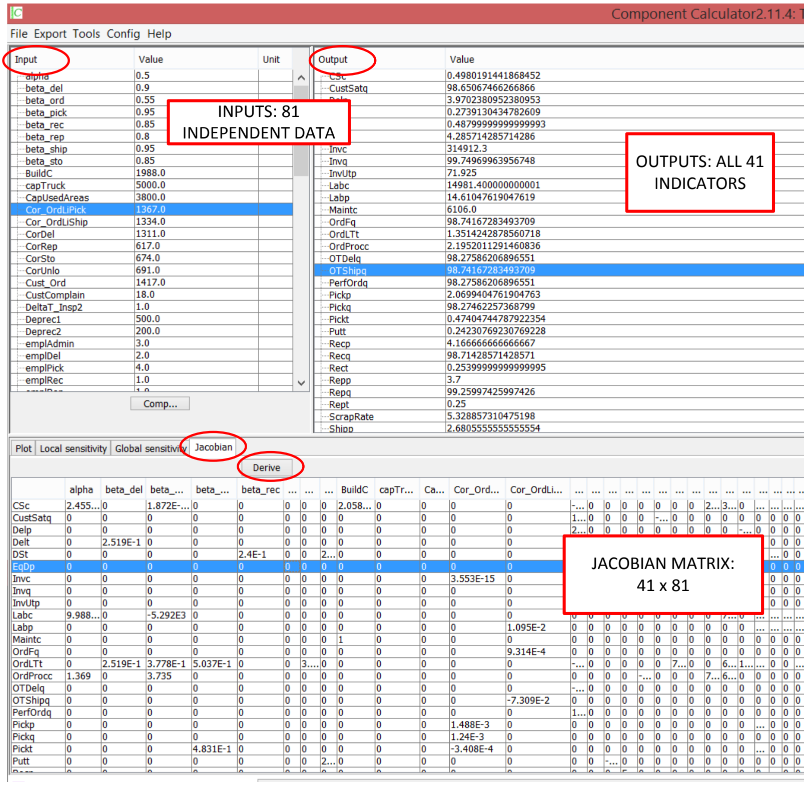


Figure 6.4: Interface of CADES® software: inputs, outputs and Jacobian matrix areas.

54 with two or more outputs. In Tables 6.2 and 6.3, the most significant values influencing positively and negatively the indicators are highlighted in red and green colors, respectively.

Table 6.3: A partial view of the Jacobian matrix with inputs related to two or more outputs.

	alpha	beta_del	beta_ord	CorDel	CorRep	CorSto	CorUnlo	emplPick	emplRec	emplRep	emplShip	emplSto
CSc	0,24550	0	0,00000	-0,00038	0	0	0	0,02593	0,02593	0,02593	0,02593	0,02593
CustSatq	0	0	0	0,00101	0	0	0	0	0	0	0	0
Delp	0	0	0	0,00298	0	0	0	0	0	0	0	0
Delt	0	0,25190	0	-0,00021	0	0	0	0	0	0	0	0
DSt	0	0	0	0	0	0	-0,00067	0	0,20400	0	0	0,20400
EqDp	0	0	0	0	0	0	0	0	0	0	0	0
Invc	0	0	0	0	0	199,8	0	0	0	0	0	0
Invq	0	0	0	0	0,00013	0,00013	0,00013	0	0	0	0	0
InvUtp	0	0	0	0	0	0,05000	0	0	0	0	0	0
Labc	9988,0	0	-5292,0	0	0	0	0	1260,0	1260,0	1260,0	1260,0	1260,0
Labp	0	0	0	0	0	0	0	-1,5	-1,5	-1,5	-1,5	-1,5
Maintc	0	0	0	0	0	0	0	0	0	0	0	0
OrdFq	0	0	0	0	0	0	0	0	0	0	0	0
OrdLTt	0	0,25190	0,37780	-0,00101	0	0	0	0,11960	0	0	0,11960	0
OrdProcc	1,4	0	3,7	0	0	0	0	0	0	0	0	0
OTDelq	0	0	0	-0,07367	0	0	0	0	0	0	0	0
Putt	0	0	0	0	0	-0,00036	0	0	0	0	0	0,21120
Recp	0	0	0	0	0	0	0,00595	0	-4,2	0	0	0
Recq	0	0	0	0	0	0	0,00184	0	0	0	0	0
Rect	0	0	0	0	0	0	-0,00033	0	0,20400	0	0	0
Repp	0	0	0	0	0,00595	0	0	0	0	-3,7	0	0

Table 6.3 presents the basis used to determine indicator relationships. The assumed preliminary hypothesis of this thesis mentions that two indicators with non-zero partial derivative for the same input might have a relationship between them. Evaluating two different rows of Table 6.3 (i.e. two indicators), we observe several common inputs. This is the case of $\mathbf{Lab}_c$ and $\mathbf{OrdLT}_t$, which have in common three inputs: β_{ord}, *emplPick*, *emplShip*, denoting a relationship between them. Therefore, after comparing two rows of Table 6.3 each time, we check all possible relations among indicators.

The interpretation of the indicator relationships is explained in the next section.

6.3.4 Analysis of indicator relationships

The results presented by the Jacobian matrix (Table 6.3) are analyzed in terms of: the number of data shared by two indicators; the numerical values of the partial derivatives. The main objective of both analysis is to try to figure out the intensity of indicator relationships.

Table 6.4 shows the number of shared data between indicators for the complete Jacobian matrix, and the colors represent: red for 1 shared data, blue for 2, and green cells represent 3 or more shared data. From this table, three main results are interesting to discuss:

- Indicators with no data in common;
- Indicators with few data in common (1 or 2);
- Indicators with several data in common (3 or more).

The white cells with zero values represent that indicators have no data in common, making easy the interpretation. Indicators that do not share data with others should have no relationships, and consequently, may not make part of the indicator group which will form the aggregated performance.

In the opposite of the white cells, the green ones show indicators sharing three or more data. One may deduce that the greater number of shared data determine higher indicator relationships. Taking the first column, of $\mathbf{CS_c}$ indicator, it is possible to see that it shares data with 11 other indicators. The three most expressive numbers of shared data are 15 with $\mathbf{Lab_c}$ and 7 with $\mathbf{Lab_p}$ and $\mathbf{OrdLT_t}$. From this result we may conclude that these indicators have high relationships, specially between $\mathbf{CS_c}$ and $\mathbf{Lab_c}$. However, the correlation between $\mathbf{CS_c}$ and $\mathbf{Lab_c}$ is only 0,55, a medium value, whereas between $\mathbf{CS_c}$ and $\mathbf{Lab_p}$

is -0,96, denoting a very high correlation (Section 6.4.2 presents the complete correlation matrix). Therefore, the hypothesis that a great number of shared data signifies a high correlation is not sustained.

Due to the conclusion for indicators with several data in common, the indicators with few data (the red and blue cells of Table 6.4, which are the majority of situations) are even more difficult to interpret.

It seems that other situation that impact the final relationship between indicators is the numerical values of the partial derivatives. Analyzing the column *beta_ord* of Table 6.3, the rows for $\mathbf{Lab_c}$ and $\mathbf{OrdProc_c}$ demonstrate expressive values of partial derivative (-5292 and 3,7 respectively) what might suggest the intensity of relationships. However, as it can be noticed in Table 6.2 and 6.3, the numerical values of the partial derivatives may differ substantially from one to another. At this time, it is interesting to recall that the input data may have different units and their values can be in a distinct scale. For example, the input "number of employees", can be often a small number compared to the "average number of products in inventory", which is usually a big quantity. Moreover, the Jacobian matrix is calculated by considering the monthly input data set. It means that for each month the Jacobian matrix can slightly change, depending on the actual variation of the inputs parameters. Due to the dynamic nature of the input data and also the numerical difference they might have (due to their units), it is hard to directly define the intensity of indicator relationships from the partial derivatives results.

Therefore, it is not possible to infer about the intensity of indicator relationships from the results obtained. The use of Jacobian matrix to define the strength of indicator relationships requires a deeper study, which is proposed as a future research direction. Regarding this thesis, we utilize the results of the Jacobian matrix to give a preliminary overview of indicator relationships in a qualitative sense, and to give support in the choice of the final indicator group used in the integrated model (Section 7.2).

From the exhaustive relationship matrix presented in Table 6.4, it is possible to create the same framework as presented in Appendix C, Figure C.3. However, due to the great quantity of indicator relations, the result is not easily interpretable as in Figure C.3. For that reason, this final framework is placed in Appendix E just for illustration.

Table 6.4: Indicator relation matrix with the number of shared data.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	CSc	**0**																																							
2	CustSatq	2	**0**																																						
3	Delp	3	2	**0**																																					
4	Delt	3	2	4	**0**																																				
5	DSt	3	0	1	1	**0**																																			
6	EqDp	1	0	1	1	1	**0**																																		
7	Invc	3	0	0	0	0	0	**0**																																	
8	Invq	0	0	0	0	2	0	2	**0**																																
9	InvUtp	0	0	0	0	0	0	4	2	**0**																															
10	Labc	15	0	1	1	3	1	0	0	0	**0**																														
11	Labp	7	0	1	1	3	1	1	0	0	6	**0**																													
12	Maintc	2	0	0	0	0	0	0	0	0	0	0	**0**																												
13	OrdFq	0	0	0	0	0	0	0	0	0	0	2	0	**0**																											
14	OrdLTt	7	2	4	6	1	1	0	0	0	5	3	0	0	**0**																										
15	OrdProcc	6	0	1	1	1	1	0	0	0	5	1	0	0	3	**0**																									
16	OTDelq	2	2	2	2	0	0	0	0	0	0	0	0	0	2	0	**0**																								
17	OTShipq	0	0	0	0	0	0	0	0	0	0	2	0	2	0	0	0	**0**																							
18	PerfOrdq	2	2	2	2	0	0	0	0	0	0	0	0	0	2	0	2	0	**0**																						
19	Pickp	2	0	1	1	1	1	2	0	0	2	2	0	0	2	1	0	0	0	**0**																					
20	Pickq	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	2	**0**																				
21	Pickt	2	0	1	1	1	1	2	0	0	2	2	0	0	4	1	0	0	0	4	2	**0**																			
22	Putt	2	0	1	1	4	1	2	2	2	2	2	0	0	1	1	0	0	0	1	0	1	**0**																		
23	Recp	2	0	1	1	4	1	0	2	0	2	2	0	0	1	1	0	0	0	1	0	1	1	**0**																	
24	Recq	0	0	0	0	2	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	**0**																
25	Rect	2	0	1	1	8	1	0	2	0	2	2	0	0	1	1	0	0	0	1	0	1	1	4	2	**0**															
26	Repp	2	0	1	1	1	1	0	2	0	2	2	0	0	1	1	0	0	0	1	0	1	1	1	0	1	**0**														
27	Repq	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	**0**													
28	Rept	2	0	1	1	1	1	0	2	0	2	2	0	0	1	1	0	0	0	1	0	1	1	1	0	1	4	2	**0**												
29	Scrapq	1	0	0	0	0	0	2	0	1	0	4	0	2	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	**0**											
30	Shipp	2	0	1	1	1	1	0	0	0	2	4	0	2	2	1	0	2	0	1	0	1	1	1	0	1	1	0	1	2	**0**										
31	Shipq	0	0	0	0	0	0	0	0	0	0	2	0	2	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	2	2	**0**									
32	Shipt	2	0	1	1	1	1	0	0	0	2	4	0	2	5	1	0	2	0	1	0	1	1	1	0	1	1	0	1	2	4	2	**0**								
33	StockOutq	1	0	0	0	0	0	5	0	0	0	1	0	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	1	0	0	0	**0**							
34	Stop	2	0	1	1	2	1	2	2	2	2	2	0	0	1	1	0	0	0	1	0	1	4	1	0	1	1	0	1	0	1	0	1	0	**0**						
35	Stoq	0	0	0	0	0	0	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	2	**0**					
36	Thp	2	0	1	1	1	1	1	0	0	1	5	0	2	1	1	0	2	0	1	0	1	1	1	0	1	1	0	1	4	3	2	3	1	1	0	**0**				
37	TOp	4	2	2	2	0	0	5	2	4	0	1	0	0	2	0	2	0	2	0	0	0	2	0	0	0	0	0	0	2	0	0	0	1	2	2	1	**0**			
38	Trc	4	2	4	4	1	1	0	0	0	2	1	0	0	4	2	2	0	2	1	0	1	1	1	0	1	1	0	1	0	1	0	1	0	1	0	1	2	**0**		
39	TrUtp	4	2	2	2	0	0	1	0	0	0	1	0	0	2	0	2	0	2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	4	3	**0**	
40	WarUtp	0	0	0	0	0	0	4	2	4	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	1	0	0	0	0	2	2	0	4	0	0	**0**

6.4 Statistical Tools Application

This section presents the application of statistical tools to analyze indicator relationships, proposing ways to aggregate them based on significant correlations.

The data matrix used to perform statistical tools is 100 x 40 where the rows present the different values taken by these indicators over time and the columns represent the different indicators. Each cell contains the indicator value for a specific month. The choice of generating data for 100 months comes from the requirements to apply the PCA tool, which specifies that the sample must be bigger than the number of variables. Using this database generated for 100 months, we first perform a normality test, to describe the characteristics of the data. Afterwards, we standardize data according to (GENTLE, 2007) (this equation has been presented in Section 4.3.1):

$$X_{new} = \frac{X_{actual} - X_{mean}}{\sigma_X} \tag{4.3}$$

where X_{new} is the new value of the variable, X_{actual} is the real variable value, X_{mean} is the time series mean of the variable dataset, σ_X is the standard deviation of the variable time series.

Once the standardization is done, the indicator correlations are measured and the principal component analysis is performed, completing the group of informations that will be used to define the integrated model, in Chapter 7.

Additionally to PCA, dynamic factor analysis is also studied to aggregate indicators. However, the best results obtained exclude a great quantity of indicators from the model (from the initial 40 indicators, only 11 remains after performing DFA). As our objective is to maintain the majority of indicators to evaluate the global performance, we do not use this result in our integrated model. We suggest further researches to apply dynamic factor analysis with this purpose. The initial results obtained are reported in Appendix F.

6.4.1 Data normality test

The objectives of testing data normality are to know data characteristics and to verify if there are outliers in the dataset. The data characteristics are sometimes useful to justify the results obtained specially in the utilization of the data in statistical tools. In the case of outliers, according to Section 3.3.2, PCA is sensitive to great differences among variables. Even if the data is normalized before PCA application, it is important to identify the existence of outliers. For this purpose, the skewness and kurtosis are measured for the variables. As stated is Section 4.3.1, if the skewness is higher than 2 or the is kurtosis is higher than 7 a special analysis of the time series should be made (NEWSOM, 2015). If these limits are exceeded, it is necessary to look for outliers in the time series, fixing the wrong values or excluding inconsistencies.

To evaluate the normality of data, we utilize the Minitab Software® to accomplish the Anderson-Darling test for each indicator time series. Moreover, the skewness and kurtosis are also provided by the software.

The Anderson-Darling test measures how well the data follow a particular distribution, considering in the null hypothesis that data follow a normal distribution. The null hypotheses is rejected if *p-value* is smaller than a chosen *alpha* (usually 0.05 for 95% of confidence and 0.01 for 99% of confidence). We chose to reject the null hypothesis (i.e. to consider that data has a not-normal distribution) for *p-values* < 0.01.

Figure 6.5 presents some examples of these tests (Anderson-Darling, skewness and kurtosis) for the indicators: Cost as a % of Sales (CS_c), Labor costs (Lab_c), Inventory quality (Inv_q). The results are highlighted by red rectangles in the figure. For the skewness and kurtosis, none of the results are greater than 2 and 7, respectively. However, the Anderson-Darling test has *p-values* smaller than 0.01 for Labor cost and Inventory quality, denoting a not-normal distribution. Indeed, the histogram shows these variables with distributions really different from the normal curve.

These tests are carried out for all 40 indicators. For skewness and kurtosis measurement, we do not identify values higher than the limit determined. For the Anderson-Darling test, the results demonstrate 14 indicators with not-normal distributions from the 40 variables analyzed (see Appendix G for all test results). Nevertheless, this result does not impede the application of statistical tools as correlation and Principal Component Analysis. As in practical situations the warehouses do not always provide normal data, we consider that these data characteristics are similar to reality to perform the aggregation analysis.

6.4.2 Correlation measurement

The correlation measurement results are evaluated in parallel with the theoretical model of relationships (Jacobian matrix) to define the

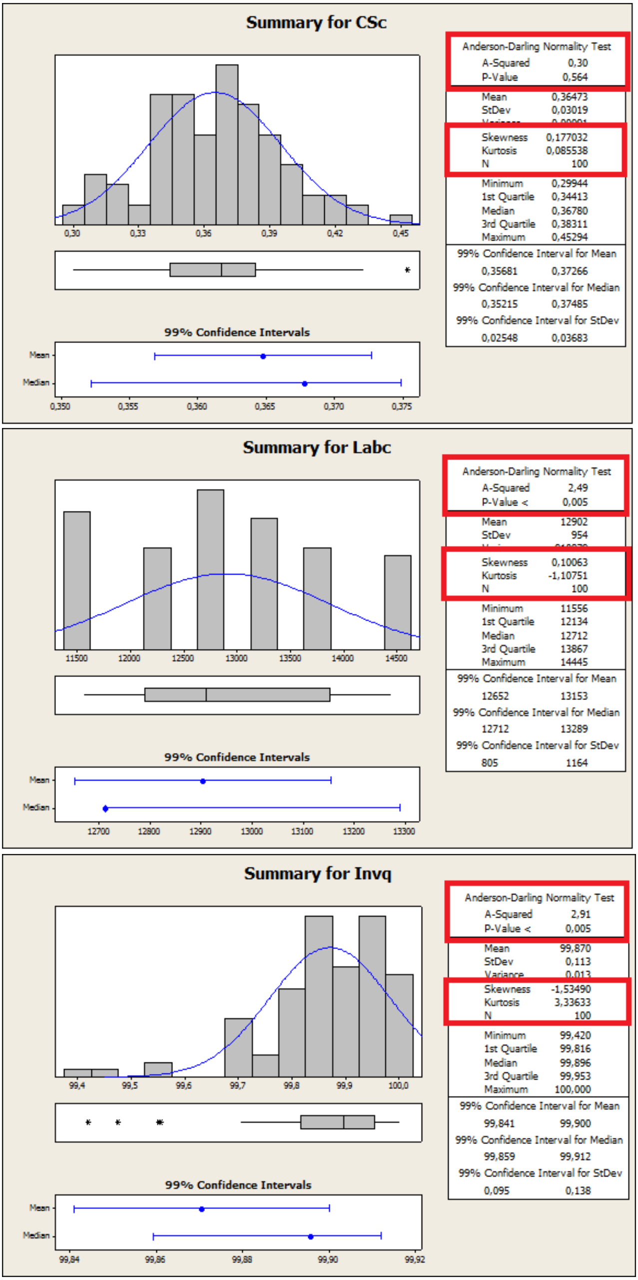


Figure 6.5: Anderson-Darling normality test for three indicators.

indicators that should be discarded of the analysis and the ones that will make part of the integrated model.

The correlation matrix, calculated using the standardized data, is presented in Table 6.5 and the numbers inside it are the correlation coefficients, named Person's r (or just r). All highlighted cells present a significant correlation, with *p-value* < 0.01. The blue cells present the absolute value of the medium correlations, established between 0.4 up to 0.59; and the pink cells show the absolute value for high correlations, determined from 0.6 up to 1.

We can verify that some indicators in Table 6.5 have weak or a few medium correlations. For example, EqD_p, Inv_q and Maint_c do not have correlations higher than 0.4 ($|r| \geq 0.4$). These indicators might have problems to be incorporated in the results of PCA, since the components are arranged based on the correlations between variables. This result is evaluated in Chapter 7 with the complete group of informations coming from the mathematical tools application.

Table 6.5: Data correlation matrix.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	CSc	1																																							
2	CustSatq	-0,1	1																																						
3	Delp	-0,6	0	1																																					
4	Delt	0,65	-0	-0,98	1																																				
5	DSt	0,02	-0,1	-0,16	0,13	1																																			
6	EqDp	-0,1	0,1	0,07	-0,1	-0,2	1																																		
7	Invc	0,1	-0,2	-0,04	0,03	0,16	-0	1																																	
8	Invq	-0,1	-0,1	0,07	-0,1	-0,1	-0	0,09	1																																
9	InvUtp	0,11	-0,2	-0,02	0,02	0,16	-0	0,97	0,1	1																															
10	Labc	0,55	-0,2	-0,52	0,52	0,1	-0	0,14	-0	0,12	1																														
11	Labp	-0,96	0,1	0,67	-0,7	-0,1	0,1	-0,13	0,1	-0,1	-0,7	1																													
12	Maintc	-0	-0,1	0,11	-0,1	-0	-0	0,03	-0	0,04	0,21	0,07	1																												
13	OrdFq	0,04	-0,2	0	0,01	0	-0	0,11	0,1	0,1	0,06	-0	-0	1																											
14	OrdLTt	0,65	-0	-0,98	1,0	0,13	-0	0,03	-0	0,02	0,52	-0,7	-0,1	0	1																										
15	OrdProcc	0,60	0	-0,97	0,99	0,14	-0	0,04	-0	0,02	0,43	-0,6	-0,1	0	0,99	1																									
16	OTDelq	-0	0,6	-0,15	0,12	0,05	-0	-0,05	0	-0	-0	-0	-0	-0,2	0,12	0,12	1																								
17	OTShipq	0,07	-0,2	-0,03	0,04	-0	-0	0,03	0	0,03	0,06	-0	-0	0,9	0,04	0,05	-0,2	1																							
18	PerfOrdq	-0	0,7	-0,03	0,03	-0	0,1	-0,03	-0	-0	-0	-0	-0	-0,1	0,03	0,02	0,9	-0,2	1																						
19	Pickp	-0,6	0	1	-0,97	-0,2	0,1	-0,05	0,1	-0	-0,5	0,66	0,11	0	-0,97	-0,97	-0,1	-0	-0	1																					
20	Pickq	-0,1	0,1	0,07	-0,1	-0	0,1	-0,18	-0	-0,1	-0,1	0,11	-0,1	-0,2	-0,1	-0,1	0,1	-0,1	0,1	0,04	1																				
21	Pickt	0,63	-0	-0,97	1,00	0,13	-0	0,03	-0	0,02	0,51	-0,7	-0,1	0	1,0	0,99	0,1	0	0	-0,98	-0,1	1																			
22	Putt	0,38	-0,1	-0,32	0,33	-0,2	-0	-0,12	-0	-0,1	0,74	-0,5	0,12	0	0,33	0,24	-0,1	0,1	-0,1	-0,3	-0	0,31	1																		
23	Recp	-0,39	0,1	0,34	-0,3	0,15	0,2	0,11	0,1	0,14	-0,76	0,51	-0,1	0	-0,3	-0,3	0,1	-0,1	0,1	0,33	0,01	-0,3	-1	1																	
24	Recq	0,08	0,1	-0,21	0,19	0,1	-0	0,01	0,2	0,04	0	-0,1	-0,1	-0,1	0,19	0,22	0,1	-0,1	0,1	-0,2	0,09	0,21	-0,1	0,04	1																
25	Rect	-0	-0,1	-0,12	0,1	1,00	-0	0,17	-0	0,17	0,02	-0	-0	0	0,1	0,11	0,1	-0	-0	-0,1	-0	0,1	-0,3	0,24	0,1	1															
26	Repp	-0,95	0,1	0,69	-0,7	-0,1	0,1	-0,14	0,1	-0,1	-0,69	0,98	0,07	-0	-0,7	-0,7	0	-0,1	0	0,68	0,08	-0,7	-0,5	0,5	-0,1	-0	1														
27	Repq	-0,1	-0	0,06	-0	0,03	-0	0,18	0,1	0,19	-0,1	0,11	0,07	0,1	-0	-0	0	0,1	-0	0,06	-0,1	-0	-0,1	0,13	0,1	0,04	0,04	1													
28	Rept	0,96	-0,1	-0,7	0,73	0,06	-0	0,13	-0	0,12	0,69	-0,98	-0,1	0	0,73	0,68	-0	0,1	-0	-0,7	-0,1	0,72	0,47	-0,5	0,1	0,01	-0,99	-0	1												
29	Scrapq	0,08	-0,3	0,03	-0	-0	0	-0,02	0,1	-0	0,12	-0,1	0,09	-0,2	-0	-0	-0,4	-0,3	-0,4	0,04	-0,3	-0	0,12	-0,1	-0,4	-0	-0	-0,41	0,03	1											
30	Shipp	-0,6	0	1,0	-0,98	-0,2	0,1	-0,05	0,1	-0	-0,5	0,67	0,11	-0	-0,98	-0,97	-0,1	-0,1	-0	1,0	0,07	-0,97	-0,3	0,34	-0,2	-0,1	0,69	0,06	-0,7	0,04	1										
31	Shipq	0,05	-0,1	0,03	-0	-0	-0	0,07	-0	0,08	0,06	-0	0	0,8	-0	-0	-0,1	0,8	-0	0,05	-0,2	-0	0,02	-0	-0,2	-0	-0	0,03	0,02	-0,3	0,01	1									
32	Shipt	0,65	-0	-0,98	1,00	0,13	-0	0,03	-0	0,02	0,52	-0,7	-0,1	0	1,00	0,99	0,1	0,1	0	-0,97	-0,1	1	0,33	-0,3	0,2	0,09	-0,7	-0	0,73	-0	-0,98	-0	1								
33	StockOutq	0,06	-0,1	-0,04	0,03	0,08	-0	0,4	0	0,19	0,11	-0,1	-0,1	0,1	0,03	0,02	-0,1	0,1	-0	-0	-0,5	0,01	0,04	-0,1	-0,1	0,07	-0,1	0,09	0,08	0,05	-0	0,07	0,03	1							
34	Stop	-0,4	0,1	0,32	-0,3	0,16	0,2	0,14	0,1	0,16	-0,7	0,48	-0,1	-0	-0,3	-0,2	0,1	-0,1	0,1	0,31	0,01	-0,3	-0,99	0,99	0,1	0,25	0,48	0,14	-0,47	-0,1	0,32	-0	-0,3	-0	1						
35	Stoq	-0	0,2	0,06	-0,1	-0,2	-0	-0,15	0,2	-0,1	-0,2	0,04	-0,2	0,2	-0,1	-0	0,1	0,1	0	0,06	0,01	-0	-0,1	0,18	0,1	-0,1	0,05	0,01	-0,04	-0,46	0,06	0,2	-0	-0,1	0,14	1					
36	Thp	-0,96	0,1	0,67	-0,7	-0,1	0,1	-0,13	0,1	-0,1	-0,69	1	0,07	-0	-0,7	-0,6	-0	-0	-0	0,66	0,11	-0,7	-0,5	0,51	-0,1	-0	0,98	0,11	-0,98	-0,1	0,67	-0	-0,7	-0,1	0,48	0,04	1				
37	TOp	-0,4	0,1	0,17	-0,2	-0,1	0	-0,88	-0	-0,91	-0,1	0,38	0,08	-0,1	-0,2	-0,2	0	-0,1	0	0,17	0,13	-0,2	0,14	-0,1	-0,1	-0,1	0,39	-0,2	-0,38	0,04	0,17	-0,1	-0,2	-0,2	-0,2	0,07	0,38	1			
38	Trc	0,59	0	-0,96	0,98	0,14	-0	0,01	-0	-0	0,41	-0,6	-0,1	-0	0,98	0,98	0,1	0	0	-0,96	-0,1	0,98	0,24	-0,3	0,2	0,11	-0,6	-0	0,66	-0	-0,97	-0	0,98	0	-0,2	-0	-0,6	-0,2	1		
39	TrUtp	-0,5	0,2	0,4	-0,4	-0,1	0,2	-0,08	0,2	-0,1	-0,96	0,64	-0,2	-0	-0,4	-0,3	0,1	-0	0,1	0,37	0,07	-0,4	-0,8	0,77	0,1	0,02	0,62	0,09	-0,62	-0,1	0,4	-0,1	-0,4	-0,1	0,75	0,18	0,64	0,04	-0,3	1	
40	WarUtp	-0,1	-0,1	0,01	-0,1	0,12	-0	0,6	0,1	0,61	0,14	0,01	0,01	0,1	-0,1	-0,1	-0,1	0	-0,2	0,01	-0,1	-0	0,06	-0,1	0,1	0,11	0,03	0,04	-0,04	0,04	0,01	0,12	-0,1	0,2	-0,1	-0,1	0,01	-0,5	-0,1	-0	1

6.4.3 Principal Component Analysis

This section performs the first PCA tests considering all variables in the model, the ones with low and with high correlations.

The free software R is used to attain the results. There are two mathematical methods available in R to perform PCA: *princomp* and *prcomp*. In *princomp* formula, calculation is done with the eigenvalues of the correlation or covariance matrix, using the divisor N (N= number of variables) for that. The *prcomp* formula, on the other hand, calculates a singular value decomposition (centered and possibly scaled) of the data matrix, using the usual divisor $N-1$. According to the R documentation, *prcomp* is the preferred method of calculation for numerical accuracy. Thus, we use this one to perform our analysis.

Two main analysis are made in this first phase: an analysis of indicators separated by their dimensions of cost, quality, time, productivity (Section 6.4.3.1) and a global PCA with all 40 indicators (Section 6.4.3.2). The objective is to verify the indicator's behavior in aggregation situations, providing more elements to define the final group which will make part of the integrated model.

As justified above (Section 6.4.1), data is standardized before their utilization in PCA due to the sensibility of the model to high data variation.

6.4.3.1 PCA for indicator dimensions

Initially, the PCA results for indicators separated by dimensions are shown in Figure 6.6 for quality, Figure 6.7 for productivity, Figure 6.8 for time, Figure 6.9 for cost. All figures are divided in three parts (as well as Figure 6.10, showing the PCA result for all 40 indicators): a table demonstrating the standard deviation, proportions of variance and cumulative proportion for the main components (in the bottom of the figure); a table of indicators *versus* components (located in the up-left-side of the figures); the scree plot in the right side of the figures. Each of these three parts is explained as follows.

The tables on the bottom of the figures have three different informations to analyze. Initially, the standard deviation of each principal component higher than one is used as one of the criteria to define the number of components to retain. As an example, in Figure 6.6 there are 5 components (from PC1 up to PC5) with standard deviation higher than one, indicating that these five components should be considered in the representation of all quality indicators. The second information, proportion of variance, demonstrates the contribution of each component to explain the data variance, whereas the cumulative proportion (third line) presents the sum of all component variances. For Figure 6.6, the cumulative proportion is 76,9%, signifying that the first five components explain 76,9% of the total quality indicators variance.

The indicator *versus* component tables demonstrate in the cells the loadings a_{ij}, giving the weight of each indicator in the respective component. The highlighted cells are the ones with $|\text{loading}| \geq 0,3$, denoting the indicators considered in each component. For example, Figure 6.9 shows PC1 and PC2 (both with standard deviation higher than one) formed by the following indicators: $\mathbf{CS_c}$, $\mathbf{Lab_c}$, $\mathbf{OrdProc_c}$, $\mathbf{Tr_c}$ for PC1 and $\mathbf{Inv_c}$, $\mathbf{Lab_c}$ and $\mathbf{Maint_c}$ for PC2. The linear combinations of indicators obtained from this table are shown in Equation 6.1 and Equation 6.2. The signs of the loadings are arbitrary, and, according to R documentation, they may differ between different PCA programs or even between different builds of R.

$$PC1 = -0,48 \times \mathbf{CS_c} - 0,40 \times \mathbf{Lab_c} - 0,55 \times \mathbf{OrdProc_c} - 0,55 \times \mathbf{Tr_c} \quad (6.1)$$

$$PC2 = 0,42 \times \mathbf{Inv_c} + 0,44 \times \mathbf{Lab_c} + 0,74 \times \mathbf{Maint_c} \quad (6.2)$$

Finally, the scree plot shows the variance of the data (y axis, measured by the square of the standard deviation [σ^2]) explained by each component (x axis). The principal components are presented in decreasing order of importance with the objective of helping analysts to easily visualize the sharp drop in the plot, which is also used as a signal that subsequent components should be ignorable.

One may expect from the PCA performed that each indicator dimension will be represented by one component (total of 4 components for all indicators), since indicators of the same dimension could be more related among them than indicators of different dimensions. Nevertheless, the results obtained do not confirm this hypothesis. The number of components to include in the model (using the criterion of standard deviation higher than one to retain components) are two for time and cost indicators, whereas for productivity and quality are three and five, respectively. It means that, if we would like to represent all 40 indicators using these results, the number of components utilized will be 12 (2 of time + 2 of cost + 3 of productivity + 5 of quality) instead of the 4 components initially expected. Since PCA has the objective to represent variables in a small number of principal components, we can infer that 12 components are not a good result. Moreover, the cumulative proportion of data variance explained by these 2 components of cost and 5 of quality are still low, with 67% and 76,9%, respectively.

Looking at indicator *versus* component tables in Figures 6.6, 6.7, 6.8, 6.9, specifically in the columns of principal components with standard deviations > 1, it is possible to see that a great quantity of indicators are allocated in more than one component, what is not desirable for PCA results. The worst results can be seen for quality and productivity dimensions, with more than half of indicators allocated in at least two components. Therefore, we conclude that indicators are not related just by their dimensions.

QUALITY INDICATORS

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
CustSatq	-0,32	0,32	0,20	0,06	-0,17	0,15	-0,10	-0,18	-0,80	0,05
Invq	0,06	0,02	-0,20	-0,46	-0,52	-0,51	-0,31	0,26	-0,13	0,06
OrdFq	0,45	0,29	0,04	0,11	-0,05	-0,15	0,07	-0,03	-0,08	-0,31
OTDelq	-0,34	0,35	0,26	0,04	-0,06	-0,28	-0,08	0,08	0,39	-0,10
OTShipq	0,45	0,29	0,01	0,15	0,03	-0,14	0,05	0,04	-0,13	-0,46
PerfOrdq	-0,34	0,35	0,33	0,09	0,01	-0,20	0,02	0,03	0,21	-0,04
Pickq	-0,18	0,07	-0,51	0,41	0,15	-0,04	-0,12	0,59	-0,14	0,09
Recq	-0,16	0,15	-0,35	-0,34	-0,01	-0,17	0,76	-0,17	-0,06	0,06
Repq	0,05	0,14	-0,10	-0,47	0,61	-0,08	-0,46	-0,22	-0,05	0,05
ScrapRate	0,05	-0,49	0,23	0,14	-0,29	-0,21	-0,08	-0,21	-0,05	0,03
Shipq	0,41	0,33	0,10	0,17	-0,05	-0,07	0,04	-0,05	0,07	0,81
StockOutq	0,13	-0,06	0,49	-0,40	0,09	0,26	0,21	0,64	-0,11	0,03
Stoq	0,03	0,29	-0,23	-0,18	-0,45	0,63	-0,19	-0,08	0,29	-0,07

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11
Standard deviation	1,77	1,6708	1,2488	1,2011	1,033	0,915	0,887	0,7366	0,613	0,387	0,362
Proportion of Variance	0,241	0,2147	0,12	0,111	0,082	0,064	0,06	0,0417	0,029	0,012	0,01
Cumulative Proportion	0,241	0,4557	0,5757	0,6867	0,769	0,833	0,894	0,9354	0,964	0,976	0,986

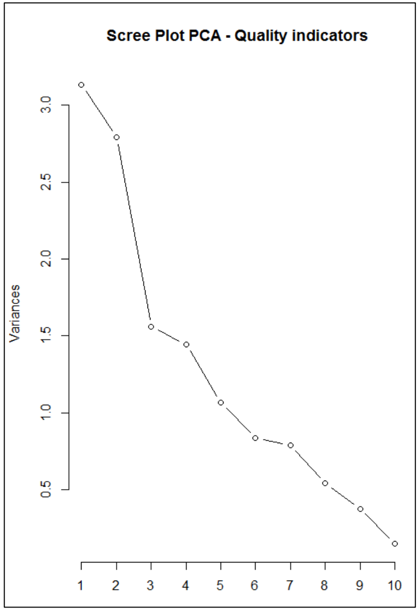


Figure 6.6: PCA results for quality indicators.

PRODUCTIVITY INDICATORS

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Delp	0,34	0,02	0,33	-0,28	-0,14	-0,07	0,05	0,15
EqDp	0,07	0,00	-0,23	-0,59	0,76	0,05	-0,11	0,01
InvUtp	-0,05	-0,58	0,20	0,04	0,04	0,43	-0,16	0,42
Labp	0,37	0,06	0,01	0,30	0,18	0,24	-0,08	0,18
Pickp	0,33	0,02	0,34	-0,29	-0,15	-0,09	0,00	-0,23
Recp	0,27	-0,27	-0,40	-0,03	-0,21	-0,22	-0,29	-0,06
Repp	0,37	0,06	0,03	0,29	0,18	0,17	-0,12	-0,63
Shipp	0,34	0,02	0,33	-0,28	-0,14	-0,08	0,04	0,15
Stop	0,26	-0,29	-0,40	-0,03	-0,20	-0,27	-0,31	0,09
Thp	0,37	0,06	0,01	0,30	0,18	0,24	-0,08	0,18
TOp	0,12	0,58	-0,08	0,17	0,08	-0,30	-0,17	0,49
TrUtp	0,30	-0,13	-0,36	0,02	0,00	0,00	0,85	0,12
WarUtp	-0,03	-0,38	0,35	0,33	0,42	-0,66	0,09	0,00

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Standard deviation	2,4838	1,5742	1,3505	0,9772	0,96	0,582	0,513	0,162
Proportion of Variance	0,4745	0,1906	0,1403	0,0735	0,071	0,026	0,02	0,002
Cumulative Proportion	0,4745	0,6652	0,8055	0,8789	0,95	0,976	0,996	0,998

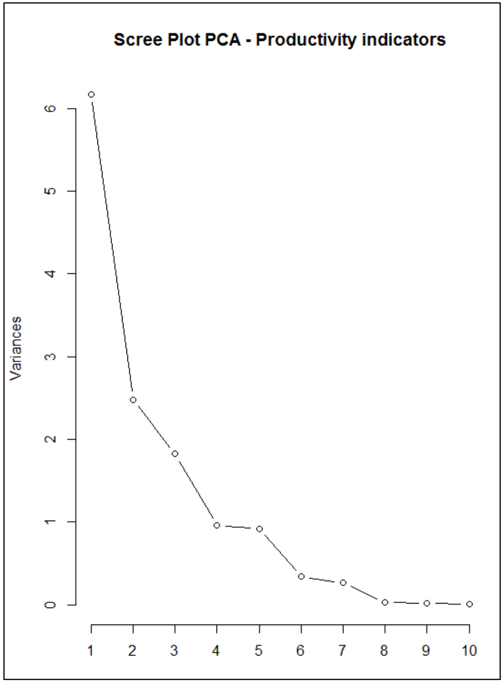


Figure 6.7: PCA results for productivity indicators.

TIME INDICATORS

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Delt	-0,45	0,00	0,16	0,14	0,30	-0,40	0,02	0,71
DSt	-0,07	0,66	-0,25	0,04	-0,01	-0,04	-0,70	0,00
OrdLTt	-0,45	0,00	0,16	0,14	0,30	-0,40	0,02	-0,71
Pickt	-0,45	0,00	0,17	0,14	-0,86	-0,01	0,01	0,00
Putt	-0,19	-0,30	-0,86	0,37	-0,01	0,01	0,07	0,00
Rect	-0,05	0,68	-0,16	0,01	0,00	0,04	0,71	0,00
Rept	-0,37	-0,08	-0,27	-0,88	-0,01	0,00	0,00	0,00
Shipt	-0,45	0,00	0,16	0,14	0,28	0,82	-0,05	0,00

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Standard deviation	2,1833	1,4445	0,8962	0,5803	0,079	0,025	0,01	0,00
Proportion of Variance	0,5958	0,2608	0,1004	0,0421	8E-04	8E-05	1E-05	0,00
Cumulative Proportion	0,5958	0,8567	0,957	0,9991	1	1	1	1,00

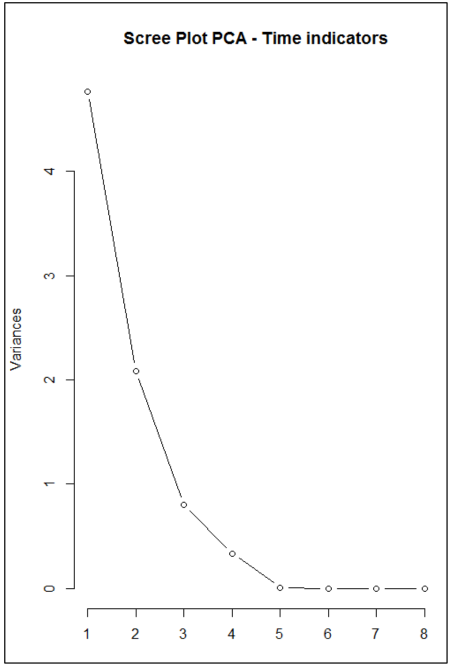


Figure 6.8: PCA results for time indicators.

COST INDICATORS

	PC1	PC2	PC3	PC4	PC5	PC6
CSc	-0,48	0,09	-0,01	0,42	-0,76	0,01
Invc	-0,07	0,42	-0,88	-0,22	-0,01	-0,02
Labc	-0,40	0,44	0,10	0,53	0,59	-0,03
Maintc	0,03	0,74	0,46	-0,45	-0,19	0,01
OrdProcc	-0,55	-0,20	0,02	-0,37	0,13	0,71
Trc	-0,55	-0,21	0,05	-0,39	0,10	-0,70

	PC1	PC2	PC3	PC4	PC5	PC6
Standard deviation	1,6802	1,0965	0,9837	0,7768	0,621	0,134
Proportion of Variance	0,4705	0,2004	0,1613	0,1006	0,064	0,003
Cumulative Proportion	0,4705	0,6709	0,8322	0,9328	0,997	1

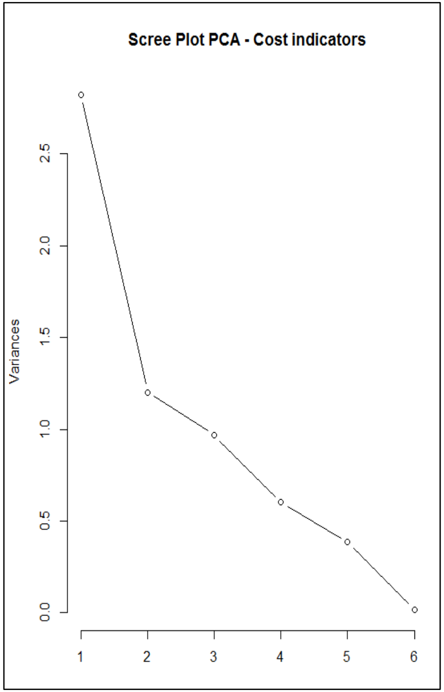


Figure 6.9: PCA results for cost indicators.

6.4.3.2 PCA with all 40 indicators

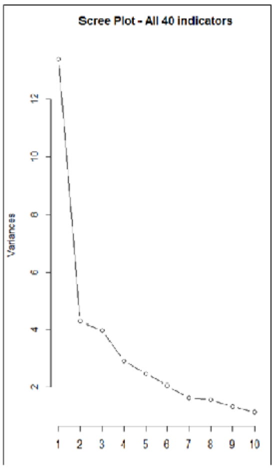
Another PCA is performed with all 40 indicators together, and the results are shown in Figure 6.10. The informations presented in Figure 6.10 are the same as described previously for each dimension. The difference is in the indicator *versus* component table, which demonstrates only the columns of principal components (PC) with standard deviation higher than one (the criterion used to choose the number of components to retain). Moreover, the minimum loading value is reduced to 0.2 ($|\text{loading}| \geq 0.2$). This limit is empirically chosen based on the loading results for the first component.

Defining the number of components to retain by the scree plot (in the right side of Figure 6.10), one could choose them as the first two; PC1 and PC2. Indeed, these components are which better contain/explain variable's variance, and the sharp drop is in that point in the plot. From the standard deviation perspective, there are 10 components with standard deviation higher than one, proposing the use of all of them to represent the indicators. Comparing the results with respect to two or ten components we can see that with 2 components, 19 indicators are excluded from the analysis and with 10 components none of them is excluded. Regarding the number of indicators designated for several components, with 2 components there is no indicator repetition, and with 10 components 17 indicators are allocated in more than one PC. Moreover, two components explain 44% of data variation whereas ten components represent 86%. This situation establishes a trade-off between both options.

As the analysis carried out on this thesis objectives to aggregate the greater number of indicators as possible, we consider initially the 10 principal components in the model. The main reason for this choice is that this result can be improved in Section 7.2 to get the final integrated model. However, in situations where there is a doubt about the number of components to retain, it is very important to analyze if the components have a sense and are in accordance to the warehouse reality. A framework to demonstrate the results presented in indicator *versus* component table, of Figure 6.10, is built in Figure 6.11.

PCA with all 40 indicators

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
CSc	-0,22	0,06	-0,05	0,01	-0,08	0,14	-0,36	0,01	-0,05	0,07
CustSatq	0,02	-0,21	0,18	-0,02	-0,36	-0,03	0,02	0,18	0,01	-0,15
Delp	0,25	0,14	-0,03	0,01	-0,08	0,01	-0,12	-0,02	-0,04	0,02
Delt	-0,26	-0,13	0,03	-0,02	0,09	0,01	0,10	0,03	0,03	0,03
DSt	-0,03	-0,12	-0,15	0,13	0,13	-0,55	-0,16	-0,07	-0,07	-0,12
EqDp	0,04	-0,08	0,07	-0,02	0,04	0,28	-0,04	0,15	0,32	0,03
Invc	-0,03	-0,01	-0,44	0,15	-0,15	0,07	0,15	0,04	0,08	-0,02
Invq	0,03	-0,05	-0,07	-0,06	0,05	0,26	0,19	-0,16	-0,34	-0,17
InvUtp	-0,02	-0,03	-0,43	0,15	-0,17	0,07	0,12	-0,06	0,18	0,02
Labc	-0,198	0,24	-0,01	0,05	-0,12	-0,16	0,07	-0,02	-0,02	0,02
Labp	0,24	-0,08	0,05	-0,03	0,11	-0,08	0,29	0,01	0,05	0,01
Maintc	0,01	0,13	0,00	0,07	-0,03	-0,15	0,14	0,07	0,03	0,58
OrdFq	-0,01	0,06	-0,19	-0,49	0,05	-0,09	-0,01	0,06	0,10	-0,03
OrdLTt	-0,26	-0,13	0,03	-0,02	0,09	0,01	0,10	0,03	0,03	0,03
OrdProcc	-0,24	-0,17	0,02	-0,03	0,11	0,03	0,11	0,02	0,03	0,02
OTDelq	-0,02	-0,22	0,13	0,02	-0,42	-0,15	0,08	0,20	0,03	-0,04
OTShipq	-0,02	0,07	-0,16	-0,50	0,05	-0,10	-0,02	0,03	0,11	0,04
PerfOrdq	0,00	-0,20	0,12	0,02	-0,46	-0,12	-0,02	0,27	0,07	0,01
Pickp	0,25	0,14	-0,03	0,01	-0,09	0,01	-0,13	0,01	-0,04	0,02
Pickq	0,03	-0,05	0,14	0,04	-0,10	-0,04	-0,05	-0,50	0,45	0,01
Pickt	-0,25	-0,14	0,04	-0,02	0,10	0,01	0,11	0,01	0,04	0,02
Putt	-0,14	0,34	0,13	-0,02	-0,11	-0,05	0,19	-0,05	-0,01	-0,10
Recp	0,15	-0,33	-0,13	0,00	0,11	0,06	-0,19	0,07	0,02	0,10
Recq	-0,04	-0,18	0,01	0,02	-0,11	0,01	0,08	-0,41	-0,25	-0,08
Rect	-0,02	-0,15	-0,16	0,13	0,14	-0,53	-0,17	-0,06	-0,07	-0,11
Repp	0,24	-0,07	0,05	-0,02	0,09	-0,08	0,27	0,05	0,06	-0,04
Repq	0,02	-0,07	-0,13	-0,07	-0,08	0,00	0,16	-0,13	-0,33	0,58
Rept	-0,24	0,07	-0,05	0,01	-0,08	0,09	-0,26	-0,04	-0,06	0,06
Scrapq	-0,01	0,18	0,00	0,28	0,33	0,11	-0,08	0,29	0,10	-0,14
Shipp	0,25	0,13	-0,03	0,03	-0,09	0,02	-0,12	-0,02	-0,04	0,02
Shipq	0,00	0,07	-0,17	-0,48	-0,03	-0,12	-0,05	0,11	0,14	-0,04
Shipt	-0,26	-0,13	0,03	-0,04	0,09	0,01	0,10	0,03	0,04	0,03
StockOutq	-0,02	0,06	-0,19	0,03	0,00	0,00	0,13	0,42	-0,38	-0,14
Stop	0,14	-0,33	-0,14	0,02	0,11	0,06	-0,19	0,05	0,01	0,11
Stoq	0,03	-0,10	0,04	-0,27	-0,12	0,13	-0,10	-0,19	-0,29	-0,26
Thp	0,24	-0,08	0,05	-0,03	0,11	-0,08	0,29	0,01	0,05	0,01
TOp	0,07	0,06	0,41	-0,11	0,17	-0,19	0,08	0,02	-0,12	-0,02
Trc	-0,24	-0,18	0,04	-0,03	0,11	0,02	0,12	0,03	0,03	0,02
TrUtp	0,17	-0,29	-0,01	-0,05	0,13	0,17	-0,03	0,01	0,01	-0,03
WarUtp	0,00	0,06	-0,30	0,09	-0,08	0,00	0,32	-0,13	0,15	-0,30



	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	**PC10**	PC11	PC12
Standard deviation	3,6571	2,0645	1,9917	1,7033	1,563	1,431	1,2734	1,24	1,15	**1,063**	0,99	0,882
Proportion of Variance	0,3344	0,1066	0,0992	0,0725	0,0611	0,051	0,0405	0,0387	0,0331	**0,0282**	0,0245	0,019
Cumulative Proportion	0,3344	0,4409	0,5401	0,6126	0,6737	0,725	0,7654	0,8042	0,8372	**0,8655**	0,89	0,909

Figure 6.10: Result of Principal component analysis for all 40 indicators.

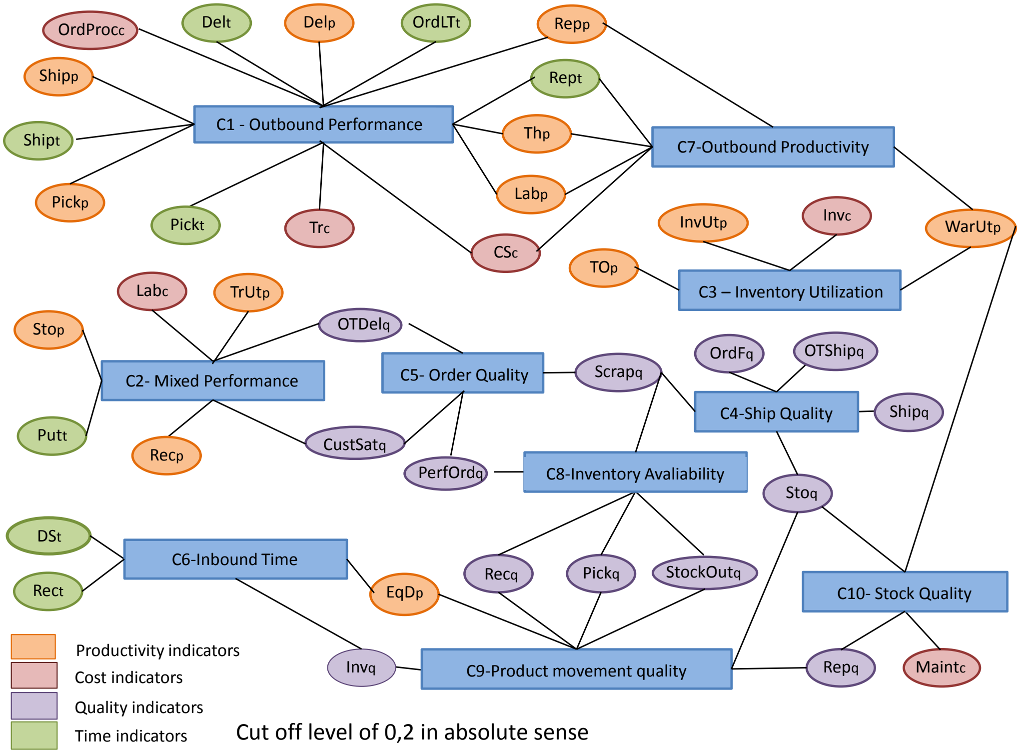


Figure 6.11: Framework of PCA result for all 40 indicators.

The names inside the blue rectangles are chosen according to the most relevant quantity of indicator activities that the component encompasses. For example, C1 (which is derived from PC1 column of Figure 6.10) is named “Outbound Performance” because the majority of indicators making part of this component are related to replenishment, picking, shipping and delivery activities. Also, C3 (representing the PC3 column of Figure 6.10) is defined as “Inventory Utilization” because indicators related to stocks and space utilization are comprised in the component. The exception is C2, named “Mixed Performance” because half of the indicators are linked to the delivery and the other half to inbound activities. This component in particular does not present a good result, since there is no “physical relation” among these outbound and inbound indicators (it is possible to see it in the Jacobian and correlation matrix). It probably happens because there are indicators with just very low correlations, and their data confuse the PCA tool during the establishment of indicator relationships. In Section 7.2 this result is analyzed again and these indicators may probably be discarded of the analysis to improve the final PCA result.

From Figure 6.11, we note a tendency in indicators’ aggregation: the majority of indicators are related in components according to their measurement domain. It means that indicators are usually grouped with others from different dimensions but all metrics are from the same warehouse area. C1, for example, are formed of productivity, time and cost indicators, and all of them are related to outbound activities. There are some exceptions among the quality indicators: C4, C5 and C8 are components containing just quality indicators. This is particularly interesting since these indicators also share data with indicators of other dimensions (as cost, time and productivity).

Comparing the results of PCA performed for each dimension and for all indicators at the same time, we conclude that the second analysis has provided better outcomes if the components are compared in a practical sense. It means that the indicators aggregated in components without dimension distinction seem to be more consistent with the reality. Thus, the PCA result for all 40 indicators is used in the next chapter as the basis to the integrated model development. As indicators with low correlations are also included in the framework presented, the next chapter analyzes the right indicators that should be excluded of the group to improve the PCA outcome.

6.5 Conclusions

In this chapter, we have created a scenario for the standard warehouse to generate the data used to calculate indicators. This scenario represents the warehouse shop-floor with its flow of products throughout the processes. An *Excel*® spreadsheet is elaborated with data following normal and random distributions, which demonstrate the effect of chained processes. This initial dataset is used to calculate performance indicators, which are employed in the mathematical tools.

A data sample of one month and the complete analytical model are coupled with CADES® software to calculate the Jacobian matrix. The assessment of the Jacobian matrix makes part of an exhaustive procedure developed to infer about indicator relationships, which calculates the partial derivatives matrix of the complete analytical model, encompassing indicator and data equations.

From the results attained, we can conclude that it is very hard to quantitatively determine from the partial derivatives the intensity of the relationship between indicators. The procedure described in this chapter is, therefore, used to qualitatively analyze their interactions, providing a preliminary view of indicator relationships and verifying if the results are coherent from an analytical point of view.

Further, the whole dataset (100 months) of indicator measures are utilized to apply statistical tools. The correlation matrix and the principal component analysis are the main tools performed to determine indicator relationships quantitatively and how they could be aggregated to estimate the integrated performance. The PCA does not provide good results in the dimensions aggregated separately nor in the total group of indicators. The problems are mainly related to inconsistencies in the indicators group (some indicators of the same component have no relationship among them) and to the great quantity of indicators designated in more than one component. One reason for these problems may be the variables not correlated with others, which can lead to misunderstandings of the statistical model. Thus, next chapter evaluates these variables proposing an improved integrated model for warehouse performance measurement.

Chapter 7

Model Solving, Implementation and Update

If it were easy it would have been done already.

Unknown

Abstract

This chapter proposes the integrated model to evaluate warehouse performance. To attain this objective, the results obtained from different sources are analyzed to determine the best number of components to consider in the model. Moreover, a scale is developed for the integrated model utilizing an optimization tool, which defines the upper and lower limits of the scale from the maximization and minimization results. The integrated model with the scale is tested in two different warehouse performance situations verifying that the utilization of the integrated model can help managers to better evaluate the warehouse as a whole.

7.1 Introduction

The last chapter has presented the application of some methods to analyze indicator relationships. The results obtained with the measurement of relationships using the Jacobian matrix, correlation matrix and PCA method are analyzed to propose an integrated performance model.

The objective of this model is to be used by managers in their periodic warehouse performance evaluations. In order to help the interpretation of the integrated model results, a scale is also proposed using the analytical model as a basis to perform an optimization, which defines the upper and lower limits of the integrated indicator.

Afterwards, the utilization of the final model with the developed scale is detailed, along with a discussion of how to update the model when necessary.

7.2 Analysis of Jacobian and Correlation matrix to improve PCA results

Chapter 6 presents indicator relationships measured by the Jacobian matrix, the Correlation matrix and the Principal Component analysis. To attain the final integrated model, the Jacobian and Correlation matrix are used as decision support to improve the PCA result, which defines the basis of the aggregated model.

From the PCA performed for all 40 indicators, presented in Section 6.4.3.2, we have verified that some indicators do not fit well the model, probably because of their low correlation with other indicators. Moreover, the retention of 10 principal components could be seen as a high number considering the 40 input variables. In cases like that, the analyst should find the best balance between simplicity (retaining as few as possible components, which cause the exclusion of indicators) and completeness (explain most of data variation).

In this thesis, the initial suggestion of which indicators should be discarded of the model come from an analysis of the Jacobian and Correlation matrix. Initially, we list the worst outcomes obtained in the Jacobian (using Table 6.4) and in the Correlation matrix (using Table 6.5). For the Jacobian, the worst results are represented by indicators with the lowest number of shared data and, for the Correlation matrix, the indicators with the lowest correlation values are the worst results. Secondly, the two lists generated with the worst results are compared to suggest which indicators should be discarded of the model.

Table 7.1 summarizes these results in three parts: on the top of the table are presented the indicators with bad results in both analysis; in the middle of the table, indicators with bad results in correlation are listed with their corresponding number of shared data (from Table

6.4) described in the right column; on the bottom of the table is the opposite: the indicators with few number of shared data (from Table 6.4) are listed with their correlation measurements (from Table 6.5).

The analysis of Table 7.1, suggesting a decreasing order of indicators to discard, is presented as follows.

From this initial list of 15 indicators presented in Table 7.1, we can see 4 of them with no correlations higher than 0.4 ($r \leq 0.4$). As PCA does not fit a good model with variables having no significant correlations, these indicators are the first candidates to be discarded ($\mathbf{EqD_p}$, $\mathbf{Maint_c}$, $\mathbf{Rec_q}$, $\mathbf{Inv_q}$). However, $\mathbf{Inv_q}$ shares data with a great quantity of indicators, demanding a deeper analysis. To determine the sequence of exclusion for the indicators, we use the decreasing order presented in Table 7.1 (i.e. the indicators with no correlations higher than 0.4 ($r \leq 0.4$) and few shared data are deleted first).

The exclusion of each indicator is confirmed if a better PCA outcome is attained. Five aspects are considered in the analysis of PCA results: (i) the number of principal components (PC) with $\sigma > 1$ should be the fewest possible; (ii) the cumulative proportion of data explained by the PC's should be as high as possible; (iii) the number of indicators designated in more than one component should be as low as possible; (iv) the loading signs should be in accordance with indicator's objectives; (v) the indicators grouped in each component should have a physical explanation in a warehouse context. These five criteria come from the literature about PCA application. The first three aspects are quantitative and used throughout the analysis of indicator's exclusion. The last two are evaluated at the moment that the exclusion of an indicator provides only few changes in the quantitative aspects.

In the cases that the indicator exclusion does not improve PCA result, the indicator is maintained in the model and the following one of the list is tested. Therefore, all indicators of Table 7.1 are tested one by one.

Table 7.2 shows the outcomes for each PCA, detailing the three quantitative parameters used to analyze the quality of the result.

Only the exclusions that have improved the PCA results are demonstrated in Table 7.2. The PCA result after the exclusion of the three worst indicators ($\mathbf{EqD_p}$, $\mathbf{Maint_c}$, $\mathbf{Rec_q}$) is improved with one PC less than step zero (see Table 7.2), fewer indicators in more components than before and data explanation of 88,6%, in comparison of 86% in step zero.

At the end, the exclusion of the majority of indicators with low or medium correlations in Table 7.1 ($\mathbf{EqD_p}$, $\mathbf{Maint_c}$, $\mathbf{Rec_q}$, $\mathbf{Rep_q}$, $\mathbf{Sto_q}$,

Table 7.1: The indicators with Correlation and Jacobian worst results.

Indicator	Correlation worst results	Jacobian worst results
$\mathbf{EqD_p}$	$\mid r \mid \leq 0.4$ with all indicators	Shares 1 data with 20 indicators
$\mathbf{Maint_c}$	$\mid r \mid \leq 0.4$ with all indicators	Shares 2 data with $\mathbf{CS_c}$
$\mathbf{Rec_q}$	$\mid r \mid \leq 0.4$ with all indicators	Shares 2 data with 4 indicators
$\mathbf{Rep_q}$	$\mid r \mid = 0.41$ with $\mathbf{Scrap_q}$	Shares 2 data with 3 indicators
$\mathbf{Pick_q}$	$\mid r \mid = 0.5$ with $\mathbf{StockOut_q}$	Shares 2 data with 4 indicators
Indicator	**Correlation worst results**	**Jacobian results**
$\mathbf{Inv_q}$	$\mid r \mid \leq 0.4$ with all indicators	Shares 2 data with 14 indicators
$\mathbf{Sto_q}$	$\mid r \mid = 0.46$ with $\mathbf{Scrap_q}$	Shares 2 data with 7 indicators
$\mathbf{StockOut_q}$	$\mid r \mid = 0.5$ with $\mathbf{Pick_q}$ and $\mid r \mid = 0.4$ with $\mathbf{Inv_c}$	Shares 1 data with 6 indicators, 2 data with 3 indicators, 5 data with $\mathbf{Inv_c}$
$\mathbf{Scrap_q}$	$\mid r \mid = 0.4$ with $\mathbf{Rec_q}$, $\mid r \mid = 0.41$ with $\mathbf{Rep_q}$ and $\mid r \mid = 0.46$ with $\mathbf{Sto_q}$	Shares 1 data with 5 indicators, 2 data with 7 indicators, 4 data with $\mathbf{Th_p}$ and $\mathbf{Lab_p}$
Indicator	**Correlation results**	**Jacobian worst results**
$\mathbf{Ship_q}$	$\mid r \mid = 0.8$ with $\mathbf{OrdF_q}$ and $\mathbf{OTShip_q}$	Shares 2 data with 7 indicators
$\mathbf{OTShip_q}$	$\mid r \mid = 0.9$ with $\mathbf{OrdF_q}$ and $\mid r \mid = 0.8$ with $\mathbf{Ship_q}$	Shares 2 data with 7 indicators
$\mathbf{OrdF_q}$	$\mid r \mid = 0.9$ with $\mathbf{OTShip_q}$ and $\mid r \mid = 0.8$ with $\mathbf{Ship_q}$	Shares 2 data with 7 indicators
$\mathbf{CustSat_q}$	$\mid r \mid = 0.6$ with $\mathbf{OTDel_q}$ and $\mid r \mid = 0.7$ with $\mathbf{PerfOrd_q}$	Shares 2 data with 9 indicators
$\mathbf{OTDel_q}$	$\mid r \mid = 0.6$ with $\mathbf{CustSat_q}$ and $\mid r \mid = 0.9$ with $\mathbf{PerfOrd_q}$	Shares 2 data with 9 indicators
$\mathbf{PerfOrd_q}$	$\mid r \mid = 0.7$ with $\mathbf{CustSat_q}$ and $\mid r \mid = 0.9$ with $\mathbf{OTDel_q}$	Shares 2 data with 9 indicators

Table 7.2: Steps performed to attain the final indicator group

Step	Indicator Eliminated	Number of indicators left	PCA Results
0	–	40	• 10 PC with $\sigma > 1$ • 17 indicators designated in more than one component • Cumulative proportion of 10 PC: 86,5%
1	$\mathbf{EqD_p}$, $\mathbf{Maint_c}$	38	• 10 PC with $\sigma > 1$ • 18 indicators designated in more than one component • Cumulative proportion of 10 PC: 89%
2	$\mathbf{Rec_q}$	37	• 9 PC with $\sigma > 1$ • 14 indicators designated in more than one component • Cumulative proportion of 9 PC: 88,6%
3	$\mathbf{Rep_q}$	36	• 9 PC with $\sigma > 1$ • 14 indicators designated in more than one component • Cumulative proportion of 9 PC: 90,5%
4	$\mathbf{Sto_q}$	35	• 8 PC with $\sigma > 1$ • 12 indicators designated in more than one component • Cumulative proportion of 8 PC: 89,3%
5	$\mathbf{Pick_q}$	34	• 7 PC with $\sigma > 1$ • 15 indicators designated in more than one component • Cumulative proportion of 7 PC: 87,5%
6	$\mathbf{StockOut_q}$	33	• 7 PC with $\sigma > 1$ • 15 indicators designated in more than one component • Cumulative proportion of 7 PC: 89,8%

$\mathbf{Pick_q}$ and $\mathbf{StockOut_q}$) improve the PCA result, providing a higher cumulative proportion of data explanation and the decrease number of PC's (from 10 to 7). $\mathbf{Inv_q}$ and $\mathbf{Scrap_q}$ are the only exceptions, being kept in the model because their exclusion cause worst results.

Even if the PCA outcome for step 5 is not demonstrated, we highlight that $\mathbf{StockOut_q}$ is excluded from the final group because it has not been designated for any PC, i.e. the loadings for all PC's are lower than 0.2 ($|\text{loading}|<0.2$).

Analyzing the indicators not excluded from the analysis but listed in Table 7.1, we might conclude that the informations provided by the correlation and the Jacobian are complementary because some indicators with low correlations have a great quantity of shared data (e.g. $\mathbf{Scrap_q}$) impeding their exclusion.

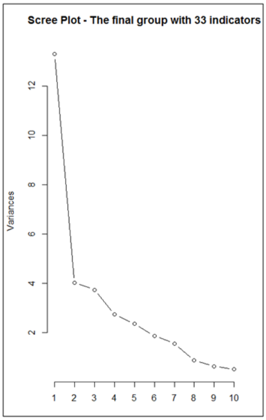
Finally, the group of indicators considered for the aggregated model are 33 from the initial 40, and the PCA result is detailed in Figure 7.1.

Figure 7.1 demonstrates that PC1 explains 40% of data variance (table in the bottom of the figure) and incorporate almost half of the indicators (14 of 33 in total) (first column of indicator *versus* PC table).

Initially, the indicators are considered in a component when the loadings are higher than 0.2 ($|\text{ loading}|\geq 0.2$). Nevertheless, this minimum loading value cause some problems in component 2. The first inconsistency is about the inclusion of $\mathbf{TrUt_p}$ and $\mathbf{OTDel_q}$ indicators in the component two, where the majority of indicators are related to inbound activities. The second problem is the sign of $\mathbf{Rec_t}$, that should be negative instead of positive. As the absolute loading values in component one are at least 0.22, we define this value as the new cut off level ($|\text{loading}| \geq 0.22$). According to PennState (2015a), the definition of which number is considered a large or small loading is a subjective decision. In the work of Lu and Yang (2010), they include in the model just loadings higher then 0,5; however, the authors have considered their criterion very conservative.

Switching the absolute cut off level value to 0.22, a "new" PCA result is obtained (see Figure 7.2), with two main differences from the previous result (Figure 7.1). Firstly, the indicator $\mathbf{TrUt_p}$ continues to be inappropriately designated to PC2 since it refers to the utilization of the delivery truck and all other indicators are related to inbound activities. However, if this indicator is eliminated the global results of other components become worst. Therefore, the indicator is maintained in the final model. Secondly, changing the cut off level reduces to 8 the number of indicators designated in more than one component, improving the final result.

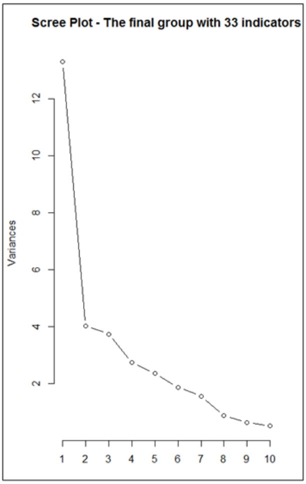
	PC1	PC2	PC3	PC4	PC5	PC6	PC7
CSc	-0,22	-0,05	0,08	-0,05	0,07	-0,09	0,38
CustSatq	0,02	0,17	-0,22	-0,01	0,40	0,00	-0,04
Delp	0,25	-0,14	0,06	-0,04	0,07	0,01	0,12
Delt	-0,26	0,13	-0,06	0,05	-0,07	-0,03	-0,09
DSt	-0,03	0,18	0,12	-0,07	-0,13	0,61	0,05
Invc	-0,03	0,10	0,43	-0,17	0,13	-0,07	-0,18
Invq	0,03	0,05	0,07	0,03	-0,08	-0,31	-0,13
InvUtp	-0,02	0,11	0,44	-0,17	0,15	-0,08	-0,16
Labc	-0,20	-0,24	0,05	-0,07	0,10	0,18	-0,10
Labp	0,24	0,08	-0,07	0,07	-0,09	0,02	-0,29
OrdFq	-0,01	-0,05	0,22	0,51	0,04	0,04	0,01
OrdLTt	-0,26	0,13	-0,06	0,05	-0,07	-0,03	-0,09
OrdProcc	-0,24	0,17	-0,06	0,06	-0,10	-0,06	-0,10
OTDelq	-0,02	0,21	-0,18	-0,03	0,46	0,09	-0,09
OTShipq	-0,02	-0,07	0,18	0,53	0,03	0,03	0,04
PerfOrdq	0,00	0,18	-0,17	-0,04	0,51	0,08	0,02
Pickp	0,25	-0,14	0,06	-0,04	0,08	0,02	0,13
Pickt	-0,25	0,14	-0,06	0,05	-0,08	-0,04	-0,10
Putt	-0,15	-0,37	-0,07	-0,02	0,09	0,07	-0,22
Recp	0,15	0,36	0,07	0,03	-0,09	-0,07	0,22
Rect	-0,02	0,21	0,12	-0,07	-0,14	0,59	0,07
Repp	0,24	0,07	-0,07	0,06	-0,08	0,03	-0,28
Rept	-0,25	-0,07	0,07	-0,04	0,07	-0,04	0,28
ScrapRate	-0,01	-0,14	0,02	-0,24	-0,34	-0,06	0,06
Shipp	0,25	-0,13	0,05	-0,05	0,07	0,01	0,12
Shipq	0,00	-0,05	0,20	0,50	0,12	0,07	0,03
Shipt	-0,26	0,13	-0,05	0,06	-0,07	-0,04	-0,09
Stop	0,15	0,37	0,08	0,01	-0,09	-0,07	0,21
Thp	0,24	0,08	-0,07	0,07	-0,09	0,02	-0,29
TOp	0,07	-0,13	-0,41	0,15	-0,15	0,17	-0,06
Trc	-0,24	0,18	-0,08	0,06	-0,09	-0,05	-0,11
TrUtp	0,17	0,29	-0,04	0,08	-0,11	-0,20	0,06
WarUtp	0,00	-0,01	0,33	-0,11	0,05	0,01	-0,41



	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Standard deviation	3,65	2,01	1,94	1,65	1,54	1,37	1,25	0,94
Proportion of Variance	0,40	0,12	0,11	0,08	0,07	0,06	0,05	0,03
Cumulative Proportion	0,40	0,53	0,64	0,72	0,79	0,85	0,90	0,92

Figure 7.1: PCA result for the final group of 33 indicators with $|\text{loadings}| \geq 0.2$.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
CSc	-0,22	-0,05	0,08	-0,05	0,07	-0,09	0,38
CustSatq	0,02	0,17	-0,22	-0,01	0,40	0,00	-0,04
Delp	0,25	-0,14	0,06	-0,04	0,07	0,01	0,12
Delt	-0,26	0,13	-0,06	0,05	-0,07	-0,03	-0,09
DSt	-0,03	0,18	0,12	-0,07	-0,13	0,61	0,05
Invc	-0,03	0,10	0,43	-0,17	0,13	-0,07	-0,18
Invq	0,03	0,05	0,07	0,03	-0,08	-0,31	-0,13
InvUtp	-0,02	0,11	0,44	-0,17	0,15	-0,08	-0,16
Labc	-0,20	-0,24	0,05	-0,07	0,10	0,18	-0,10
Labp	0,24	0,08	-0,07	0,07	-0,09	0,02	-0,29
OrdFq	-0,01	-0,05	0,22	0,51	0,04	0,04	0,01
OrdLTt	-0,26	0,13	-0,06	0,05	-0,07	-0,03	-0,09
OrdProcc	-0,24	0,17	-0,06	0,06	-0,10	-0,06	-0,10
OTDelq	-0,02	0,21	-0,18	-0,03	0,46	0,09	-0,09
OTShipq	-0,02	-0,07	0,18	0,53	0,03	0,03	0,04
PerfOrdq	0,00	0,18	-0,17	-0,04	0,51	0,08	0,02
Pickp	0,25	-0,14	0,06	-0,04	0,08	0,02	0,13
Pickt	-0,25	0,14	-0,06	0,05	-0,08	-0,04	-0,10
Putt	-0,15	-0,37	-0,07	-0,02	0,09	0,07	-0,22
Recp	0,15	0,36	0,07	0,03	-0,09	-0,07	0,22
Rect	-0,02	0,21	0,12	-0,07	-0,14	0,59	0,07
Repp	0,24	0,07	-0,07	0,06	-0,08	0,03	-0,28
Rept	-0,25	-0,07	0,07	-0,04	0,07	-0,04	0,28
Scrapq	-0,01	-0,14	0,02	-0,24	-0,34	-0,06	0,06
Shipp	0,25	-0,13	0,05	-0,05	0,07	0,01	0,12
Shipq	0,00	-0,05	0,20	0,50	0,12	0,07	0,03
Shipt	-0,26	0,13	-0,05	0,06	-0,07	-0,04	-0,09
Stop	0,15	0,37	0,08	0,01	-0,09	-0,07	0,21
Thp	0,24	0,08	-0,07	0,07	-0,09	0,02	-0,29
TOp	0,07	-0,13	-0,41	0,15	-0,15	0,17	-0,06
Trc	-0,24	0,18	-0,08	0,06	-0,09	-0,05	-0,11
TrUtp	0,17	0,29	-0,04	0,08	-0,11	-0,20	0,06
WarUtp	0,00	-0,01	0,33	-0,11	0,05	0,01	-0,41



	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Standard deviation	3,65	2,01	1,94	1,65	1,54	1,37	1,25	0,94
Proportion of Variance	0,40	0,12	0,11	0,08	0,07	0,06	0,05	0,03
Cumulative Proportion	0,40	0,53	0,64	0,72	0,79	0,85	0,90	0,92

Figure 7.2: PCA result for the 33 indicators with |loadings| ≥ 0.22.

The sign of the loadings in Figure 7.2 should be in accordance with the indicator objectives. In the case of cost and time indicators, the sign must be negative, whereas for productivity and quality ones, the sign must be positive to represent a better performance. In the case of component equations (presented in the next section) sharing both types of loadings, they should be interpreted considering that the greater the resulting value, the better the performance.

Regarding the number of PC's to use in the aggregated model, the scree plot suggests that 2 components is a good trade-off between variance explained and number of components (the sharp drop point in the plot). However, we want to maintain the same number of indicators in the model. Analyzing indicator *versus* PC table of Figure 7.2, we can see that PC7 is just a repetition of indicators already designated in previous components. Thus, the performance indicators will be aggregated in the first six components (from PC1 up to PC6). Figure 7.3 summarizes the results demonstrating on the top of the figure the indicators eliminated from the model and on the center the final framework with six components (named C1 up to C6).

Analyzing the loading signs, we can see that some of cost and time indicators do not have negative signs as expected and the same happens for some quality and productivity indicators. For the six components, the loadings of C1, C2, C4 and C5 have the right signs and the ones from C3 and C6 present the opposite signs compared to indicator's objective. R documentation affirms that the signs are defined arbitrarily and if it is necessary to change them, it should be made for all loadings of the component. Therefore, the signs of indicators in components three and six will be inverted when the component equations are used to find a scale for the integrated model interpretation.

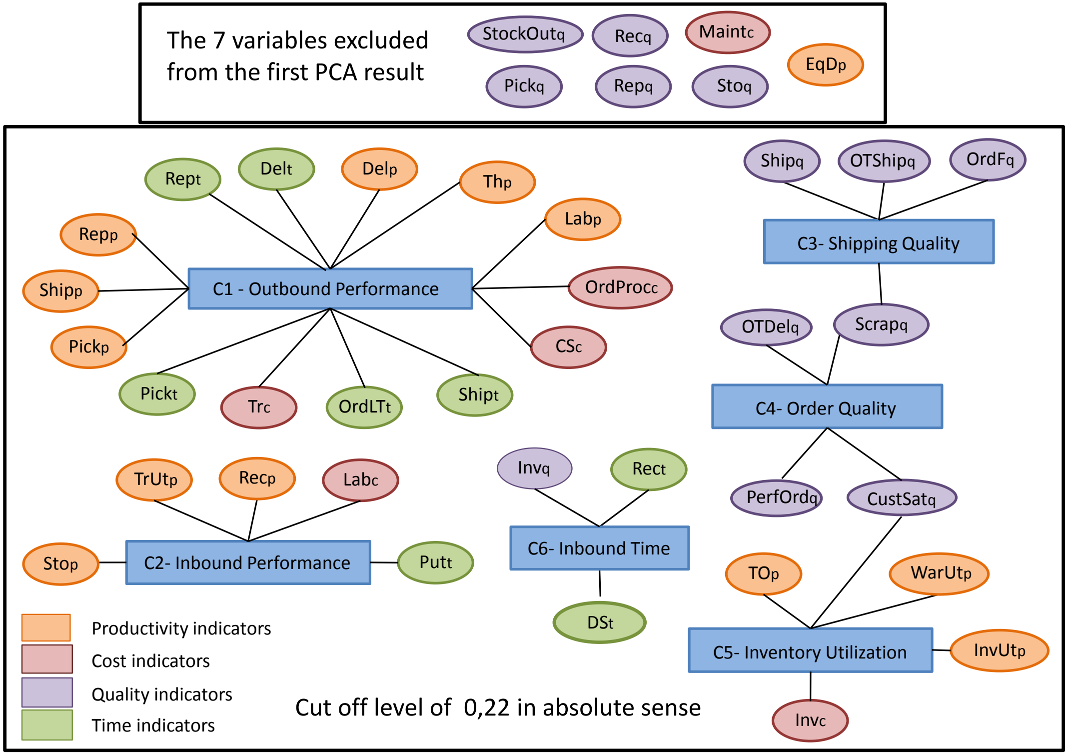


Figure 7.3: The indicators eliminated from the analysis and a framework of the final group with 33 indicators.

The next section presents the final integrated model for warehouse performance management.

7.3 Integrated performance model proposition

Section 4.4.1 presents a generic group of equations to describe the integrated performance model. In this section, these equations are rewritten according to the result obtained in Figure 7.2. Equation 7.1 up to Equation 7.6 demonstrate the six components chosen with their loadings. We recall that the signs of C3 and C6 are modified as explained in the previous section. The modified signs are highlighted with red color in the equations.

$$\begin{aligned} C1 = &- 0,22 \times CS_c + 0,25 \times Del_p - 0,26 \times Del_t + 0,24 \times Lab_p \\ &- 0,26 \times OrdLT_t - 0,24 \times OrdProc_c + 0,25 \times Pick_p - \\ &0,25 \times Pick_t + 0,24 \times Rep_p - 0,25 \times Rep_t + 0,25 \times Ship_p \\ &- 0,26 \times Ship_t + 0,24 \times Th_p - 0,24 \times Tr_c \end{aligned} \tag{7.1}$$

$$\begin{aligned} C2 = &- 0,24 \times Lab_c - 0,37 \times Put_t + 0,36 \times Rec_p \\ &+ 0,37 \times Sto_p + 0,29 \times TrUt_p \end{aligned} \tag{7.2}$$

$$\begin{aligned} C3 = &+0,22 \times CustSat_q - 0,43 \times Inv_c - 0,44 \times InvUt_p \\ &+0,41 \times TO_p - 0,33 \times WarUt_p \end{aligned} \tag{7.3}$$

$$\begin{aligned} C4 = &+ 0,51 \times OrdF_q + 0,53 \times OTShip_q \\ &- 0,24 \times Scrap_q + 0,50 \times Ship_q \end{aligned} \tag{7.4}$$

$$\begin{aligned} C5 = &+ 0,40 \times CustSat_q + 0,46 \times OTDel_q \\ &+ 0,51 \times PerfOrd_q - 0,34 \times Scrap_q \end{aligned} \tag{7.5}$$

$$C6 = -0,61 \times DS_t + 0,31 \times Inv_q - 0,59 \times Rec_t \tag{7.6}$$

It is important to highlight that indicator values entries in Equation 7.1 up to 7.6 must be standardized before their inclusion in equations (see Section 6.4).

Once the standardized indicator results are inserted in equations, it reduces their variance, making possible to verify which indicators most influence the component result through the loading values. For example, in Equation 7.5 the indicators $\mathbf{OTDel_q}$ and $\mathbf{PerfOrd_q}$ have the highest loading values, demonstrating that they are more important in C5 than $\mathbf{CustSat_q}$ and $\mathbf{Scrap_q}$. However, not all components have this distinction between indicators. For instance, in the first component equation (C1, Equation 7.1) the loading values are very similar for all indicators, resulting nearly in the same absolute numerical impact on C1 result.

Equation 7.1 up to Equation 7.6 shows the model to measure the integrated performance with six component equations. Depending on manager objectives, it is possible to choose just one component to evaluate performance, probably the most important for company's goals. In this case, the aggregation stops here and the manager loses a great quantity of information considered in other components. Considering the six component equations to analyze the warehouse performance, it is necessary to develop a scale for each component, allowing the manager to evaluate each group of indicators separately. However, it does not seem a practical choice if the objective is to analyze the global warehouse performance. The component results are very subjective and difficult to compare with other components, even if there is a scale for each one to help this interpretation.

As the main idea of this work is to define a model which aggregates all indicators to facilitate the global performance interpretation, we propose the sum of all principal components in an unique measure, defining a global indicator as described in Equation 7.7.

$$GP = \sum_{i=1}^{i=m} n_i \times C_i \tag{7.7}$$

where *GP* is global performance, C_i is the principal component with $i = 1, \ldots, m$ and n is the weight defined for the component i.

In this dissertation, the weight of each component is considered equal, and each n_i of Equation 7.7 is defined by $(\frac{1}{m})$ ($m = 6$ in our case). Nevertheless, the manager can adjust each weight according to company's goals and strategy, defining some of them as more or less important than the others.

Finally, the integrated performance measurement model comprises Equation 7.1 up to Equation 7.7. Figure 7.4 demonstrates the framework with indicators aggregated in components (left side of the figure) and the components composing the global performance, GP (right side of the figure).

To interpret the GP result it is necessary to formulate a scale, which is developed in the next section.

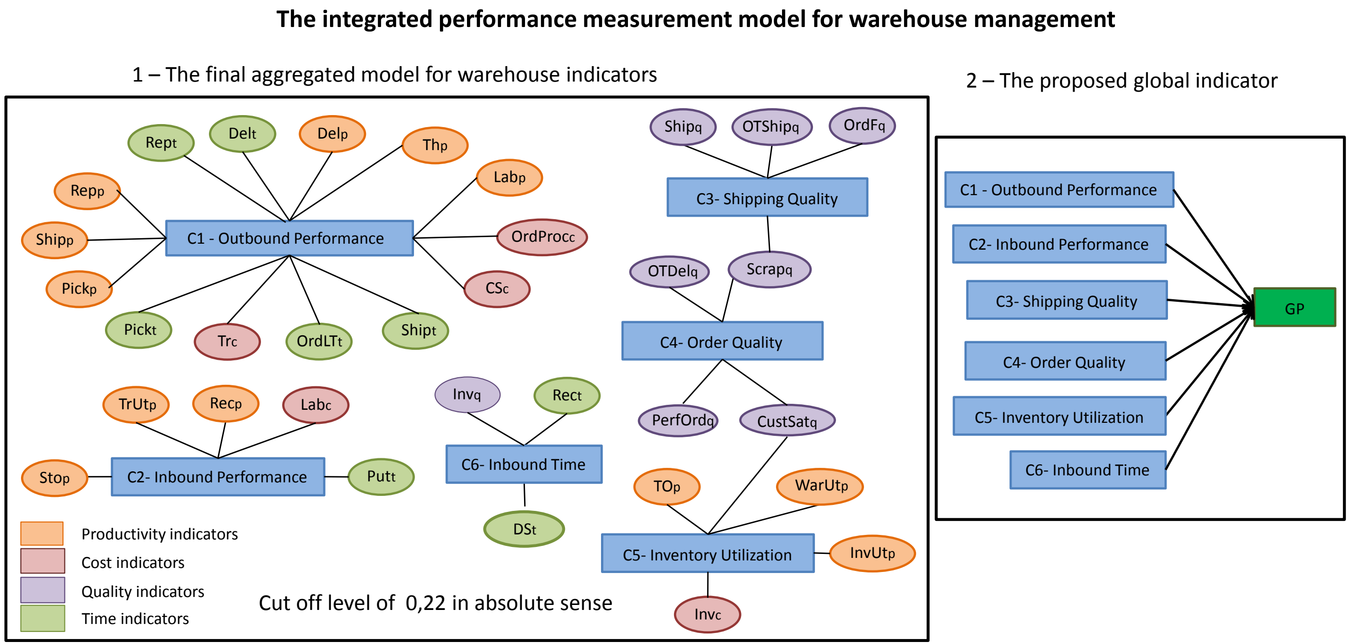


Figure 7.4: The integrated performance measurement model comprises: (1) the final aggregated model and, (2) the global indicator.

7.4 Scale for the Integrated Indicator

The procedure performed in this section can be used for one component (if the manager considers just one) as well as for the proposed global performance "GP" (Equation 7.7). In our case, we will present a scale for GP.

In summary, it is necessary to define the following aspects to obtain a scale by using optimization (presented in Figure 4.5):

1. Analytical model adjustment;

2. Objective function;

3. Optimization algorithm;

Each one of these aspects will be presented in the following sections.

7.4.1 The analytical model adjustment

The first analytical model, used for Jacobian matrix assessment, needs to be adjusted to perform the optimization. The adjustments signify mainly the inclusion of new equations in the model as:

- Component equations, i.e., Equation 7.1 up to 7.6;

- Equations standardizing indicator values;

- Equations to limit optimization search space.

The last two kinds of equations are presented in the next sections.

7.4.1.1 Equations standardizing indicator values

Equations 7.1 up to 7.6 request standardized indicator values to calculate components. As the data inputs of the analytical model are not standardized, it is necessary to include equations which shift indicator values to standardized ones. Thus, 33 equations like Equation 7.8 (i.e., one for each indicator) are added to the model. The mean and standard deviation values inserted for each indicator are taken from their data generation. The complete list is presented in Appendix I.

$$OrdF_q\_NORM = \frac{\mathbf{OrdF_q} - Mean\_OrdF_q}{\sigma_{OrdF_q}} \tag{7.8}$$

7.4.1.2 Equations to limit optimization search space

Some equations defining data dependencies are included in the optimization model to limit the optimization search space so that the results fall within reasonable practical values. This is done by constraining some additional variables. These equations have also been defined in the spreadsheet used for data generation.

The complete list of equations and the optimization model are demonstrated in Appendix H.

As an example, let us analyze Equation A.3. If it is not included in the model, the optimization algorithm treats the variables Cor Unlo and *Prob Unlo* as independents. However, in practice, they must respect the relationship defined by Equation A.3.

$$\mathsf{Pal\ Unlo} = \mathsf{Cor\ Unlo} + \mathit{Prob\ Unlo} \tag{A.3}$$

Other equations limiting the optimization search space are defined by the prefix **Ctrl**. One example is **Ctrl_0** (Equation 7.9) that determines the total effective working hours made by the administrative employees. These can not be higher than the total number of administrative working hours available in a month.

$$\begin{aligned} \textbf{Ctrl\_0} \rightarrow \quad \mathit{WH\ Admin} \geqslant & HAdmin_{sto} + HAdmin_{rep} \\ & + HAdmin_{pick} + HAdmin_{ship} \\ & + HAdmin_{del} + HAdmin_{orders} \end{aligned} \tag{7.9}$$

Other examples are related to the warehouse product flow, impeding that one activity processes more products than the previous one. For instance, **Ctrl_1** (Equation 7.10) defines that the number of pallets stored can not be higher than the total of pallets unloaded in the whole month. Other constraints similar to **Ctrl_1** are: **Ctrl_2**, **Ctrl_3**, **Ctrl_4**, **Ctrl_5** (Equations 7.11, 7.13, 7.14, 7.16, respectively). Some terms used in these equations are defined in Appendix A.

$$\textbf{Ctrl\_1} \rightarrow \quad \mathsf{Pal\ Unlo} \geqslant \mathsf{Pal\ Sto} \tag{7.10}$$

The replenishment is the activity of reallocating pallets from the bulk storage area to the forward picking area. Due to its characteristics, there are two constraints related to this activity (**Ctrl_2** and **Ctrl_2A**). As the forward picking stock usually has a limited space, the products are not replenished if they do not have orders to be fulfilled (**Ctrl_2**, Equation 7.11). Similarly, the total number of pallets moved to the forward area can not exceed the number of pallets stored plus the inventory remaining from the previous month (named '*Remain inv*') (**Ctrl_2A**, Equation 7.12).

$$\textbf{Ctrl\_2} \rightarrow \quad \frac{(\textsf{Cust Ord} * \textit{Prod Ord})}{\textit{Prod pal}} \geqslant \textsf{Pal Moved} \tag{7.11}$$

$$\textbf{Ctrl\_2A} \rightarrow \quad \textsf{Pal Sto} + \frac{\textit{Remain inv}}{\textit{Prod pal}} \geqslant \textsf{Pal Moved} \tag{7.12}$$

Regarding the number of orders picked during a month, **Ctrl_3** shows that it can not be higher than the number of customer orders received (Cust Ord). In Equation 7.13, *Line Ord* means the average number of lines per customer order, being used to put the number of order lines picked (OrdLi Pick) in the same unit of customer orders.

$$\textbf{Ctrl\_3} \rightarrow \quad \textsf{Cust Ord} \geqslant \frac{\textsf{OrdLi Pick}}{\textit{Line Ord}} \tag{7.13}$$

The **Ctrl_4** and **Ctrl_4A** have the same meaning, just the units are different. In Equation 7.14, the number of orders shipped can not overcome the total of orders picked and Equation 7.15 measures it in terms of number of products.

$$\textbf{Ctrl\_4} \rightarrow \quad \frac{\textsf{OrdLi Pick}}{\textit{Line Ord}} \geqslant \textsf{Ord Ship} \tag{7.14}$$

$$\textbf{Ctrl\_4A} \rightarrow \quad \textsf{OrdLi Pick} \times \textit{Prod Line} \geqslant \textsf{Prod Proc} \tag{7.15}$$

As presented for the previous warehouse activities, **Ctrl_5** represents the limitations imposed by the activity flows. Equation 7.16 determines that the number of orders shipped (Ord Ship) is higher or equal to the number of orders delivered (Ord Del).

$$\textbf{Ctrl\_5} \rightarrow \quad \textsf{Ord Ship} \geqslant \textsf{Ord Del} \tag{7.16}$$

Finally, **Ctrl_6** defines that the number of orders delivered on time (Ord Del OT) is always greater than the number of orders delivered on time, without damages and correct documents (Ord OT, ND, CD), since this last one demands more order requirements than just orders delivered on time.

$$\textbf{Ctrl\_6} \rightarrow \quad \textsf{Ord Del OT} \geqslant \textsf{Ord OT, ND, CD} \tag{7.17}$$

After the definition of optimization limits by these equations, it is missing only the definition of the objective function, presented in the next section.

7.4.2 Objective function definition

The objective function is determined by the GP equation, Equation 7.7, which calculates a weighted mean of all components defined in PCA. The maximization (Equation 7.18) and the minimization (Equation 7.19) of GP achieve the best and worst possible performances, respectively, which are considered the upper and lower limits of the scale. As defined in Section 7.3, we assume that the weights are defined equal for all components in GP equation.

It is important to note that these best and worst performances are only related to the warehouse studied, and can not be generalized to other warehouses. The main reason is that the optimization search space is established according to the warehouse conditions (e.g. processing capacity, number of employees).

$$max\ GP = (\frac{1}{6}) \times [C_1 + C_2 + C_3 + C_4 + C_5 + C_6] \tag{7.18}$$

$$min\ GP = (\frac{1}{6}) \times [C_1 + C_2 + C_3 + C_4 + C_5 + C_6] \tag{7.19}$$

After the analytical model and objective function determination, we define, in the next section, the optimization algorithm chosen and the results obtained.

7.4.3 The choice of the optimization algorithm

The analytical model that has been created has many outputs that must be constrained in order to solve the problem. Thus, we are interested in algorithms that are able to deal with several constraints. To that end, the fast and deterministic SQP algorithm (Sequential Quadratic Programming) has been chosen.

The main reason for that choice is the possibility to manage tens, hundreds or even thousands of unknown parameters in a constrained output problem. The coupling of the model with the SQP requires the determination of the Jacobian matrix associated to the model outputs. The *CADES Component Optimizer®* has the SQP algorithm built in the software and it is used for the optimization.

7.4.4 The setting of the optimization tool

The optimization model implemented in CADES comprehends: the analytical model, the objective function, the component equations, the 33 equations to standardize indicators and the ones used to limit the optimization search space.

When the model is compiled, it generates an icar component containing the input and output relationships and the associated Jacobian matrix. In order to use the SQP to solve the problem, the inputs must be set with an initial value. Additionally, the inputs can also be left free to vary in a range, defining the optimization search space. The outputs can be left free to vary, have a fixed value assigned to it or constrained in a range. Figure 7.5 illustrates the setting of the inputs and outputs.

One of the potential problems that may arise from the utilization of the SQP is that the solution may depend on the starting values of the inputs (local minimum). Therefore, it is a good practice to test several combinations of these initial values in order to increase the possibility of finding a global optimum. Such investigation is made to define the initial values of the inputs that are used in the optimization study presented on this chapter.

Regarding the limits proposed for variables, they need to fit the conditions of the studied warehouse. It is important to incorporate manager's opinion in the definition of the possible upper and lower limits that the warehouse can attain to develop achievable scale boundaries. In our case, the variable limits are established based on some predefined warehouse characteristics (e.g. warehouse capacity) and according to the limits presented by the data generated.

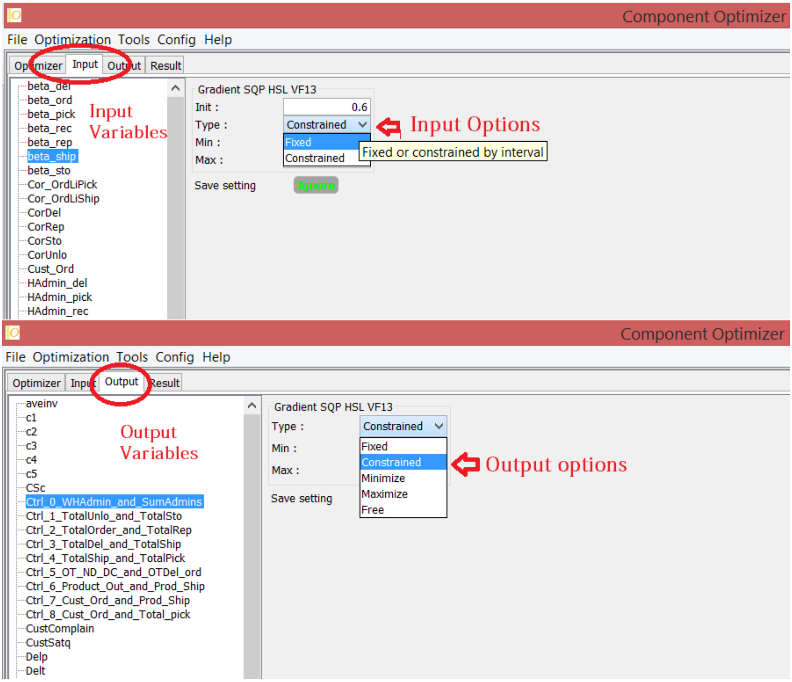


Figure 7.5: The options provided by *CADES Component Optimizer®* for input and output variables.

The constraints defined in Section 7.4.1.2 must be adapted to be used in CADES. CADES requires the definition of a minimum and a maximum value for each constraint output. Therefore, the inequality equations must be rewritten. For example, Equation 7.16 is modified for the following form to define the minimum value:

$$\mathbf{Ctrl\_5} \rightarrow \quad \mathsf{Ord\ Ship} - \mathsf{Ord\ Del} \geqslant 0 \tag{7.20}$$

The maximum limit set in CADES for Equation 7.20 is determined by the maximum allowed value of the Ord Ship. All the constraints are defined in CADES using the same principle.

The variables are classified as inputs, intermediate outputs and outputs. The input limits shown in Table 7.3 are separated by type of data and the unit of each variable is presented in brackets. Some variables are considered fixed in the optimization, as the product cost (*Prod*

Table 7.3: Input limits for optimization.

INPUT LIMITS

Time data [unit]	Limits in Hours	
	Max	Min
β_del	1	0,3
β_ord	1	0,3
β_pick	1	0,3
β_rec	1	0,3
β_rep	1	0,3
β_ship	1	0,3
β_sto	1	0,3
$Hadmin_{del}$ [hour]	210	1
$HAdmin_{pick}$ [hour]	210	1
$HAdmin_{rec}$ [hour]	210	1
$HAdmin_{rep}$ [hour]	210	1
$HAdmin_{ship}$ [hour]	210	1
$HAdmin_{sto}$ [hour]	210	1

Replenishment data [unit]	Limits	
	Max	Min
Cor Rep [pallet]	2000	0
error data system 3 [pallet]	40	0
$scrap_3$ [pallet]	40	0
Other_Prob_rep [pallet]	40	0

Cost data	Limits in $	
	Max	Min
Maintc	R$ 50 000,0	R$ 1 000,0
Truck Maint C	R$ 200 000,0	R$ 50,0

Fixed data [unit]	Values
N [nb of components]	6
pal_truck [pallet]	25
Prod Cost [R$]	R$ 100,00
$ oil [R$]	R$ 2,20

Picking, Shipping and Delivery data [unit]	Limits	
	Max	Min
Prod noAvail [orders]	3000	0
No_OT_del [orders]	3000	0
No_OT_ship [orders]	3000	0
No Cust Complain [orders]	3000	0
NoComplet Ord Ship [orders]	3000	0
Other_Prob_pick [orders]	40	0
Other_Prob_del [orders]	3000	0
Other_Prob_ship [orders]	3000	0
Cor OrdLi Pick [orders]	3000	0
Cor OrdLi Ship [orders]	3000	0
Cor Del [orders]	3000	0
$scrap_4$ [orders]	40	0
$scrap_5$ [orders]	3000	0
$scrap_6$ [orders]	3000	0

Unloading and Storing data [unit]	Limits	
	Max	Min
Cor Sto [pallet]	1000	0
Cor Unlo [pallet]	1000	0
$scrap_1$ [pallet]	20	0
$scrap_2$ [pallet]	20	0
Other_Prob_sto [pallet]	20	0
Other_Prob_unlo [pallet]	20	0
error data system 1 [pallet]	20	0
error data system 2 [pallet]	20	0

Other data [unit]	Limits	
	Max	Min
War WH [hour]	210	80
Prod Ord [product]	30	10
war used area [m2]	4000	1000
nb_Travel [travels]	300	1
mean_Insp [h]	1	0,1
Cust Ord [orders]	3000	10

Cost) and oil value (*$ oil*).

To establish the limits presented in Table 7.3 and Table 7.4, we consider that the standard warehouse has capacity to process up to 40.000 products per month (the mean value defined in data generation is 28.000 with standard deviation of 2.000), and a maximum of 3.000 orders. Transforming the 40.000 products in number of pallets (each pallet has 40 products), we have 1.000 pallets as inbound capacity for unloading and storing activities. For replenishment, the limit is of 2.000 pallets because we consider the sum of the stock capacity (1.000 pallets) and the inbound capacity (1.000 pallets).

We note that the variables *Prob OrdLi Pick*, *Prob Rep*, *Prob Sto*,

Table 7.4: Limits for intermediate outputs.

INTERMEDIATE OUTPUT LIMITS

Constraints [unit]	Limits	
	Max	Min
CTRL_0 [hour]	210	0,1
CTRL_1 [pallet]	1000	0
CTRL_2 [pallet]	2000	0
CTRL_2A [pallet]	2000	0
CTRL_3 [order]	3000	0
CTRL_4 [order]	3000	0
CTRL_4A [product]	50000	0
CTRL_5 [order]	3000	0
CTRL_6 [order]	3000	0

Component Equation	Limits
C1	FREE
C2	
C3	
C4	
C5	
C6	

Data [unit]	Limits	
	Max	Min
aveinv [product]	80000	1
Prob Data [pallet]	80	0
Cust Complain [orders]	3000	0
ΔT(Insp) [hour]	FREE	
nb_trucks [trucks]	FREE	
Prod noAvail [products]	50000	0
Ord Del OT [orders]	3000	0
Ord OT, ND, CD [orders]	3000	0
Ord Ship OT [orders]	3000	0
PalProcInv [pallets]	4000	0
Prob OrdLi Pick [orders]	40	0
Prob OrdLi Ship [orders]	3000	0
Prob Del [orders]	3000	0
Prod Proc [products]	40000	0
Prob Rep [pallet]	40	0
Prob Sto [pallet]	20	0
Prob Unlo [pallet]	20	0
Remain_Inv [products]	40000	0
WarCapUsed	5000	500
Pal Sto [pallet]	1000	300
Pal Unlo [pallet]	1000	300
Pal Moved [pallet]	2000	500
OrdLi Pick [orders]	3000	700
Ord Ship [orders]	3000	700
Ord Del [orders]	3000	700

Table 7.5: Limits for final outputs.

FINAL OUTPUT LIMITS

Time Indicators [unit]	Limits	
	Max	Min
OrdLTt [h/order]	500	0,05
DSt [h/pallet]	200	0,02
Delt [h/order]	200	0,02
Pickt [h/order]	200	0,02
Putt [h/pallet]	200	0,02
Rect [h/pallet]	200	0,02
Rept [h/pallet]	200	0,02
Shipt [h/order]	200	0,02

Quality Indicators	Limits in %	
	Max	Min
CustSatq	100%	0%
Invq	100%	0%
OrdFq	100%	0%
OTDelq	100%	0%
OTShipq	100%	0%
PerfOrdq	100%	0%
Shipq	100%	0%
Scrapq	100%	0%

Global Performance	Limits	
	Max	Min
GP	150,0	-150,0

Productivity Indicators	Limits	
	Max	Min
Thp	1500	0
Labp	200	0,1
Delp	200	0,01
Pickp	200	0,01
Recp	200	0,01
Repp	200	0,01
Shipp	200	0,01
Stop	200	0,01
TOp	50	0
TrUtp	100%	0%
InvUtp	105%	0%
WarUtp	100%	0%

Cost Indicators	Limits in $	
	Max	Min
CSc	R$ 1,00	0,00
Invc	FREE	
Labc		
OrdProcc		
Trc		

Prob Unlo (see Table 7.4) have a limit smaller than the ones defined for shipping and delivery activities (20 pallets for *Prob Sto* and *Prob Unlo* instead of 1.000 pallets; 40 orders for *Prob OrdLi Pick* and *Prob Rep* instead of 3.000 orders). The reason for this limit is the absence of quality indicators related to these activities in component equations; consequently, the optimization model do not maximize or minimize these inputs. Therefore, we establish 2% of the total capacity as the maximum quantity of problems each activity can have (as made in data generation).

The final output limits are presented in Table 7.5. The range of indicator values are defined very large and cost indicators are left free. The cost indicators are not constrained since their possible results are a consequence of several other variables.

The results for the maximization and minimization are presented in next section.

Table 7.6: Output results after maximization and minimization.

FINAL OUTPUT RESULTS

Time Indicators [unit]	Results	
	Maximization	Minimization
OrdLTt [h/order]	0,09	2,79
DSt [h/pallet]	0,05	1
Delt [h/order]	0,02	0,6
Pickt [h/order]	0,03	1,2
Putt [h/pallet]	0,02	0,69
Rect [h/pallet]	0,03	0,32
Rept [h/pallet]	0,03	0,422
Shipt [h/order]	0,03	0,9

Quality Indicators	Results	
	Maximization	Minimization
CustSatq	100%	0%
OrdFq	100%	100%
OTDelq	100%	0%
OTShipq	100%	0%
PerfOrdq	100%	0%
Invq	100%	99,2%
Shipq	100%	0%
Scrapq	0%	37,6%

Global Performance	Results	
	Maximization	Minimization
GP	15,35	-123,27

Productivity Indicators	Results	
	Maximization	Minimization
Thp	500	41,8
Labp	55,5	4,65
Delp	18,75	1,67
Pickp	9,37	0,83
Recp	25	3,43
Repp	12,5	2,38
Shipp	12,5	1,1
Stop	25	3,43
TOp	2	0,88
TrUtp	100%	5,9%
InvUtp	50%	25%
WarUtp	32%	86%

Cost Indicators	Results	
	Maximization	Minimization
CSc	R$ 0,09	1,00
Invc	R$ 200 000,00	R$ 100 000,00
Labc	R$ 5 987,20	R$ 15 718,50
OrdProcc	R$ 0,15	R$ 0,54
Trc	R$ 0,70	R$ 292,80

7.4.5 The integrated indicator scale

The maximization and minimization results for the final outputs are shown in Table 7.6. The maximization and minimization results for the inputs and the intermediate outputs are presented in Appendix J.

It is interesting to make some remarks about the optimization outcomes.

We establish that the number of warehouse working hours War WH could vary between 80 and 210 hours per month (see Table 7.3). In the maximization, the War WH converges to 80 hours (equivalent to 10 working days in a month) whereas the minimization results in 210 hours, which is equivalent to 25 working days in a month (see the last table at the bottom of Appendix J). In the 80 hours, 40.000 products are shipped (*Prod Proc*) and for 210 hours just 8.790 products. It means that if time is efficiently used, the excess of capacity will appear.

As expected, the maximization results for time indicators are low and for the productivity indicators are high (see Table 7.6). The capacity measures $\mathbf{InvUt_p}$ and $\mathbf{WarUt_p}$ have low values, demonstrating that the warehouse can process more products due to its extra capacity. The $\mathbf{InvUt_p}$ values (see Table 7.6) show the maximization having higher results than minimization. The reason for these results is the quantity of products processed in each situation. As described above, the number of products shipped in minimization is almost 5 times less than in maximization, which reduce the number of products that pass through the inventory (see Appendix J). Consequently, the same occur for $\mathbf{Inv_c}$ indicator, since in minimization the average inventory is of 10.000 and in maximization 20.000 products.

The $\mathbf{Inv_q}$ and $\mathbf{OrdF_q}$ indicators present values in the minimization near to the maximum (see Table 7.6). In $\mathbf{OrdF_q}$ case, the optimizer prioritizes the reduction of indicators with the highest loadings in component equations. Another point is an optimization model restriction, which impedes an order to have more than one kind of problem. As the loadings of $\mathbf{OrdF_q}$ is 0,51 and of $\mathbf{OTShip_q}$ is 0,53 (Equation 7.4), the software prefers to put all orders shipped late but complete. In the case of $\mathbf{Inv_q}$, the reason is the established 2% as the maximum number of problems for unloading, storing, replenishment and picking activities. This decision also reflects in the $\mathbf{Scrap_q}$ indicator.

Finally, it is important to discuss the GP results. As Table 7.6 demonstrates, the variation range is of 138,65, with the maximum of 15,35 and the minimum of -123,3. The reason for this expressive difference between the positive and negative values comes from the mean and standard deviation established for performance indicators. As these fixed values are used to standardize the indicators included in component equations, when the indicator value in a month is lower than its mean, the result of the standardized indicator is negative. For example, Equation 7.8 presents the standardization of $\mathbf{OrdF_q}$. Considering that the average of $\mathbf{OrdF_q}$ is 97% and, at this month, $\mathbf{OrdF_q}$ value is 95%, the standardized indicator has a negative sign because the performance is lower than the average. Therefore, analyzing Table I.1 in Appendix I, it is possible to see that the majority of quality indicators have means equal or higher than 99%. It means that there is few space for performance improvements, what is reflected by the low value of 15,35 as the upper scale limit.

To support the scale interpretation, we transform the scale limits from -123,3 and 15,35 to 0 up to 100 (see Figure 7.6).

Using traditional scale transformation rules, Equation 7.21 is used to transform the values of the optimized scale (OS) to the normal scale (NS).

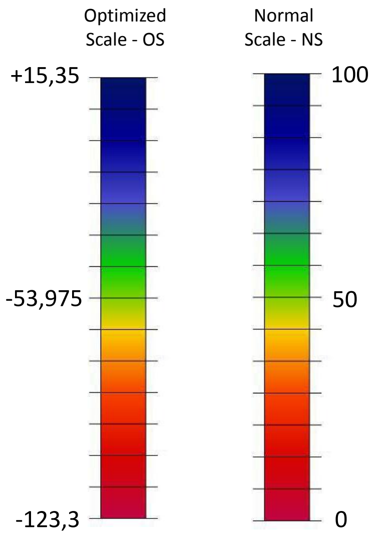


Figure 7.6: Scale transformation.

$$\frac{(OS + 53,975)}{138,65} = \frac{NS - 50}{100} \rightarrow \quad NS = \frac{100 \times (OS + 53,975)}{138,65} + 50 \quad (7.21)$$

To exemplify the use of Equation 7.21, let us verify the corresponding value in the normal scale (NS) for the zero value in the optimized scale (OS). The zero value in OS signifies that all indicators are equal to their mean. Applying Equation 7.21, the result for the normal scale is 88,93. We can infer from this result that globally, the warehouse already have a good performance.

In the next section is explained how the integrated model and scale are implemented and should be used in practice.

7.5 Integrated Model Implementation

After finishing the model and scale development, we present in this section how to use the integrated performance for periodic management.

The model parts used for periodic management are: the 33 indicator equations (presented in Chapter 5); the 6 component and GP equations (Equations 7.1 up to 7.7); optimized scale with transformation to normal scale (Equation 7.21). These equations can be included in a spreadsheet to facilitate data update. Every month's indicator values are actualized and all other formulas can be automatically calculated.

For example, Table 7.7 demonstrates the results for all 33 indicators in two different months. The component and GP values for each month (in optimized scale - OS - and normal scale - NS) are described in Table 7.8.

The indicator values are established in order to evaluate warehouse performance in two different situations. In month 1, we consider that inbound activities have some performance problems, affecting their indicators of time, productivity and quality (they are lower than the average). In this special example, the indicators related to replenishment activity are also considered with problems. The outbound indicators, on the other hand, have very good results, higher than the average. In month 2 the opposite situation is established: inbound indicators have good performance whereas outbound indicators have bad results.

It is interesting to note that the global performance of the first month is better than the second one. This result could maybe support some manager's practices preferring to improve the outbound activities.

To attain a performance result in accordance to warehouse reality is imperative to use an updated model. Usually, new situations in the market impact on enterprises (and also on their warehouses) requesting a reevaluation of the initial model. Described in the next section is when and how to update the model.

7.6 Model Update

It is difficult to establish a period of time to review the integrated model. It depends on the variability of the market, changes in warehouse capacity (structural and human) or goals.

In this work the updates are classified as minor or major. The minor revisions are related to little changes requiring a new optimization to update the scale. The variables could be:

- the component weights in GP equation can be reconsidered for changes in strategic goals (e.g. the warehouse wants to be faster than the concurrents);

- the fixed warehouse conditions (e.g. number of pallets space, employees, equipments) should be updated in indicator equations and scale model;

Table 7.7: Indicator values for two different months.

Indicator	Indicator value Month 1	Indicator value Month 2
CSc	0,3	0,3
CustSatq	100	92
Delp	6	3,5
Delt	0,15	0,35
DSt	0,95	0,4
Invc	250000	70000
Invq	95	100
InvUtp	75	55
Labc	10500	16000
Labp	15	13
OrdFq	100	98
OrdLTt	1	1,8
OrdProcc	0,6	0,92
OTDelq	100	94
OTShipq	100	94
PerfOrdq	100	90
Pickp	2,8	1,8
Pickt	0,3	1
Putt	0,2	0,08
Recp	5	10
Rect	0,8	0,4
Repp	3	5
Rept	0,3	0,1
Scrapq	2	7
Shipp	5	1,5
Shipq	99,5	96
Shipt	0,3	0,45
Stop	5	10
Thp	170	100
TOp	1,5	0,9
Trc	2,4	5
TrUtp	87	75
WarUtp	50	55

Table 7.8: GP result for two different months.

C	Month 1	Month 2
C1	6,24	-4,02
C2	-5,16	3,41
C3	-0,99	-3,73
C4	2,69	-11,48
C5	2,99	-23,79
C6	-19,50	5,03
GP (OS)	**-2,29**	**-5,76**
GP (NS)	**87,28**	**84,77**

The major updates usually require the remodeling of the entire methodology. Some examples are: changes in indicator equations; modification of variable limits in the optimization model due to big changes in capacity or process. Moreover, the indicator relationships can change over time, and the manager needs to revise the model when he observes this tendency.

7.7 Conclusions

The chapter presents the final integrated performance model with a scale used to analyze the integrated indicator results.

To determine the final integrated performance model, an analysis of the Jacobian and correlation results is carried out in order to improve the PCA outcome. The main objectives are to keep the greatest quantity of indicators as possible with a minimum number of principal components. The comparison of the worst results obtained from the Jacobian and correlation matrix establishes an order in which indicators should be excluded.

At the end, seven indicators are eliminated from the analysis and the remain 33 are designated in six different principal components. It is interesting to note that from the seven indicators, five are related to quality measures in receiving, storing, replenishment and picking activities.

The six component equations compose the global performance measure. The GP is optimized to obtain the upper and lower values of the GP scale. The method used to define the optimization model can be generalized; however, each warehouse should construct its own optimization model since it is necessary to define the variable limits according to the warehouse reality. The optimized scale, OS, is transformed in a named "normal" scale, NS, to facilitate the interpretation of the aggregated indicator.

Finally, the utilization of the aggregated model simulating two different warehouse performances is tested. In the first situation, the outbound indicators have their performance improved and inbound measures have bad results. For the second test we define the opposite, outbound indicators have bad results whereas the inbound indicators are great. The global performance indicator provides better result when outbound indicators are better.

Regarding the exclusion of quality indicators in some warehouse activities (during PCA analysis) and the result of the test considering different indicator results, it might confirm that the time and productivity are the essential performance axes for the majority of internal warehouse activities, and the quality level must be guaranteed at the end of the process chain, with measures related to customer satisfaction. However, this hypothesis needs to be tested in different kinds of warehouses to allow us to make such inferences.

Chapter 8

Conclusions and suggestions for future research

Si nous attribuons les phénomènes inexpliqués au hasard, ce n'est que par des lacunes de notre connaissance.

Pierre Simon de Laplace

Abstract

The chapter is divided in two main sections: firstly, the general conclusions about the developments carried out throughout this thesis are discussed regarding the objectives presented in Chapter 1; secondly, research directions are proposed in two different subsections, which split the suggestions by their complexity in short-term and long-term future researches.

8.1 Conclusions

A dissertation is developed to attain predefined objectives. The conclusions serve as a check out of the accomplishments according to the goals, closing the loop. In the following items we review the objectives presented in Chapter 1 and discuss the outcomes achieved.

- **Definition and classification of warehouse performance indicators:** From the structured literature review on warehouse performance carried out in this thesis, the warehouse performance indicators extracted from papers are classified as direct or indirect measures. Direct indicators are usually expressed in simple mathematical expressions whereas indirect indicators consist, in many cases, of a concept measure. Even if there is a tendency in the literature to develop "indirect measures", they are not used for daily management since they require a great quantity of data, which are sometimes difficult to obtain. Therefore, we can conclude that direct indicators continue to be the basis for warehouse performance measurement.

  The main insight coming from the literature analysis is that, for the direct indicators, there is not always a consensus on the definitions of some of the indicators and their boundaries across the warehouse, resulting in different measures for the same metric. Therefore, we present indicator definitions based on paper database if the definitions are given, or based on the best common sense if the definitions are not provided.

  An activity-based framework is developed to clarify the boundaries of the indicators obtained from the literature. In this framework we classify indicators not only according to quality, cost, time and productivity dimensions, but also in terms of warehouse activities (receiving, storage, picking, shipping and delivery). The most frequently used indicators are labor productivity, throughput, on-time delivery, order lead time and inventory costs. The result of this classification shows that the number of outbound indicators is much higher than the number of inbound indicators. This is not very surprising as the warehouse activities are getting more and more customer oriented. This reveals that the outbound processes/activities are considered more critical than the inbound ones and hence they are subject to more control.

- **Creation of a methodology to determine an integrated warehouse performance measurement:** It consists in four main steps executed to achieve the best aggregation of the indicator set according to their relationships. The main outcomes are few (or just one) equation(s) used to measure the global performance with a scale to allow the interpretation of the results.

  The proposed methodology encompasses different disciplines to achieve the aggregated model: the analytical model and the Jacobian matrix measurement to analyze indicator relationships; the statistical tools to propose indicator groups; the optimization model to develop the scale for the integrated indicator. This multidisciplinary approach permits a good model construction to manage warehouse performance. Moreover, the methodology can be viewed as general; it gives some alternatives that one can choose when developing his integrated model. Each warehouse can present different objectives, processes, particularities, and the fact of not specifying all parameters allows the adaptation of the methodology for specific situations.

- **Development of an analytical model of performance indicators and data equations:** This is the first step for the methodology application and it is considered an outcome of the thesis because usually the performance measurement does not evaluate how the indicators are measured.

  To apply the methodology, it is necessary to identify the indicator set that will be used to evaluate warehouse performance. In our application, performed in a theoretical warehouse, the metric system to assess the standard warehouse performance is defined, firstly based on the literature review. After some adjustments, a total of 41 indicators compose the metric system, representing all activities that the standard warehouse have in charge.

  Even if the analytical model can not be generalized, it could be adapted for some warehouses with similar operations or serve as a reference for the development of further models.

  The most interesting kind of indicators that are not found in the literature are the ones related to the replenishment activity. Indeed, we have not found any indicator dimension related to this activity. The inclusion of replenishment indicators in our analytical model brings new informations for managers to better evaluate the warehouse performance.

- **Discovery of a method to determine indicator relationships analytically:** The use of the Jacobian matrix to identify indicator relationships is one of the most innovative contributions of this thesis, even if further developments should be done to allow its sole utilization to support decisions.

  The Jacobian matrix calculates the partial derivatives of the independent inputs related to the outputs. To verify the independent inputs of the indicator equations, the last ones are expanded, creating the data equations. This group of equations builds the complete analytical model, which describe analytically all relations among data. The utilization of the Jacobian matrix in this thesis is nominated as an exhaustive procedure which we can make inferences about indicator relationships. An evaluation of the results provided by the Jacobian matrix (indicators x data) permits the development of a quadratic matrix (indicators x indicators) which inform in the cells the number of data shared among performance indicators.

This result is compared with the correlation matrix of indicators. We note that the majority of indicators with very low correlations corroborate with the indicators sharing the least amount of data in the Jacobian matrix. However, the results are not conclusive, since there are exceptions and the number of shared data can not define the relationship's strength as in correlation matrix. We just verify that the informations provided by the correlation and the Jacobian seems to be complementary, since some indicators are maintained in the integrated model having a great quantity of shared data but very low correlations.

Finally, we conclude that it is very hard to quantitatively determine from the partial derivatives the intensity of the relationship between indicators. The procedure described is only used in this thesis to quantify the number of shared data, which provides a preliminary view of indicator relationships and verifies if the results are coherent from an analytical point of view.

- **Determination of an optimization model to design a scale for the integrated performance:** The literature about scale definition is vast, but it is usually defined for a unique variable. For instance, the quality and productivity performance indicators are evaluated using different scales. Thus, the development of a scale for several variables is less common. There are some propositions in the literature to overcome this issue. In this thesis, we use an optimization approach to obtain the upper and lower limits of the performance scale.

  The optimization model contains the integrated performance model (composed of six component equations), the analytical model with indicator and constraint equations and the global performance indicator (which is the aggregation of the components in one measure). The method used to define the optimization model can be generalized; however, each warehouse should construct its own optimization model since it is necessary to define the variable limits according to the warehouse reality.

The algorithm used to perform the optimization is the SQP, which can handle several constraints. However, it is very sensitive to the starting values defined for the inputs. Tests are made to reduce the chances of getting stuck in a local minimum, but other kinds of tests to verify the results are not done. We believe that this first optimization attained reasonable results regarding the purpose of this thesis, facilitating the interpretation of the aggregated indicator.

Since the specific objectives are achieved, we conclude that the same happens for the general one: **Development of a methodology for an integrated warehouse performance evaluation through indicators' aggregation.**

The methodology application achieves an integrated model which keeps the majority of the indicators initially proposed using a minimum number of principal components to represent them. It denotes a very good result, since one of the objectives of this thesis is to develop a tool that will help managers in the evaluation of a great quantity of information. The usability of the integrated model with its scale is tested with indicator values of two different months. In the first month the outbound indicators have their performance improved and inbound measures are worst and in the second month is simulated the opposite. The result in the case that outbound indicators are prioritized attains better global performance.

Finally, we conclude that the methodology proposed in this thesis achieves the objective of providing insights about indicator relationships, the global warehouse performance and its relative evaluation by the utilization of a performance scale.

In summary, the main contributions provided by this thesis are:

1. the clarification of warehouse indicator concepts, defining their boundaries;

2. the framework to classify performance indicators according to their dimensions and warehouse activity;

3. the transformation of indicators' definitions in equations;

4. the development of the complete analytical model with indicator and data equations;

5. the use of the Jacobian matrix to verify indicator relationships;
6. the model used to generate the database for the standard warehouse including data variability and chained processes;
7. the global performance indicator, a unique measure aggregating several indicators from different dimensions;
8. the scale development using an optimization approach;
9. the aggregation of several different methods (basic statistical tools, partial derivatives analysis, optimization tool, dimension-reduction methods) in a unique methodology.

8.2 Future Research Directions

This section is divided in two different subsections because we understand that the suggestions presented here have considerable differences in the development time. The short-term research directions treat new studies in the warehouse performance subject and possible applications of the methodology. On the other hand, the long-term research directions are, in our point of view, new developments that demand more study and time to be accomplished.

8.2.1 Short-term Research Directions

In this section, we basically report some new developments that can be made to improve the results obtained in this dissertation.

- The first one is the application of the proposed methodology in a real warehouse, comparing the results obtained in theory with the practice.
- In future studies, it will be interesting to incorporate other indicators in the analysis that are not considered in this work as, for example, measures related to reverse logistics activities, administrative productivity, sustainable practices.
- The SEM (Structural Equation Modeling) method is usually used to verify if a predefined model (i.e. framework defining variable relationships) fits the data. As our study is exploratory (we did not know how indicators would be aggregated) we did not use this method in the thesis. However, from the proposed integrated

model it is possible to make a confirmatory test using SEM. It is important to note that the application of SEM using autocorrelated data (e.g. time series) requires special mathematical manipulations.

- An interesting study consists in the utilization of different dimension-reduction statistical tools to compare the indicator relationships obtained with the PCA method. Among the tools, the DFA theory (Dynamic Factor Analysis) suggest this method as the best one for our study purpose due to data characteristics. An initial test is performed in this thesis (Appendix F) but the results are not consistent and reliable, indicating that more studies should be carried out for DFA utilization.

- The investigation of using the Jacobian matrix to measure strengths between indicator relationships is another point for improvement. The suggestion here is to find out a manner to transform the partial derivatives in coefficients interpreted similarly to the ones of the correlation matrix. One suggestion could be to standardize the input data and calculate the Jacobian to analyze the relationships, verifying which are strong or weak. However, to be sure that the results are reliable to define relation strengths, it is necessary to determine a standard Jacobian matrix. The complexity of constructing the standard Jacobian resides in the input data used to calculate the partial derivatives. As they come from the time series, which change each new period, consequently the Jacobian result also changes over time.

8.2.2 Long-term Research Directions

Warehouses are essential for logistics operations and they have been extensively studied in the literature. However, the research effort focusing on warehouse performance measurement is not so abundant as for logistics performance. Based on the tendencies identified in the selected papers, we highlight several future research directions in warehouse management as follows:

- Regarding the kind of problems treated by the literature on warehouse performance subject, we identify new study tendencies in two main directions: the assessment of relationships among different warehouse performance areas (e.g. degree of automation influencing warehouse productivity (De Koster; BALK, 2008));

and the evaluation of concepts not usually expressed as ratios and, therefore, not measured yet (e.g. VAL activities (De Koster; WARFFEMIUS, 2005)).

- There are different types of warehouses. For instance, the manufacturing company can own the warehouse in which only their products are processed. A warehouse could be a distribution center or owned by a third party logistics provider in which several products coming from different suppliers are treated. Or, a warehouse could be a retailer's warehouse. In all these cases, the key performance issues can differ since the goals may differ. Similarly, the management policies within a warehouse may also affect the way the performance needs to be measured. For instance, for a warehouse implementing crossdocking techniques, the time related performance measures are more crucial compared to those which do not implement this technique. One future research direction is to investigate to what extent the warehouse type influences the choice of indicators for performance evaluation.

- The performance of administrative personnel in warehouse operations is another point for analysis. The indicators found in papers usually focus on operational labor. However, the administrative process has also an important role in the warehouse performance. For instance, indicators like order lead time and number of perfect orders are directly impacted by the administrative task performance. Nevertheless, the performance of the warehouse administration is not measured separately and its impact on the other performance indicators are rarely investigated. This could be another research direction to improve the global warehouse performance.

- Indicators about "reverse logistics" have already been developed to evaluate backorder operations, for example. The productivity and costs of these operations are important for the enterprise as a whole since they involve customer satisfaction. However, papers integrating these operations with the main warehouse performance indicators are still missing. Papers regarding the impact of returns in forward warehouse performance processes can bring some insights about this issue.

- An important subject in progress is the issue of sustainability in logistics. Sellitto et al. (2011) measure environmental performance of logistics operations comparing emissions and waste indi-

> cators with the maximum levels allowed by ISO 14001. Matopoulos and Bourlakis (2010) go further including indicators of the three pillars of sustainability (economic, environmental, social) to evaluate warehouses. Sustainable operations have been widely studied in past years, but the inclusion of metrics in warehouse management still offers a fruitful site for examination.

Regarding specifically the methodology proposed in this dissertation, other studies can be suggested.

Firstly, we propose a study verifying the applicability of the proposed methodology for strategic areas (e.g. the enterprise performance). One important point, that may be verified, is the indicators used in the analytical model. Since strategic performance encompasses other actors of the supply chain (e.g. suppliers, third party logistics, stakeholders) besides the focal company, the inclusion of indicators strongly influenced by external factors can make the evaluation of performance difficult because it restricts the actions that could improve results.

Secondly, the generalization of the proposed scale is another point for development. A suggestion is to define it by a benchmarking study, evaluating the best practices among companies of the same area and determining the scale from the results obtained. This development has, for example, huge difficulties as the determination of the same analytical model for all companies (that can compete in the same area but with different strategies) and the definition of the optimization limits due to the diverse situations found among enterprises.

Finally, we observe, in the last decade, an increasing complexity in the warehouse operations. This complexity is very well demonstrated by the implementation of sophisticated IT tools in warehouses and DCs. Since 2000, more complicated algorithms and simulations start to appear in publications on warehouse management, usually proposing the utilization or development of decision support systems for performance evaluation and performance improvement in warehouses. Information systems, such as warehouse management system (WMS), are recognized as useful means to manage resources in the warehouse (LAM; CHOY; CHUNG, 2011). The trend of using information systems in warehouse management is a growing tendency and the related new technologies (e.g. augmented reality, RFID, Internet of Things), will certainly influence the way the performance is measured and used for decision making in the future. Therefore, studies regarding the impact and use of these new technologies to measure and evaluate warehouse performance are welcome.

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Appendix A

Complete Analytical Model of Performance Indicators and Data

This section describes the total group of equations creating the complete analytical model.

The analytical model is presented according to indicator equations given in Chapter 5. The division of indicators by their dimensions (time, productivity, cost, quality) are also used here. Table A.2, Table A.4, Table A.6 and Table A.8 present the data equations on the right column of the table whereas the indicator equations (Sections 5.2.4, 5.2.5,5.2.6, 5.2.7) are repeated in the left column. For example, the first indicator presented in Table A.2 is $\mathbf{Rec_t}$ (Equation 5.1), which is measured by the ratio $\sum_{p=1}^{PalUnlo} \Delta t(\mathsf{Rec})_p$ per $\mathsf{Pal\ Unlo}$. These data are defined in the right side of the table by the Equations A.1 and A.3, respectively.

The definitions of the components inside data equations are showed in Table A.1, A.3, A.5 and A.7 with the data units in parenthesis, which follow the same logic as presented for indicator measures. In these tables, just the data from right-side equations are detailed, indicator names and data which have already been defined in Section 5.2 are not repeated. Moreover, a data used in several indicator equations have its equation repeated as many times as necessary. As there are a lot of data definitions in each table, the data is in alphabetic order to facilitate the analysis.

There are three distinguish formats in this complete analytical model, which can be viewed as "hierarchical levels" of data details (presented in decreasing order): indicator's name are in bold, as $\mathbf{Rec_t}$; data used in indicator equation are in sans serif style (e.g. Pal Unlo); the components inside data equation are in *slanted* style like *Prob Rep*. In the cases where the same component is used in indicator equation and in data equation, we choose to format it in the higher "level". For instance, the term Cor Unlo is used as indicator data in Equation 5.28 and also as data in Equation A.3; so, it is formated in sans serif style.

A.1 Time indicator model

The time data equations are presented on the right side of Table A.2 and the meaning of the new equation terms are explained in Table A.1.

In practice, the total time of an activity is usually acquired by the difference between the beginning and the end of the process, independently of the tasks performed inside it. But in this study, it is necessary to define time components for relationship analysis. For that, the time component equations describes the main important tasks performed by each activity. For example, Equation A.1 details the arrival of a supplier order as: the time used by administration area to assign truck to docks and verify documentation ($HAdmin_{rec}$); the inspection time ($\Delta tInsp$); the effective time used to unload products (represent by *WEfRec*); the queuing time ($\Delta tQueue_{rec}$), which is not a task but exists in practice when the total time is obtained. It is important to note that the unit of each detailed task already represents the total time to perform it in a month, e.g. $\Delta tInsp$ is the total time of all pallets inspected in a month.

The interpretation of the other time equations is similar of the explained for receiving.

The terms $\Delta tOthers$ refer to other tasks executed by a specific warehouse.

Analyzing the time data with the productivity data, we can conclude that terms like *WEfRec* constitute the major part of WH Rec, in some cases even attaining the equality.

Table A.1: Time data definitions

Data	Meaning
$\beta =$	index to represent how many hours of the total available labor hours the employees are effectively working. $\beta_{rec} \ldots \beta_{del}$ are distinguished because they can be different for each activity.
$\beta_{ord} =$	index to represent how many hours of the total available labor hours the employees are dedicated to customer orders administration.
$\Delta t(Insp) =$	total time for pallet inspection on its arrival or total time for order inspection on its dispatch per month $(hour/month)$
$\Delta t(Queue) =$	total time that the pallet/order line/order (depending on the activity performed it is used a different unit) is waiting to be processed per month. The $\Delta t(Queue)$ can be divided by activities: $\Delta tQueue_{rec}$, $\Delta tQueue_{sto}$, $\Delta tQueue_{rep}$, $\Delta tQueue_{pick}$, $\Delta tQueue_{ship}$, $\Delta tQueue_{del}$ $(hour/month)$
$\Delta t(Others)_{1-6} =$	total time for other activities/situations not considered in previous equation terms per month $(hour/month)$
Cor Del $=$	number of orders delivered correctly per month $(orders/month)$
Cor OrdLi Pick $=$	number of order lines picked correctly per month $(orderline/month)$
Cor OrdLi Ship $=$	number of order lines shipped correctly per month $(orderline/month)$
Cor Rep $=$	number of pallets moved correctly from reserve stock to picking inventory area per month $(pallets/month)$
Cor Sto $=$	number of pallets stored correctly per month $(pallets/month)$
Cor Unlo $=$	number of pallets unloaded correctly per month $(pallets/month)$

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Table A.1 – Continued

Data	Meaning
HAdmin =	time effective used to perform administrative operations per month. The *HAdmin* can divided by activities: $HAdmin_{rec}$, $HAdmin_{sto}$, $HAdmin_{rep}$, $HAdmin_{pick}$, $HAdmin_{ship}$, $HAdmin_{del}$, $HAdmin_{orders}$. The $HAdmin_{orders}$ refers to the total time between the customer order receiving and the assignment of the order for picking ($hour/month$)
Prob Del =	number of orders with problems during delivery activity per month ($orders/month$)
Prob OrdLi Pick =	number of order lines with problems during picking activity per month ($orderline/month$)
Prob OrdLi Ship =	number of order lines with problems during shipping activity per month ($orderline/month$)
Prob Rep =	number of pallets with problems in replenishment operation per month ($pallets/month$)
Prob Sto =	number of pallets stored with problems per month ($pallets/month$)
Prob Unlo =	number of pallets unloaded with problems per month ($pallets/month$)
WEfDel =	total effective working hours in delivery activity per month ($hour/month$)
WEfPick =	total effective working hours in picking activity per month ($hour/month$)
WEfRec =	total effective working hours in receiving activity per month ($hour/month$)
WEfRep =	total effective working hours in replenishment activity per month ($hour/month$)
WEfSto =	total effective working hours in storage activity per month ($hour/month$)
WEfShip =	total effective working hours in shipping activity per month ($hour/month$)
WH Del =	total employee labor hours available for delivery activity per month ($hour/month$)
WH Pick =	total employee labor hours available for picking activity per month ($hour/month$)
WH Rec =	total employee labor hours available for receiving activity per month ($hour/month$)

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Table A.1 – Continued

Data	Meaning
WH Rep =	total employee labor hours available for replenishment activity per month (*hour/month*)
WH Sto =	total employee labor hours available for storing activity per month (*hour/month*)
WH Ship =	total employee labor hours available for shipping activity per month (*hour/month*)

Table A.2: Time data equation

Indicator Equation		Data Equations	
$\mathbf{Rec_t} = \dfrac{\sum_{p=1}^{PalUnlo} \Delta t(\mathsf{Rec})_p}{\mathsf{Pal\ Unlo}} \left(\frac{hour}{pallet}\right)$	(5.1)	$\sum_{p=1}^{PalUnlo} \Delta t(\mathsf{Rec})_p = WEfRec + HAdmin_{rec} + \Delta tQueue_{rec} + \Delta tInsp_1 + \Delta tOthers_1$	(A.1)
		$WEfRec = \beta_{rec} \times \mathsf{WH\ Rec}$	(A.2)
		$\mathsf{Pal\ Unlo} = \mathsf{Cor\ Unlo} + Prob\ Unlo$	(A.3)
$\mathbf{Put_t} = \dfrac{\sum_{p=1}^{PalSto} \Delta t(\mathsf{Sto})_p}{\mathsf{Pal\ Sto}} \left(\frac{hour}{pallet}\right)$	(5.2)	$\sum_{p=1}^{PalSto} \Delta t(\mathsf{Sto})_p = WEfSto + HAdmin_{sto} + \Delta tQueue_{sto} + \Delta tOthers_2$	(A.4)
		$WEfSto = \beta_{sto} \times \mathsf{WH\ Sto}$	(A.5)
		$\mathsf{Pal\ Sto} = \mathsf{Cor\ Sto} + Prob\ Sto$	(A.6)
$\mathbf{DS_t} = \dfrac{\sum_{p=1}^{PalSto} \Delta t(\mathsf{DS})_p}{\mathsf{Pal\ Unlo}} \left(\frac{hour}{pallet}\right)$	(5.3)	$\sum_{p=1}^{PalSto} \Delta t(\mathsf{DS})_p = \Delta t(\mathsf{Rec}) + \Delta t(\mathsf{Sto})$	(A.7)
		$\mathsf{Pal\ Unlo} = \mathsf{Cor\ Unlo} + Prob\ Unlo$	(A.3)

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Table A.2 – continued from previous page

Indicator Equation	Data Equations
$\mathbf{Rep_t} = \dfrac{\sum_{p=1}^{PalMoved} \Delta t(\mathsf{Rep})_p}{\mathsf{Pal\ Moved}} (\frac{hour}{pallet}) \quad (5.4)$	$\sum_{p=1}^{PalMoved} \Delta t(\mathsf{Rep})_p = WEfRep + HAdmin_{rep} + \Delta tQueue_{rep} + \Delta tOthers_3 \quad (A.8)$ $WEfRep = \beta_{rep} \times \mathsf{WH\ Rep} \quad (A.9)$ $\mathsf{Pal\ Moved} = \mathsf{Cor\ Rep} + Prob\ Rep \quad (A.10)$
$\mathbf{Pick_t} = \dfrac{\sum_{l=1}^{OrdLiPick} \Delta t(\mathsf{Pick})_l}{\mathsf{OrdLi\ Pick}} (\frac{hour}{orderline}) \quad (5.5)$	$\sum_{l=1}^{OrdLiPick} \Delta t(\mathsf{Pick})_l = WEfPick + HAdmin_{pick} + \Delta tQueue_{pick} + \Delta tOthers_4 \quad (A.11)$ $WEfPick = \beta_{pick} \times \mathsf{WH\ Pick} \quad (A.12)$ $\mathsf{OrdLi\ Pick} = \mathsf{Cor\ OrdLi\ Pick} + Prob\ OrdLi\ Pick \quad (A.13)$
$\mathbf{Ship_t} = \dfrac{\sum_{l=1}^{OrdLiShip} \Delta t(\mathsf{Ship})_l}{\mathsf{OrdLi\ Ship}} (\frac{hour}{orderline}) \quad (5.6)$	$\sum_{l=1}^{OrdLiShip} \Delta t(\mathsf{Ship})_l = WEfShip + HAdmin_{ship} + \Delta tQueue_{ship} + \Delta tInsp_2 + \Delta tOthers_5 \quad (A.14)$ $WEfShip = \beta_{ship} \times \mathsf{WH\ Ship} \quad (A.15)$ $\mathsf{OrdLi\ Ship} = \mathsf{Cor\ OrdLi\ Ship} + Prob\ OrdLi\ Ship \quad (A.16)$

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Table A.2 – continued from previous page

Indicator Equation		Data Equations	
$\mathbf{Del_t} = \frac{\sum_{o=1}^{OrdDel} \Delta t(\mathsf{Del})_o}{\mathsf{Ord\ Del}} (\frac{hour}{order})$	(5.7)	$\sum_{o=1}^{OrdDel} \Delta t(\mathsf{Del})_o = WEfDel + HAdmin_{del} + \Delta tQueue_{del} + \Delta tOthers_6$	(A.17)
		$WEfDel = \beta_{del} \times \mathsf{WH\ Del}$	(A.18)
		$\mathsf{Ord\ Del} = \mathsf{Cor\ Del} + Prob\ Del$	(A.19)
$\mathbf{OrdLT_t} = \frac{\sum_{o=1}^{OrdDel} \Delta t(\mathsf{Ord})_o}{\mathsf{Ord\ Del}} (\frac{hour}{order})$	(5.8)	$\sum_{o=1}^{OrdDel} \Delta t(\mathsf{Ord})_o = \Delta t(\mathsf{Pick}) + \Delta t(\mathsf{Ship}) + \Delta t(\mathsf{Del}) + HAdmin_{ord}$	(A.20)
		$HAdmin_{ord} = \beta_{ord} \times \mathsf{WH\ Admin}$	(A.21)
		$\mathsf{Ord\ Del} = \mathsf{Cor\ Del} + Prob\ Del$	(A.19)

A.2 Productivity indicator model

The productivity indicators can be classified in two main groups (shown in Table A.4): indicators related to labor activities (Equation 5.9 - 5.15) and indicators associated with warehouse capacity and productivity (Equations 5.16 - 5.21).

The first group of indicators are related to specific activities. As defined in Section 5.2.5, Equations 5.9 - 5.15 have the objective of evaluating the employees' productivity considering all available time to work, measured as the total hours that the warehouse is open (War WH).

Regarding the number of employees working in a warehouse, usually the employees are not dedicated to an activity. For example, the warehouse may have all its reception in the morning. In this case, the manager assigns a lot of people in the receiving dock during this period and after the activity is finished the employees are designated for another task. To model this situation, we take into account that the number of employees working in an activity is the average number of employees that should work all day long to execute the same task.

The global labor productivity is presented in Equation A.22. We note that the delivery productivity is not encompassed by Equation A.22, which is limited to the warehouse boundaries. Even considering in this work the delivery activity as part of warehouse management, the indicators are maintained according to their original definitions.

The second group of indicator equations are related to capacity utilization (e.g. warehouse utilization, Equation 5.19) and global warehouse productivity (represented by Turnover, Equation 5.17, and Throughput, Equation 5.21). We remark three details about capacity indicators: (i) it is shown in Equation A.30 that Inv Cap is measured in the number of pallets available, but depending on the product characteristics other alternative is to use the unit m^3; (ii) the inventory capacity used, Inv CapUsed, demonstrated in Equation A.29, also makes part of the warehouse used areas in Equation A.35, since the inventory area is an important part of warehouse space. The Inv CapUsed just needs to be transformed to m^2 to stay in accordance with the indicator unit; (iii) the kilograms available, Kg Avail, in Equation A.34, are calculated in a dynamic way since it considers the number of travels that a truck can make in a month. Other alternative is to determine the Kg Avail in a static way, by summing up the total of truck's capacity.

With respect to the warehouse productivity indicators, it is important to note that turnover, Equation 5.17, is measured in financial terms because the data available in the company are usually in this format. Indeed, the company takes out of the information system the data CGoods and Ave Inv ready, without necessity of making calculations. Anyway, the CGoods and Ave Inv equations are presented in A.31 and A.32, respectively. Analyzing the Cost of Goods, it makes part of turnover, Equation 5.17, and sales, Equation A.49. A product is considered sold when it is delivered to the client. So, CGoods is measured by the number of products delivered times their costs. As the average inventory is defined in products and not in orders, the number of orders delivered, Ord Del, are also multiplied by the number of products per order, *Prod Ord*.

Table A.3: Productivity data definitions

Data	Meaning
ave inv =	average number of products in inventory (*products/month*)
area used war =	warehouse floor area occupied (m^2)
cap =	capacity in kg of each truck (*kg/truck*)
Cor Del =	number of orders delivered correctly (*orders/month*)
Cor OrdLi Pick =	number of order lines picked correctly per month (*orderline/month*)
Cor OrdLi Ship =	number of order lines shipped correctly per month (*orderline/month*)
Cor Rep =	number of pallets moved correctly from bulk stock to picking inventory area (*pallets/month*)
Cor Sto =	number of pallets stored correctly (*pallets/month*)
Cor Unlo =	number of pallets unloaded correctly (*pallets/month*)
days month =	total number of working days in the month (*days/month*)
empl =	average number of employees working in an activity per month. It is divided by activity: *empl Rec*, *empl Sto*, *empl Rep*, *empl Pick*, *empl Ship*. The *empl Del* is a fix number during all available time because the employees only work in delivery activity (*employees*)
HEq Stop =	total number of hours during which equipments are stopped per month (*hours/month*)
HEq Work =	total number of hours during which the equipments are working per month (*hours/month*)
HWarOperate =	total number of hours during which the warehouse operates per day (*hours/day*)
kg Prod =	weight of each product (*kg/product*)
nb_travel =	number of travels made per truck for delivery in a month (*travel/month*)
Prob Del =	number of orders with problems during delivery activity (*order/month*)
Prob OrdLi Pick =	number of order lines with problems during picking activity (*orderlines/month*)

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Table A.3 – Continued

Data	Meaning
Prob OrdLi Ship =	number of order lines with problems during shipping activity per month (*orderlines/month*)
Prob Rep =	number of pallets with problems in replenishment operation (*nb/month*)
Prob Sto =	number of pallets stored with problems per month (*pallets/month*)
Prob Unlo =	number of pallets unloaded with problems per month (*pallets/month*)
Prod Cost =	cost of products arriving in warehouse, the purchasing price ($/*product*)
Prod Line =	average number of products per order lines (*products/orderline*)
Prod Ord =	average number of products per customer order (*products/order*)
Prod pal =	average number of products stocked per pallet (*products/pallet*)
Prod Proc =	total of products processed by the warehouse per month (*products/month*)
War WH =	total number of hours during which the warehouse is open per month (*hour/month*)
WH Del =	total employee labor hours available for delivery activity per month (*hour/month*)
WH Others =	sum of employee labor hours working in other activities (*hour/month*)
WH Pick =	total employee labor hours available for picking activity per month (*hour/month*)
WH Rec =	total employee labor hours available for receiving activity per month (*hour/month*)
WH Rep =	total employee labor hours available for replenishment activity per month (*hour/month*)
WH Sto =	total employee labor hours available for storing activity per month (*hour/month*)
WH Ship =	total employee labor hours available for shipping activity per month (*hour/month*)

Table A.4: Productivity data equations

Indicator Equation	Data Equations
$\mathbf{Lab_p} = \frac{\mathsf{Prod\ Proc}}{\mathsf{WH}}(\frac{products}{hour}) \quad (5.9)$	$\mathsf{Prod\ Proc} = \mathsf{Prod\ Ship} = \mathsf{OrdLi\ Ship} \times \mathit{Prod\ Line} \quad (5.42)$ $\mathsf{WH} = \mathsf{WH\ Rec} + \mathsf{WH\ Sto} + \mathsf{WH\ Rep} + \mathsf{WH\ Pick} + \mathsf{WH\ Ship} + \mathit{WH\ Others} \quad (A.22)$
$\mathbf{Rec_p} = \frac{\mathsf{Pal\ Unlo}}{\mathsf{WH\ Rec}}(\frac{pallets}{hour}) \quad (5.10)$	$\mathsf{Pal\ Unlo} = \mathsf{Cor\ Unlo} + \mathit{Prob\ Unlo} \quad (A.3)$ $\mathsf{WH\ Rec} = \mathit{empl\ Rec} \times \mathit{War\ WH} \quad (A.23)$
$\mathbf{Sto_p} = \frac{\mathsf{Pal\ Sto}}{\mathsf{WH\ Sto}}(\frac{pallets}{hour}) \quad (5.11)$	$\mathsf{Pal\ Sto} = \mathsf{Cor\ Sto} + \mathit{Prob\ Sto} \quad (A.6)$ $\mathsf{WH\ Sto} = \mathit{empl\ Sto} \times \mathit{War\ WH} \quad (A.24)$
$\mathbf{Rep_p} = \frac{\mathsf{Pal\ Moved}}{\mathsf{WH\ Rep}}(\frac{pallets}{hour}) \quad (5.12)$	$\mathsf{Pal\ Moved} = \mathsf{Cor\ Rep} + \mathit{Prob\ Rep} \quad (A.10)$ $\mathsf{WH\ Rep} = \mathit{empl\ Rep} \times \mathit{War\ WH} \quad (A.25)$
$\mathbf{Pick_p} = \frac{\mathsf{OrdLi\ Pick}}{\mathsf{WH\ Pick}}(\frac{orderline}{hour}) \quad (5.13)$	$\mathsf{OrdLi\ Pick} = \mathsf{Cor\ OrdLi\ Pick} + \mathit{Prob\ OrdLi\ Pick} \quad (A.13)$ $\mathsf{WH\ Pick} = \mathit{empl\ Pick} \times \mathit{War\ WH} \quad (A.26)$
$\mathbf{Ship_p} = \frac{\mathsf{OrdLi\ Ship}}{\mathsf{WH\ Ship}}(\frac{orderline}{hour}) \quad (5.14)$	$\mathsf{OrdLi\ Ship} = \mathsf{Cor\ OrdLi\ Ship} + \mathit{Prob\ OrdLi\ Ship} \quad (A.16)$ $\mathsf{WH\ Ship} = \mathit{empl\ Ship} \times \mathit{War\ WH} \quad (A.27)$

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Table A.4 – continued from previous page

Indicator Equation	Data Equations
$$\mathbf{Del_p} = \frac{\mathsf{Ord\ Del}}{\mathsf{WH\ Del}}\left(\frac{order}{hour}\right) \quad (5.15)$$	$$\mathsf{Ord\ Del} = \mathsf{Cor\ Del} + Prob\ Del \quad (A.19)$$ $$\mathsf{WH\ Del} = empl\ Del \times War\ WH \quad (A.28)$$
$$\mathbf{InvUt_p} = \frac{\mathsf{Inv\ CapUsed}}{\mathsf{Inv\ Cap}} \times 100(\%) \quad (5.16)$$	$$\mathsf{Inv\ CapUsed} = \frac{\sum_{i=1}^{n} ave\ inv_i}{Prod\ pal} \quad (A.29)$$ $$i = 1, \ldots, n = \text{SKU's}$$ $$\mathsf{Inv\ Cap} = total\ amount\ of\ pallet\ space \quad (A.30)$$
$$\mathbf{TO_p} = \frac{\mathsf{CGoods}}{\mathsf{Ave\ Inv}}(times) \quad (5.17)$$	$$\mathsf{CGoods} = \sum_{i=1}^{n}((\mathsf{Ord\ Del} \times Prod\ Ord)_i \times Prod\ cost_i) \quad (A.31)$$ $$\mathsf{Ave\ Inv} = \sum_{i=1}^{n}(ave\ inv_i \times Prod\ cost_i) \quad (A.32)$$ $$i = 1, \ldots, n = \text{SKU's}$$

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Table A.4 – continued from previous page

Indicator Equation	Data Equations
$\mathbf{TrUt_p} = \frac{\textsf{Kg Tr}}{\textsf{Kg Avail}} \times 100(\%) \quad (5.18)$	$\textsf{Kg Tr} = \sum_{i=1}^{n} (\textsf{Ord Del} \times Prod\ Ord)_i \times kg\ Prod_i \quad (A.33)$ $i = 1, \ldots, n = \text{SKU's}$ $\textsf{Kg Avail} = \sum_{a=1}^{m} cap_a \times nb\_travel_a \quad (A.34)$ $a = 1, \ldots, m = \text{number of trucks}$
$\mathbf{WarUt_p} = \frac{\textsf{War CapUsed}}{\textsf{War Cap}} \times 100(\%) \quad (5.19)$	$\textsf{War CapUsed} = \sum_{b=1}^{war\ area} war\ used\ area \quad (A.35)$ $b = 1, \ldots, war\ area$ where $war\ area = \text{areas utilized in warehouse activities}$ $\textsf{War Cap} = total\ useful\ warehouse\ area \quad (A.36)$
$\mathbf{EqD_p} = \frac{\textsf{HEq Stop}}{\textsf{HEq Avail}} \times 100(\%) \quad (5.20)$	$\textsf{HEq Avail} = \textsf{HEq Stop} + \textsf{HEq Work} = \sum_{c=1}^{z} HEq\ Stop_c + \sum_{c=1}^{z} HEq\ Work_c \quad (A.37)$ $c = 1, \ldots, z = nb\ of\ equipments$
$\mathbf{Th_p} = \frac{\textsf{Prod Ship}}{\textsf{War WH}} (\frac{products}{hour}) \quad (5.21)$	$\textsf{Prod Ship} = \textsf{OrdLi Ship} \times Prod\ Line \quad (A.38)$ $\textsf{War WH} = HWarOperate \times days\ month \quad (A.39)$

A.3 Cost indicator model

The cost equations are presented in Table A.6 whereas their definitions are in Table A.5.

The distribution costs (Equation 5.23) are measured but not included in the total warehouse costs (Equation A.48). The salary costs of delivery employees are also included in Equation 5.23, instead of being considered in labor cost indicator (Equation 5.26).

Regarding the labor cost indicator (Equation 5.26), only the employees working inside the warehouse are taken into account. The time of the administrative employees are divided in: hours dedicated to customer orders and hours dedicated to other warehouse activities. The first part, hours dedicated to customer orders, are included in order processing costs (Equation 5.24), and the second part, hours dedicated to other warehouse activities, are included in the labor cost (Equation 5.26). When the total warehouse costs (Equation A.48) are assessed, order processing cost and labor cost are summed up, and the administrative costs are entirely considered.

The interpretation of LostC, Equation A.41 could lead to misunderstandings. LostC should be interpreted as the quantity of profit lost due to the absence of inventory to fulfill customer orders. The lack of stock is measured by the quality indicator stock out (Equation 5.40). This percentage of missing stock is multiplied by the total products picked in a month (named Prod Out, Equation A.47) and the average profit gain with each product sold.

Table A.5: Cost data definitions

Data	Meaning
$\alpha =$	index representing the partial quantity over the Salary payed as Charges per month
$\beta_{ord} =$	index to represent how many hours of the total available labor hours the employees are dedicated to customer orders administration.
\$ oil =	oil price per liter ($\$/l$)
$\$/h =$	cost per hour worked in each activity. It is divided by activities: $\$/h_{rec}$, $\$/h_{sto}$, $\$/h_{rep}$, $\$/h_{pick}$, $\$/h_{ship}$, $\$/h_{del}$, $\$/h_{admin}$, $\$/h_{other}$ ($\$/hour$)
Ave Inv =	average inventory in warehouse ($\$/month$)
CGoods =	total cost of items sold (\$)
Cor Del =	number of orders delivered correctly per month ($orders/month$)

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Table A.5 – Continued

Data	Meaning
$deprec_{1-2}$ =	depreciation costs of company assets used in activities per month ($\$/month$)
l_used =	mean of oil liters used by trucks for one travel ($liter/travel$)
nb_travel =	number of travels made per truck for delivery in a month ($travel/month$)
$Other_{1-2}$ =	other costs not considered in equation ($\$/month$)
$Prob\ Del$ =	number of orders with problems during delivery activity ($orders/month$)
$Prod\ Cost$ =	cost of products arriving in warehouse, the purchasing price ($\$/product$)
$Prod\ Out$ =	number of products taken out of the inventory ($products/month$)
$Profit$ =	average gross profit of products sold ($\$/product$)
$Rate$ =	monthly financial rate (%)
$Charges_{tr}$ =	Labor charges payed over salary value ($\$/month$)
SL =	service level offered to the customer (%)
$Salary_{tr}$ =	total salaries of delivery employees per month ($\$/month$)
$Truck\ MaintC$ =	total cost of truck maintenance ($\$/month$)
$WH\ Admin$ =	total employee labor hours available in administration activity ($hour/month$)
WH Del =	total employee labor hours available for delivery activity per month ($hour/month$)
$WH\ Others$ =	sum of employee labor hours working in other activities ($hour/month$)
WH Pick =	total employee labor hours available for picking activity per month ($hour/month$)
WH Rec =	total employee labor hours available for receiving activity per month ($hour/month$)
WH Rep =	total employee labor hours available for replenishment activity per month ($hour/month$)
WH Sto =	total employee labor hours available for storing activity per month ($hour/month$)
WH Ship =	total employee labor hours available for shipping activity per month ($hour/month$)

Table A.6: Cost data equations

Indicator Equation	Data Equations
$\mathbf{Inv_c} = \mathsf{InvC} + \mathsf{LostC}(\$) \quad (5.22)$	$\mathsf{Ave\ Inv} = \sum_{i=1}^{n}(ave\ inv_i \times Prod\ cost_i) \quad (A.32)$ $\mathsf{InvC} = \mathsf{Ave\ Inv} \times Rate \quad (A.40)$ $\mathsf{LostC} = (1 - SL) \times Profit \times \mathsf{Prod\ Out} \quad (A.41)$ $SL = 1 - (\frac{\mathbf{StockOut}_q}{100}) \quad (A.42)$
$\mathbf{Tr_c} = \frac{\mathsf{TrC}}{\mathsf{Ord\ Del}}(\frac{\$}{order}) \quad (5.23)$	$\mathsf{TrC} = Truck\ MaintC + (\$\ oil \times l\_used \times nb\_travel) + Salary_{tr} + Charges_{tr} + deprec_1 + Other_1 \quad (A.43)$ $Salary_{tr} = \$/h_{del} \times \mathsf{WH\ Del} \quad (A.44)$ $Charges_{tr} = \alpha \times Salary_{tr} \quad \text{and} \quad 0 < \alpha < 1 \quad (A.45)$ $\mathsf{Ord\ Del} = \mathsf{Cor\ Del} + Prob\ Del \quad (A.19)$
$\mathbf{OrdProc_c} = \frac{\mathsf{Ord\ ProcC}}{\mathsf{Cust\ Ord}}(\frac{\$}{order}) \quad (5.24)$	$\mathsf{Ord\ ProcC} = \$/h_{admin} \times \beta_{ord} \times WH\ Admin + Charges_{admin} + deprec_2 + Other_2 \quad (A.46)$ $\mathsf{Cust\ Ord} = number\ of\ customer\ orders\ per\ month \quad (A.47)$

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Table A.6 – continued from previous page

Indicator Equation	Data Equations
$\mathbf{CS_c} = \frac{\text{War Cost}}{\text{Sales}}(\%) \quad (5.25)$	$\text{War Cost} = (\text{Ord ProcC} \times \text{Cust Ord}) + \mathbf{Lab_c} + \mathbf{Maint_c} \quad (A.48)$ $\text{Sales} = \text{CGoods} + (\mathit{Profit} \times \text{Ord Del} \times \mathit{Prod\ Ord}) \quad (A.49)$ $\text{CGoods} = \sum_{i=1}^{n}((\text{Ord Del} \times \mathit{Prod\ Ord})_i \times \mathit{Prod\ cost}_i) \quad (A.31)$ $i = 1, \ldots, n = \mathit{SKU's}$
$\mathbf{Lab_c} = \text{Salary} + \text{Charges} + \text{Others}(\frac{\$}{month}) \quad (5.26)$	$\text{Salary} = \$/h_{rec} \times \text{WH Rec} + \$/h_{sto} \times \text{WH Sto} + \$/h_{rep} \times \text{WH Rep}$ $+ \$/h_{pick} \times \text{WH Pick} + \$/h_{ship} \times \text{WH Ship} + \$/h_{admin} \times (1 - \beta_{ord}) \times \mathit{WH\ Admin}$ $+ \$/h_{other} \times \mathit{WH\ Others} \quad (A.50)$ $\text{Charges} = \alpha \times \text{Salary} \quad \text{and} \quad 0 < \alpha < 1 \quad (5.46)$
$\mathbf{Maint_c} = \text{BuildC} + \text{EqMaintC} + \text{Others}(\frac{\$}{month}) \quad (5.27)$	$\text{BuildC} = \mathit{building\ maintenance\ costs} \quad (A.51)$ $\text{EqMaintC} = \mathit{maintenance\ cost\ of\ all\ equipments} \quad (A.52)$

A.4 Quality indicator model

The expressions of the quality problems presented in Equations A.53 - A.59 are inequalities. The objective of these expressions is to show the main data shared by different quality indicators. For example, the number of order lines picked with problem (Equation A.57) contain as the main errors: scraps, data error and order lines no available. The "problems" represented by scrap and items no available are also used in $\mathbf{Scrap_q}$ and $\mathbf{StockOut_q}$ quality indicators, respectively.

Regarding the inequality result, the total number of order lines picked with problem is equal or smaller than the sum of problems since in a real situation an order line can have more than one problem at the same time. The correct orders are the ones with no problem in any analyzed component (e.g. punctuality, correctness). To be a correct order, it must fulfill all requirements made by the warehouse.

An important consideration about the scraps inserted in indicator equations is that they do not impact the final number of orders processed. It is determined that these scraps are the ones that have been replenished during the same month. As this situation can happen in practice (scraps not replenished in the same month), we include scraps not solved in the data generation, presented in Section 6.2.

The new terms introduced in the right side of Table A.8 are presented in Table A.7.

Table A.7: Quality data definitions

Data	**Meaning**
Cor Del =	number of orders delivered correctly per month (*orders/month*)
Cor OrdLi Pick =	number of order lines picked correctly per month (*orderline/month*)
Cor OrdLi Ship =	number of order lines shipped correctly per month (*orderline/month*)
Cor Rep =	number of pallets moved correctly from the reserve storage to the forward picking area per month (*pallets/month*)
Cor Sto =	number of pallets stored correctly per month (*pallets/month*)
Cor Unlo =	number of pallets unloaded correctly per month (*pallets/month*)
data error =	number of products with data system errors from outbound area per month (*products/month*)

Table A.7 – continued from previous page

Data	**Meaning**
error data system$_{1-3}$ =	number of pallets with data system errors from the activities: unloading, storing and replenishment. It is the complement of *cor data in system* (*orders/month*), and the sum of all errors result in Prob Data (*orders/month*)
NoComplet Ord Ship =	number of orders shipped incomplete on first shipment per month (*orders/month*)
Ord Ship =	number of orders shipped per month (*orders/month*)
others =	number of other problems not defined per month (*nb/month*)
ord late =	number of orders with delays per month. The opposite of order on time (*orders/month*)
OrdLi noAvail =	number of order lines per month that are not available in stock when the customer makes an order (*orderlines/month*)
Prob data =	number of pallets with inaccuracies between the physical inventory and the system per month (*pallets/month*)
Prob Del =	number of orders with problems during delivery activity per month (*orders/month*)
Prod Line =	average number of products per order lines (*products/orderline*)
Prob OrdLi Pick =	number of order lines with problems during picking activity per month (*orderline/month*)
Prob OrdLi Ship =	number of order lines with problems during shipping activity per month (*orderline/month*)
Prod pal =	average number of products stocked per pallet (*products/pallet*)
Prod Proc =	number of products processed by the warehouse per month. Products processed refers to the number of products shipped in the warehouse (*products/month*)
Prob Rep =	number of pallets with problems in replenishment operation (*pallets/month*)
Prob Sto =	number of pallets stored with problems per month (*pallets/month*)
Prob Unlo =	number of pallets unloaded with problems per month (*pallets/month*)
Prod noAvail=	number of products per month that are not available in stock when the customer makes an order (*product/month*)
Prod Ord =	average number of products per customer orders (*products/order*)
Prod Out =	number of products taken out of the inventory per month (*products/month*)

Table A.7 – continued from previous page

Data	Meaning
$scrap_{1-3}$ =	number of pallets with losses from handling problems or accidents per month ($pallets/month$). $scrap_{4-5}$ has the same meaning, it is just measured by ($orderlines/month$). $scrap_6$ is measured in ($orders/month$)

Table A.8: Quality data equations

Indicator Equation	Data Equations
$\mathbf{Rec_q} = \dfrac{\textsf{Cor Unlo}}{\textsf{Pal Unlo}} \times 100(\%) \quad (5.28)$	$\textsf{Pal Unlo} = \textsf{Cor Unlo} + Prob\ Unlo \quad (A.3)$ $Prob\ Unlo \leqslant \textsf{scrap}_1 + error\ data\ system_1\ + others \quad (A.53)$
$\mathbf{Sto_q} = \dfrac{\textsf{Cor Sto}}{\textsf{Pal Sto}} \times 100(\%) \quad (5.29)$	$\textsf{Pal Sto} = \textsf{Cor Sto} + Prob\ Sto \quad (A.6)$ $Prob\ Sto \leqslant scrap_2 + error\ data\ system_2\ + others \quad (A.54)$
$\mathbf{Rep_q} = \dfrac{\textsf{Cor Rep}}{\textsf{Pal Moved}} \times 100(\%) \quad (5.30)$	$\textsf{Pal Moved} = \textsf{Cor Rep} + Prob\ Rep \quad (A.10)$ $Prob\ Rep \leqslant scrap_3 + error\ data\ system_3 + others \quad (A.55)$
$\mathbf{Inv_q} = \dfrac{\textsf{Pal Unlo + Pal Sto + Pal Moved - Prob data}}{\textsf{Pal Unlo + Pal Sto + Pal Moved}} \times 100 \quad (5.31)$	$\textsf{Pal Unlo} = \textsf{Cor Unlo} + Prob\ Unlo \quad (A.3)$ $\textsf{Pal Sto} = \textsf{Cor Sto} + Prob\ Sto \quad (A.6)$ $\textsf{Pal Moved} = \textsf{Cor Rep} + Prob\ Rep \quad (A.10)$ $\textsf{Prob Data} = \sum_{m=1}^{3} error\ data\ system_m \quad (A.56)$ $m = error\ data\ system_1, error\ data\ system_2, error\ data\ system_3$

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Table A.8 – continued from previous page

Indicator Equation		Data Equations
$\mathbf{Pick_q} = \frac{\mathsf{Cor\ OrdLi\ Pick}}{\mathsf{OrdLi\ Pick}} \times 100(\%)$	(5.32)	$\mathsf{OrdLi\ Pick} = \mathsf{Cor\ OrdLi\ Pick} + \mathit{Prob\ OrdLi\ Pick}$ (A.13) $\mathit{Prob\ OrdLi\ Pick} \leqslant scrap_4 + \ data\ error + OrdLi\ noAvail + others$ (A.57)
$\mathbf{Ship_q} = \frac{\mathsf{Cor\ OrdLi\ Ship}}{\mathsf{OrdLi\ Ship}} \times 100(\%)$	(5.33)	$\mathsf{OrdLi\ Ship} = \mathsf{Cor\ OrdLi\ Ship} + \mathit{Prob\ OrdLi\ Ship}$ (A.16) $\mathit{Prob\ OrdLi\ Ship} \leqslant scrap_5 + data\ error + No\ OT\ Ship + NoComplet\ Ord\ Ship + others$ (A.58)
$\mathbf{Del_q} = \frac{\mathsf{Cor\ Del}}{\mathsf{Ord\ Del}} \times 100(\%)$	(5.34)	$\mathsf{Ord\ Del} = \mathsf{Cor\ Del} + \mathit{Prob\ Del}$ (A.19) $\mathit{Prob\ Del} \leqslant scrap_6 + data\ error + ord\ late + no\ complete\ ord + others$ (A.59)
$\mathbf{OTDel_q} = \frac{\mathsf{Ord\ Del\ OT}}{\mathsf{Ord\ Del}} \times 100(\%)$	(5.35)	$\mathsf{Ord\ Del\ OT} = \mathsf{Ord\ Del} - \mathsf{No\ OT\ Del}$ (A.60) $\mathsf{Ord\ Del} = \mathsf{Cor\ Del} + \mathit{Prob\ Del}$ (A.19)
$\mathbf{OTShip_q} = \frac{\mathsf{Ord\ Ship\ OT}}{\mathsf{Ord\ Ship}} \times 100(\%)$	(5.36)	$\mathsf{Ord\ Ship\ OT} = \mathit{Ord\ Ship} - \mathit{No\ OT\ Ship}$ (A.61) $\mathsf{Ord\ Ship} = \sum_{p=1}^{\mathit{OrdLi\ Ship}} \mathsf{OrdLi\ Ship}_p$ (A.62)

Continued on next page...

Table A.8 – continued from previous page

Indicator Equation	Data Equations
$\mathbf{OrdF_q} = \frac{\text{Complet 1st Ship}}{\text{Ord Ship}} \times 100(\%)$ (5.37)	$\text{Complet 1st Ship} = \text{Ord Ship} - \textit{NoComplet Ord Ship}$ (A.63) $\text{Ord Ship} = \sum_{p=1}^{\textit{OrdLi Ship}} \text{OrdLi Ship}_p$ (A.62)
$\mathbf{PerfOrd_q} = \frac{\text{(Ord OT, ND, CD)}}{\text{Ord Del}} \times 100(\%)$ (5.38)	$\text{Ord OT, ND, CD} = \textit{orders on time, with no damages and correct documents}$ $\text{Ord Del} = \text{Cor Del} + \textit{Prob Del}$ (A.19)
$\mathbf{CustSat_q} = \frac{\text{Ord Del - Cust Complain}}{\text{Ord Del}} \times 100(\%)$ (5.39)	$\text{Cust Complain} = \textit{customer complaints regarding warehouse processes}$ (A.64) $\text{Ord Del} = \text{Cor Del} + \textit{Prob Del}$ (A.19)
$\mathbf{StockOut_q} = \frac{\text{Prod noAvail}}{\text{Prod Out}} \times 100(\%)$ (5.40)	$\text{Prod noAvail} = \textit{products not available in stock}$ $\text{Prod Out} = \text{Ord LiPick} \times \textit{Prod Line}$ (A.47)
$\mathbf{Scrap_q} = \frac{\text{Nb Scrap}}{\text{Prod Proc}} \times 100(\%)$ (5.41)	$\text{Nb Scrap} = (scrap_1 + scrap_2 + scrap_3) \times \textit{Prod pal} + (scrap_4 + scrap_5) \times \textit{Prod Line} + scrap_6 \times \textit{Prod Ord}$ (A.65) $\text{Prod Proc} = \text{Prod Ship} = \text{OrdLi Ship} \times \textit{Prod Line}$ (5.42)

Appendix B

Data Generation

This appendix details how data is created for the standard warehouse. The next sections present separately the product flow and data equations for warehouse operations, demonstrating the considerations made for each activity.

B.1 Receiving data

The receiving activity is detailed in Figure B.1, which is divided in five parts: four rectangles with data equations and one activity flow schema in the up right side of the figure. The four rectangles shows, respectively: the Global variables; the internal inputs named 'IntInput'; the 'Outputs' and internal outputs 'IntOutput'; the Number of problems occurred during the month.

The Global variables are general information that can be used in any part of the warehouse to calculate other data or indicators. The number of days worked in a month 'nb_days/month', for example, varies every month between 20 and 25 days, following a uniform distribution of probabilities. Once the number of days is defined for a month, this information is used for all data and indicators in that month. To simplify the figure, we illustrate only the global variables related to receiving operation and used to calculate inputs or outputs.

The internal inputs 'IntInput' and internal outputs 'IntOutput' comprehend data related specifically to the receiving performance indicators.

The 'Outputs' are also data used on performance indicators, but the difference is that these outputs are also the inputs of the next activity,

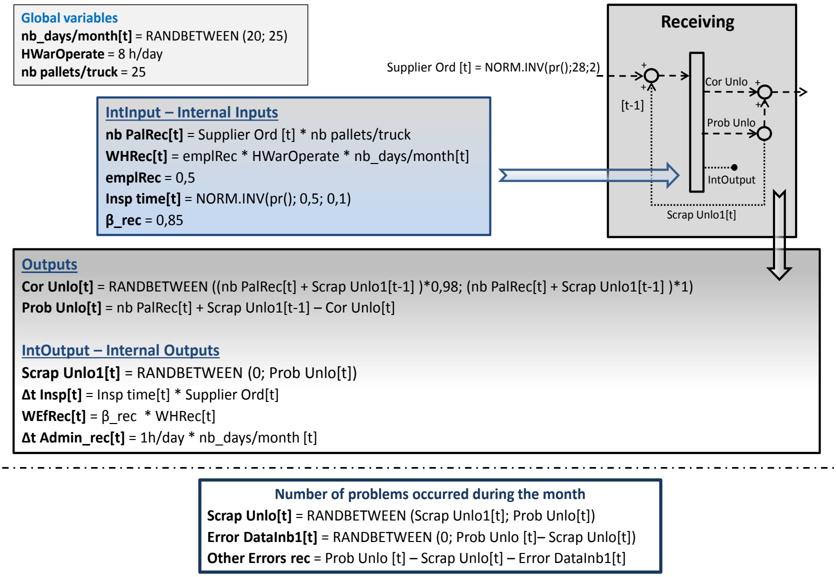


Figure B.1: Receiving flows and data equations.

demonstrating the product flow in the warehouse, which also impact indicator interactions. Finally, the rectangle on the bottom of Figure B.1 demonstrates the total 'Number of problems occurred during the month'. These data are a sum of all problems occurred during the month in the activity (solved or not), and some of these informations are also utilized in indicator equations.

The design of Figure B.1 and the information inside rectangles are used as standard for all other warehouse activities presented in next sections. Moreover, the notation of the equations inside the rectangles are the same presented in the complete analytical model described in Appendix A.

The equations presented in Figure B.1 are explained detailedly as follows.

B.1.1 Equations of Receiving data

In the receiving flow schema of Figure B.1, the number of supplier orders 'Supplier Ord' arriving in the warehouse are a random number varying according to a normal distribution with mean 28 and standard deviation 2. As the performance indicators in receiving are measured in pallets, we assess the number of pallets received, 'nb PalRec[t]' (first equation of 'IntInput'), multiplying the number of supplier orders received in the month t and the number of pallets per truck, 'nb pallets/truck'. This equation demonstrates that we consider all supplier orders arriving with the same quantity, a complete truck of 10 tons loaded with 25 pallets.

The number of labor hours available to work in a month, 'WHRec[t]', change according to the working days and the number of employees performing the activity. As stated before, in this scenario, the number of employees are considered constant over time for all activities.

The last two 'IntInput' equations correspond to the time to perform product quality inspections, Insp time[t] and β_{ord} is the index to represent how many hours of the total available labor hours the employees are effectively receiving. The 'Insp time' uses the normal function to define the time, in hours, taken by administrative employees to perform inspection, which is defined as 30 min (0.5 hour) on average for each supplier order with a standard deviation of 6 minutes (0.1 hour). Insp time[t] and β_{ord} are used to calculate the total inspection time and effective hours receiving in the month *[t]*, named Δt Insp[t] and WEfRec[t], respectively. The equations are showed in the 'IntOutput' area of the Figure B.1.

The last formula of IntOutput is Δt Admin_rec[t] which means the time taken by administrative personnel to execute activities related to receiving and supplier orders. This time is fixed in one hour per day.

The type of receiving 'problems' occurred in a month are not exhaustively detailed. The Scrap Unlo[t] and Error DataInb1[t] are demonstrated separately because their values are used in $\mathbf{ScrapRate_q}$ and $\mathbf{Inv_q}$ indicators, respectively. All other possible errors are identified in equation 'Other Errors rec', besides its value is not used for indicator measurement. It is important to note that according to the equations, the number of Error DataInb1[t] has as limit the number of problems minus products with scrap problems. Thus, another constraint of the model is not allowing an order with two different errors at the same month.

The outputs of receiving, Cor Unlo[t] and Prob Unlo[t], variates every month between 98 % to 100% of the total pallets unloaded for Cor Unlo[t] and of 0% up to 2% for Prob Unlo[t]. According to Figure B.1, the Cor Unlo[t] is measured using a uniform random probability between 98% and 100% of the total inputs, which are the total of pallets received, nb PalRec[t], and the number of scraps not solved in the previous month [t-1] (Scrap Unlo1[t-1]). The Prob Unlo[t], in contrast, is calculated just with the difference between the total of inputs and the pallets unloaded correctly, Cor Unlo[t]. Therefore, the inputs of the storage activity (presented in the next section) are the resultant of $CorUnlo[t] + ProbUnlo[t] - ScrapUnlo1[t]$ equation.

All other activities have their equations developed based on the same logic presented here for the receiving activity. Thus, just particularities not discussed yet are presented in next sections.

B.2 Storage data

The data equations used in storage activity are presented in Figure B.2.

In storage activity, the outputs Cor Sto[t] and Prob Sto[t], variates every month between 96 % to 98% of the total pallets stored for Cor Sto[t] and of 0% up to 2% for Prob Sto[t]. It results, in some months, that a number of products could be not all processed, remaining as "Sto in Process" for the next month. The "Sto in Process" is the sum of products with problems not solved (information arrow getting out of Prob Sto and entering in 'No Proc') with products not processed 'No Proc'. It is interesting to note that the problems not solved are the number of scraps not replaced during the month, represented by Scrap Sto1[t].

B.3 Replenishment data

The data equations used in replenishment activity are shown in Figure B.3. The replenishment activity consist on the movement of pallets from the reserve storage area to the forward picking area. As this activity aims to replenish the inventory picking area, the number of pallets to move depends on the quantity of products picked (represented by Cor Pick[t] + Prob Pick[t] in Figure B.3).

We note that the replenishment indicators are measured by pallets and the Cor Pick[t] and Prob Pick[t] have order lines as units. Thus, the equations presented in Figure B.3 also transform these different kinds of information in the same unit.

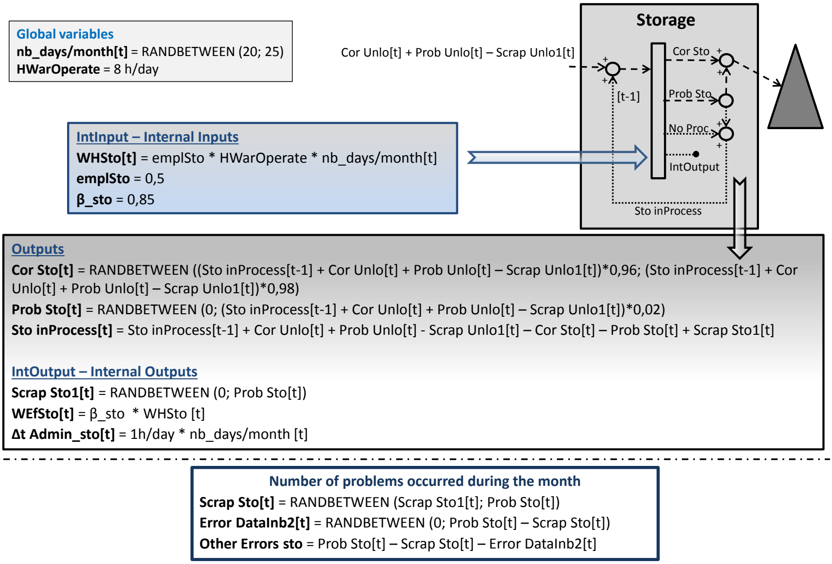


Figure B.2: Storage flows and data equations.

B.4 Picking data

The data equations used in picking activity are depicted in Figure B.4.

B.5 Shipping data

Figure B.5 presents the shipping activity with its equations. The indicator Order Fill rate (Equation 5.37) measures the number of orders delivered complete. Instead of generating the number of complete orders, we evaluate the number of partial orders delivered, represented by NoComplet_Ord Ship[t].

B.6 Delivery data

Figure B.6 shows the delivery activity with its equations.

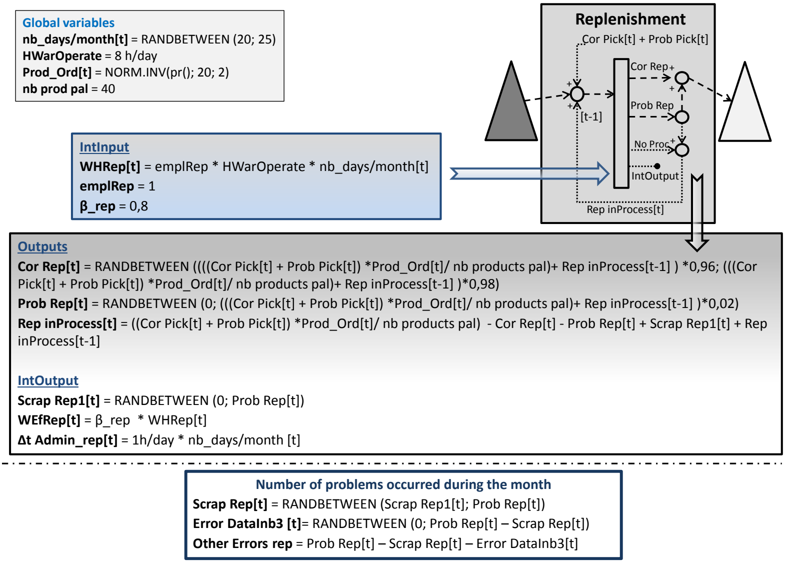


Figure B.3: Replenishment flows and data equations.

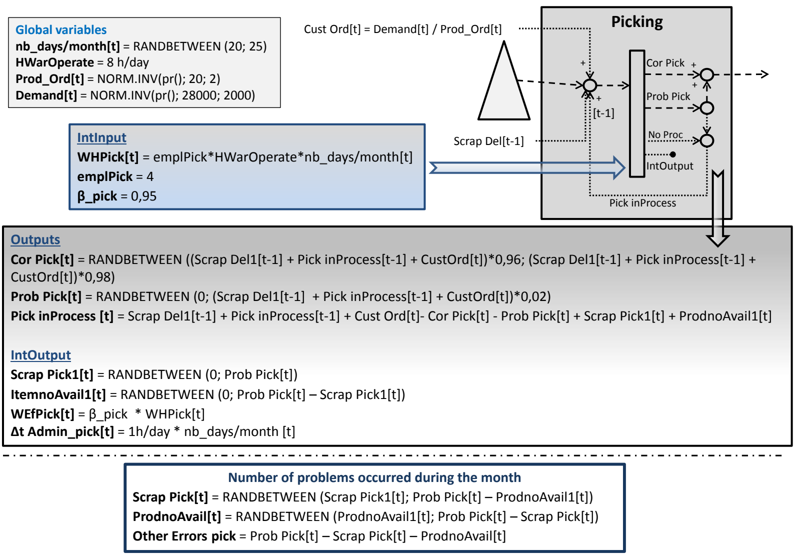
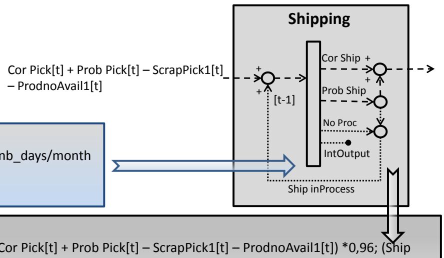


Figure B.4: Picking flows and data equations.

Global variables
nb_days/month[t] = RANDBETWEEN (20; 25)
HWarOperate = 8 h/day



IntInput
WHShip[t] = emplShip*HWarOperate*nb_days/month
emplShip = 3
β_ship = 0,95

Outputs
Cor Ship[t] = RANDBETWEEN ((Ship inProcess[t-1] + Cor Pick[t] + Prob Pick[t] – ScrapPick1[t] – ProdnoAvail1[t]) *0,96; (Ship inProcess[t-1] + Cor Pick[t] + Prob Pick[t] – ScrapPick1[t] – ProdnoAvail1[t]) *0,98)
Prob Ship[t] = RANDBETWEEN (0; (Ship inProcess[t-1] + Cor Pick[t] + Prob Pick[t] – ScrapPick1[t] – ProdnoAvail1[t]) *0,02)
Ship inProcess [t] = Ship inProcess[t-1] + Cor Pick[t] + Prob Pick[t] - Scrap Pick1[t] - ProdnoAvail1[t] - Cor Ship[t] – Prob Ship[t] + Scrap Ship1[t]

IntOutput
Scrap Ship1[t] = RANDBETWEEN (0; Prob Ship[t])
WEfShip[t] = β_ship * WHShip[t]
Δt Admin_ship[t] = 1h/day * nb_days/month[t]

Number of problems occurred during the month
Scrap Ship[t] = RANDBETWEEN (Scrap Ship1[t]; Prob Ship[t])
NoComplet_Ord Ship[t] = RANDBETWEEN(0; Prob Ship[t] – Scrap Ship[t])
Other Errors ship = Prob Ship[t] – Scrap Ship[t] – NoComplet_Ord Ship[t]
OTShip[t] = RANDBETWEEN (Cor Ship[t]; Cor Ship[t] + Prob Ship[t] – Scrap Ship1[t])

Figure B.5: Shipping flows and data equations.

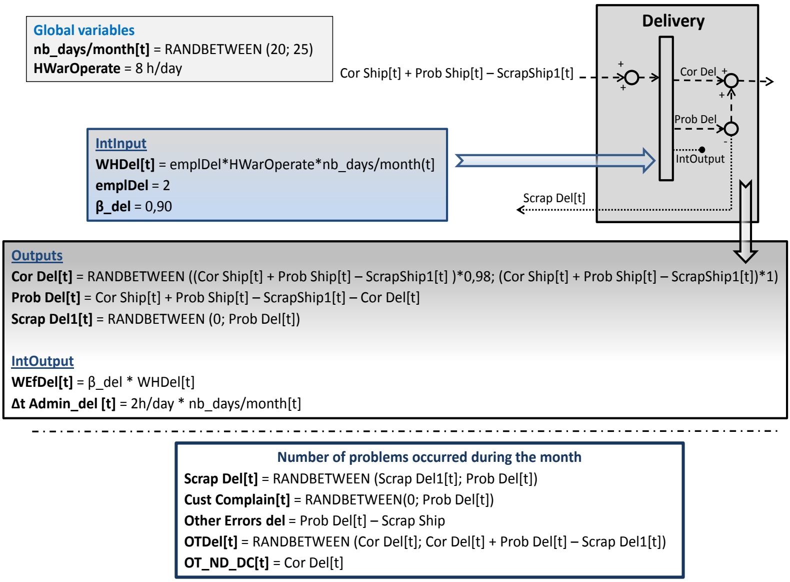


Figure B.6: Delivery flows and data equations.

B.7 Warehouse and Inventory data

This section demonstrates the equations related to the warehouse as a whole (Figure B.7), emphasizing the inventory area in Figure B.8.

The warehouse building and the truck make part of company assets; it means that all costs associated with their maintenance are taken into account in cost indicators.

The charges, total paid over salary for all employees are considered as 50% of salary value. The average of liters used per travel is 2, considering that each travel has 10 km and 5 km is made with one oil liter. The depreciations (deprec1 and deprec2) are considered fixed values over time.

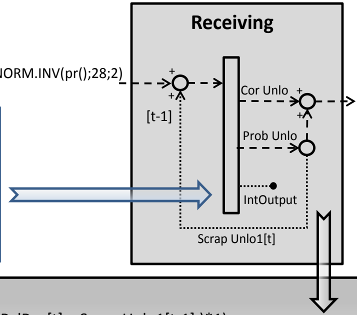
Global variables

nb_days/month[t] = RANDBETWEEN (20; 25)
HWarOperate = 8 h/day
nb pallets/truck = 25

IntInput – Internal Inputs

nb PalRec[t] = Supplier Ord [t] * nb pallets/truck
WHRec[t] = emplRec * HWarOperate * nb_days/month[t]
emplRec = 0,5
Insp time[t] = NORM.INV(pr(); 0,5; 0,1)
β_rec = 0,85

Supplier Ord [t] = NORM.INV(pr();28;2)



Outputs

Cor Unlo[t] = RANDBETWEEN ((nb PalRec[t] + Scrap Unlo1[t-1])*0,98; (nb PalRec[t] + Scrap Unlo1[t-1])*1)
Prob Unlo[t] = nb PalRec[t] + Scrap Unlo1[t-1] – Cor Unlo[t]

IntOutput – Internal Outputs

Scrap Unlo1[t] = RANDBETWEEN (0; Prob Unlo[t])
Δt Insp[t] = Insp time[t] * Supplier Ord[t]
WEfRec[t] = β_rec * WHRec[t]
Δt Admin_rec[t] = 1h/day * nb_days/month [t]

Number of problems occurred during the month

Scrap Unlo[t] = RANDBETWEEN (Scrap Unlo1[t]; Prob Unlo[t])
Error Datalnb1[t] = RANDBETWEEN (0; Prob Unlo [t]– Scrap Unlo[t])
Other Errors rec = Prob Unlo [t] – Scrap Unlo[t] – Error Datalnb1[t]

Figure B.7: Warehouse flows and data equations.

Figure B.8 shows in IntOutput rectangle the equations inv_end[t] and aveinv. The equation inv_end[t] means the inventory on hand at the end of a given period. It is calculated by: the inventory from the previous period (inv_end[t-1]), summed up with the products get in stock (CorSto[t] + ProbSto[t] - ScrapSto1[t]), less the demand in the given period (CorPick[t] + ProbPick[t]). To calculate the average stock during an entire month, a data used in some indicators, the equation aveinv is applied for this purpose.

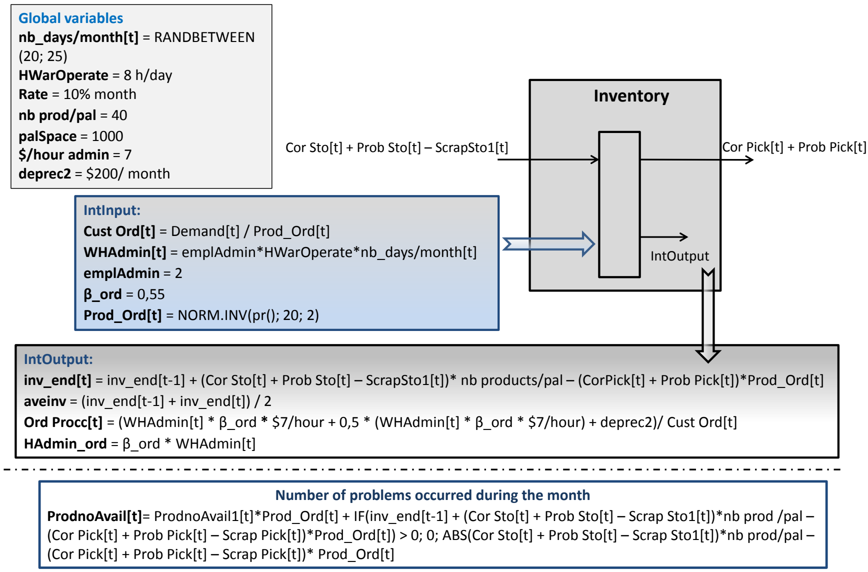


Figure B.8: Inventory flows and data equations.

Appendix C

Manual Procedure to determine indicator relationships

This appendix demonstrate the initial analysis performed to determine indicator relationships manually.

Initially, we construct a schema (Figure C.1) showing the all 40 indicators and the main data used to measure them (data from indicator equations of Sections 5.2.4, 5.2.5, 5.2.6, 5.2.7). The indicators are represented by ellipses and data by rectangular blocks. The lines represent the connection between data and the indicator. For example, the indicator $\mathbf{EqD}_p$ (in the up left corner of Figure C.1) is calculated by *HEq Stop* per *HEq Avail* (the green rectangles), so there are lines connecting both data with the indicator $\mathbf{EqD}_p$.

In Figure C.1 we present data just once to simplify the interpretation. It means that if there is a data used in two or more indicator equations with different units, it will appear just in one rectangle. That is the case, for example, of "Ave Inv" that is measured in units for $\mathbf{InvUt_p}$ (Equation 5.16) and in dollars for $\mathbf{Inv_c}$ (Equation 5.22) and $\mathbf{TO_p}$ (Equation 5.17).

The violet blocks referring to Unload pallet "Pal Unlo", Pallet stored "Pal Sto", Pallet moved "Pal Moved", Order lines picked "OrdLiPick", Order lines shipped "OrdLiShip" and Orders delivered "Ord Del" means the total of products processed in each activity. For these data, we distinguish the main data parts to clarify what is being used to calculate

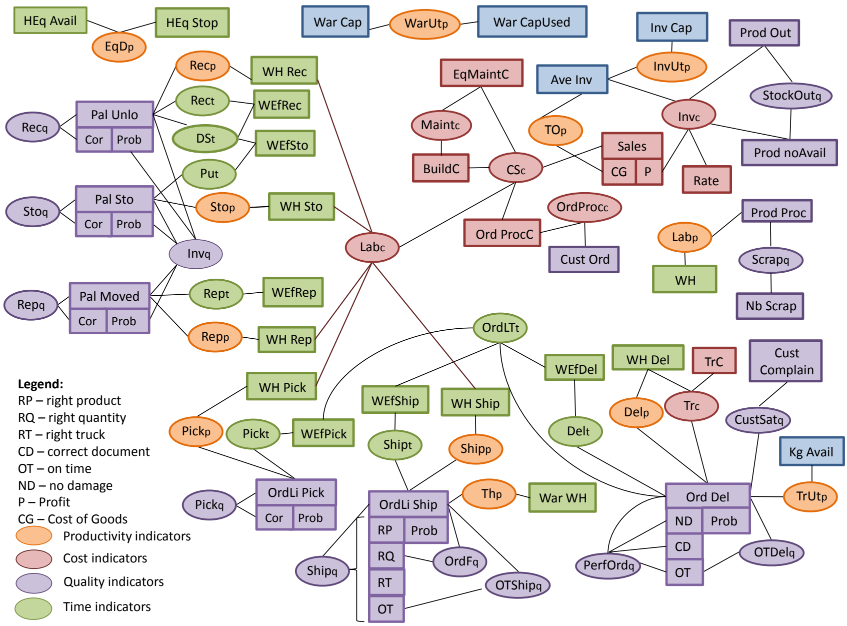


Figure C.1: Indicator relationships based on data.

the indicators. For receiving, storage, replenishment and picking there are just two divisions: correct ‘Cor’ and problem ‘Prob’. In the case of order lines shipped and orders delivered, the acronyms mean, respectively: RP, right product; RQ, right quantity; RT, right truck; ND, no damage; CD, correct documents; OT, on time. Finally, the red rectangular block, denoting sales (Equation A.49) is calculated by the sum of profit (represented by the red block P) with cost of goods (represented by the red block CG).

The colors denote the classification of indicators and data, according to their dimensions. The green figures refer to data and indicators of time, the red ones refers to cost, orange to productivity, blue to capacity data and violet is related to the product and order quantity with its quality.

Figure C.1 shows that the majority of indicators are related with at least one other indicator, forming a big cloud of relationships. The exceptions are equipment downtime and warehouse utilization, $\mathbf{EqD}_p$ and $\mathbf{WarUt_p}$.

Analyzing the interconnections, it is possible to visualize some groups formed from this relations. Taking the left side of Figure C.1, we observe that the violet rectangles (e.g., Pal Unlo) connect essentially indicators of time, quality and productivity. In the right side of Figure C.1 it is possible to note a distinct group of indicators mainly associated to costs can be identified.

In order to clarify the indicator relations, in the next section we present initially a manual procedure to determine a framework where just indicator relations are exhibited.

C.1 The Manual Procedure

After the identification of indicator relations in Figure C.1, we use a simple procedure to get a new schema without data on it.

To construct a relationship framework, all indicators are listed and their relations are identified by means of structures like the one presented in Figure C.2. The indicator under analysis is located in the center and the ones that are related to it are connected by arrows. The number on the arrows represents the number of data shared by indicators. Taking one example of the four demonstrated in Figure C.2, shipping quality "$\mathbf{Ship_q}$" shares one data with $\mathbf{Ship_t}$, $\mathbf{Ship_p}$, $\mathbf{Th_p}$ and two data with $\mathbf{OrdF_q}$ and $\mathbf{OTShip_q}$.

C.2 The indicator relationships schema for the manual procedure

After the construction of this structure for all indicators, the framework is produced connecting indicators with different lines depending on the number of data shared. The result is demonstrated in Figure C.3.

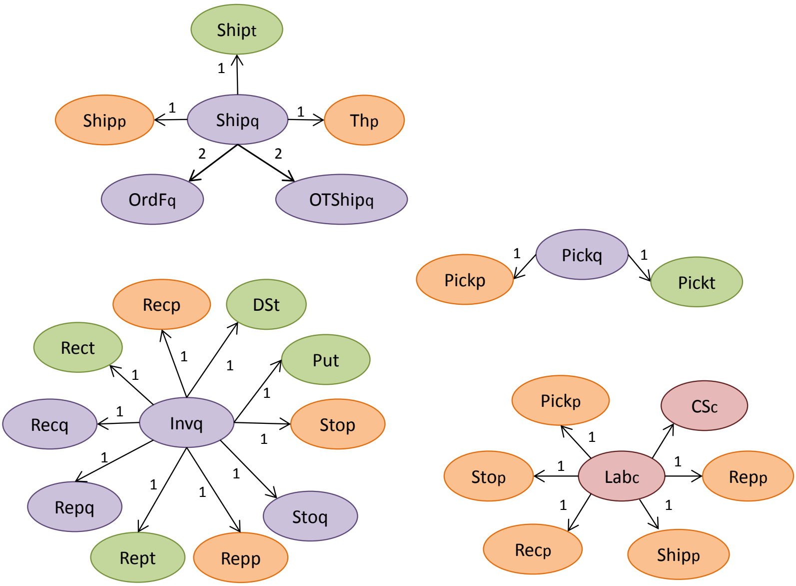


Figure C.2: Manual procedure to construct the indicator's framework.

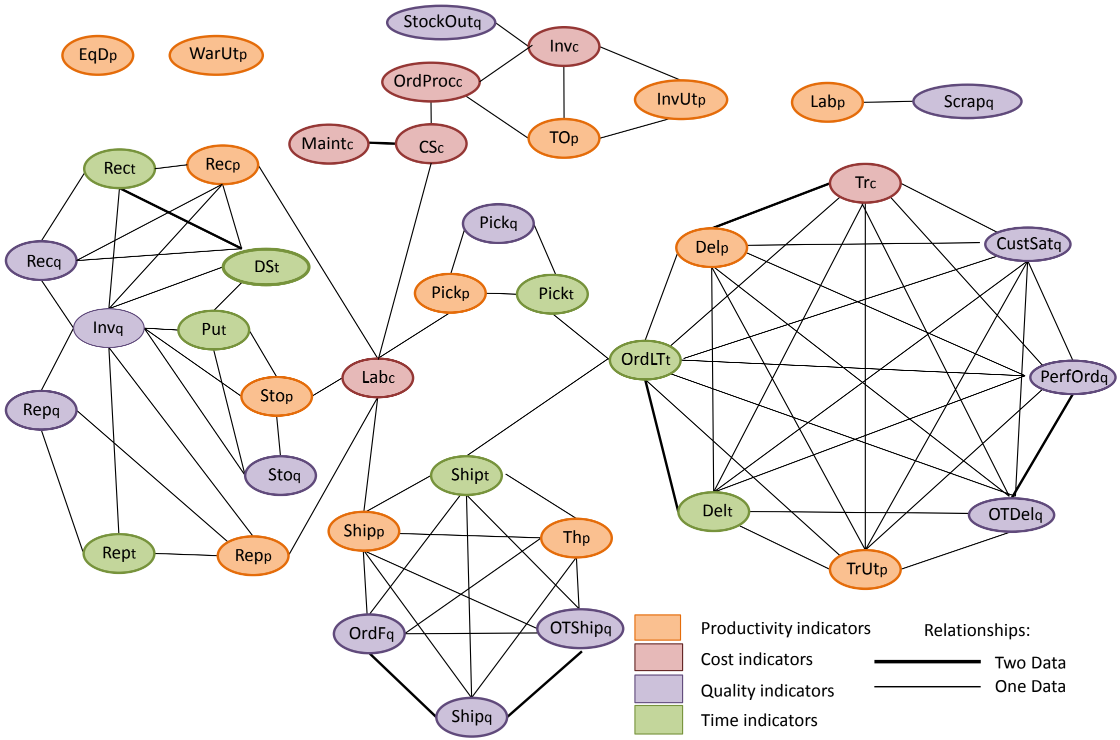


Figure C.3: Direct indicator relations.

Looking at Figure C.3, the first impression could be that the majority of indicators form a big group of relations. But analyzing Figure C.3 in detail, it is possible to observe that the indicators are arranged in clusters. The more visible cluster on the right side of Figure C.3 consists mainly of indicators about delivery process and order quality. The second group of measures are related to shipping activity, and are located in the bottom of the figure. The three indicators of picking activity constitute a little group in the center of the figure. The inbound area, in the left side of the figure, could be viewed as other important relationship group. However, the relations among inbound indicators do not seem to be as strong as for the delivery cluster. The last group of measures is located on the top of the figure, aggregating mainly cost and capacity measures.

It is apparent from Figure C.3 that indicators are rather connected to others by their processes than by their dimensions. In other words, the indicator relationships seems to be established per warehouse process, instead of by the dimensions of quality, cost, time, productivity.

There is two types of lines in Figure C.3: one representing that indicators share one data and the other one representing two data sharing. We could assume that indicators with two shared data have a stronger relationship than the others with just one. However, other informations need to be analyzed to make this kind of conclusion. It is discussed later in Chapter 7 with more information available.

Figure C.3 shows the main relations, but the procedure performed is not exhaustive. The analytical model has shown that data are very connected, with some data making part of more general ones. For example, "WH" is a sum of all "WH Activities"(means the sum of WHRec, WHSto, etc.), as presented in Equation A.22. This situation was not taken into account in this section. Indeed, Figure C.1 presents "WH" and "WH Activities" separately. To take into account all data associations, next section presents the exhaustive procedure using the Jacobian matrix.

Appendix D

List of independent input values

Input	Value	Input	Value
α	0.5	mean_Insp	0.5
β_del	0.9	nbMachine	2.0
β_ord	0.55	nb_travel	3.0
β_pick	0.95	NoComplet Ord Ship	17.0
β_rec	0.85	Ord Del OT	1311.0
β_rep	0.8	Ord Ship OT	1334.0
β_ship	0.95	pal_truck	25.0
β_sto	0.85	pallet_area	1.2
BuildC	1988.0	Prob OrdLi Pick	24.0
cap	5000.0	Prob OrdLi Ship	17.0
Cor OrdLi Pick	1367.0	Prob Del	23.0
Cor OrdLi Ship	1334.0	Prob Rep	4.6
Cor Del	1311.0	Prob Sto	2.0
Cor Rep	617.0	Prob Unlo	9.0
Cor Sto	674.0	Prod Ord	18.4
Cor Unlo	691.0	Prod pal	40.0
Cust Ord	1417.0	Prod noAvail	275.0
Cust Complain	18.0	Prod Cost	99.9
ΔT(Insp)$_2$	1.0	Profit	100.0
deprec$_1$	500.0	Rate	0.1
deprec$_2$	200.0	Remain_Inv	30500.0
empl Admin	3.0	scrap$_1$	23.0
empl Del	2.0	Scrap_Del1	13.0
empl Pick	4.0	scrap$_2$	5.0
empl Rec	1.0	Scrap_Pick1	4.0
empl Rep	1.0	scrap$_3$	4.0
empl Ship	3.0	scrap$_4$	17.0
empl Sto	1.0	Scrap_Ship1	17.0
EqMaintC	4118.0	scrap$_5$	1.0
error data system$_1$	1.0	scrap$_6$	7.0
error data system$_2$	3.0	Truck Maint C	1165.0
error data system$_3$	1.0	War Cap	5000.0
HAdmin$_{del}$	63.0	war used area	3800.0
HAdmin$_{pick}$	21.0	War WH	168.0
HAdmin$_{rec}$	21.0	$\$/h_{admin}$	7.0
HAdmin$_{rep}$	21.0	$\$/h_{del}$	5.0
HAdmin$_{ship}$	21.0	$\$/h_{pick}$	5.0
HAdmin$_{sto}$	21.0	$\$/h_{rec}$	5.0
HEq Stop	14.4	$\$/h_{rep}$	5.0
Inv Cap	1000.0	$\$/h_{ship}$	5.0
kg Prod	10.0	$\$/h_{sto}$	5.0
l_used	2.0	$ oil	2.39

Figure D.1: Independent input values used for Jacobian assessment.

Appendix E

Theoretical Framework of indicator relationships

Here we show the theoretical framework of indicator relationships resulted from Jacobian analysis. To create this schema we perform the same of manual procedure presented in Appendix C.

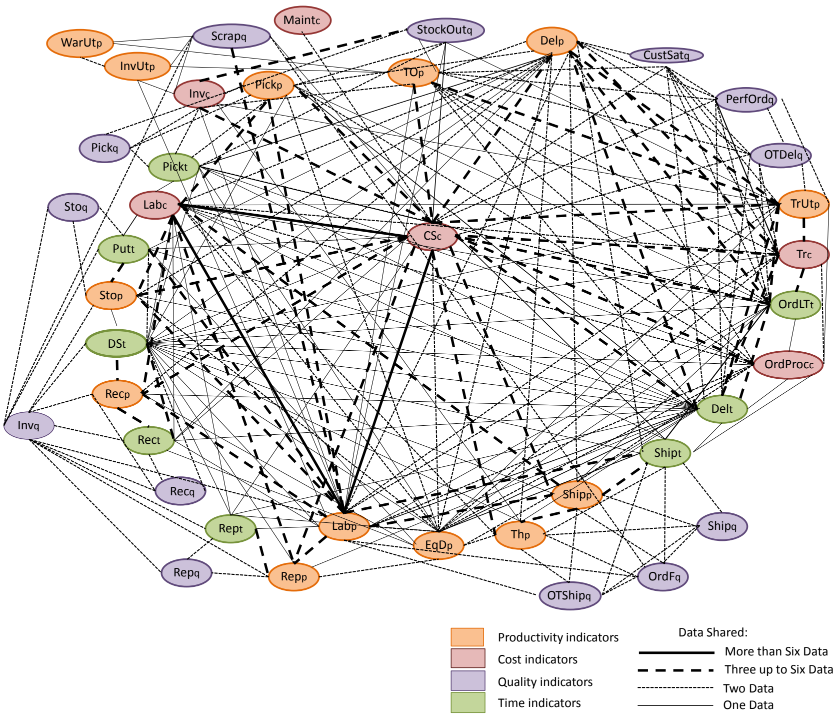


Figure E.1: Indicator relations according to the number of shared data.

Appendix F

Results of Dynamic Factor Analysis application

This appendix reports the initial results obtained with the Dynamic Factor Analysis application. The R code and the procedure to perform DFA in R are from Holmes (2015), available in the website: http://faculty.washington.edu/eeholmes/

The R code is applied for 50 month time series data of the 40 standardized indicators. The main reason to reduce the dataset to 50 month is because a big dataset does not allow the convergence of the model. As presented in Chapter 3, Equation 3.9, the objective is to obtain the Z values, which correspond to the loadings of the PCA method.

Table F.1 demonstrates the DFA results for two different R matrix propositions with the number of trends, m, varying from 1 up to 8. The R matrix measures the covariance matrix of the observation errors. It can be calculated considering four error conditions: diagonal and equal, diagonal and unequal, equal variance covariance and unconstrained. It is shown just two different conditions in Table F.1 because are the best results obtained for our database.

The logLik (loglikelihood) and the AICc (Akaike Information Criterion with a Correction for finite sample sizes) are the measures to evaluate the quality of the results. The lower the logLik and AICc values, better the model. The column K shows the number of parameters in the model and m represents the number of trends used to represent data.

The bold line in Table F.1 shows the best result for these test: a model with just one trend. Table F.2 shows the loading values obtained

R	m	logLik	K	AICc
diagonal and unequal	1	-2383,03	80,00	4932,81
diagonal and unequal	2	-2096,71	119,00	4446,61
diagonal and unequal	3	-2043,87	157,00	4428,67
diagonal and unequal	4	-1684,87	194,00	3799,65
diagonal and unequal	5	-1542,66	230,00	3605,39
diagonal and unequal	6	-1380,38	265,00	3372,07
diagonal and unequal	7	-1261,68	299,00	3226,89
diagonal and unequal	8	-1200,32	332,00	3197,27
unconstrained	**1**	**70,60**	**860,00**	**2878,99**
unconstrained	2	112,88	899,00	3043,34
unconstrained	3	166,17	937,00	3196,85
unconstrained	4	205,20	974,00	3390,58
unconstrained	5	236,82	1010,00	3611,29
unconstrained	6	256,13	1045,00	3869,29
unconstrained	7	277,26	1079,00	4136,78
unconstrained	8	295,63	1112,00	4423,39

Table F.1: DFA results for 40 indicators.

and the highlighted cells have $|\text{values}| \geqslant 0.15$. It is possible to see that many loadings are really low, resulting that these indicators can not be considered in the model. According to Table F.1, only 11 indicators from the initial 40 are included in the aggregated model.

Several other tests have been made but the best results according to the logLik and AICc values are always for m = 1, which exclude a great quantity of indicators from the model. As our objective is to maintain the majority of indicators to evaluate the global performance, we do not use this result in our integrated model.

Indicator	Loading	Indicator	Loading
CSc	-0,190	Pickq	0,012
CustSatq	-0,029	Pickt	-0,022
Delp	0,107	Putt	0,019
Delt	-0,109	Recp	0,151
DSt	-0,014	Recq	0,022
EqDp	-0,029	Rect	-0,031
Invc	-0,049	Repp	0,179
Invq	0,006	Repq	0,077
InvUtp	0,243	Rept	-0,002
Labc	-0,118	Scrapq	-0,123
Labp	0,200	Shipp	0,105
Maintc	0,017	Shipq	0,209
OrdFq	0,188	Shipt	0,004
OrdLTt	-0,087	StockOutq	-0,086
OrdProcc	-0,117	Stop	0,145
OTDelq	0,039	Stoq	0,007
OTShipq	0,145	Thp	0,192
PerfOrdq	0,028	TOp	-0,174
Pickp	0,106	Trc	-0,084
		TrUtp	0,196
		WarUtp	0,163

Table F.2: Loadings for DFA result of m=1 and R= unconstrained.

Appendix G

Results of Anderson Darling Test

The statistic analysis is performed for each indicator using the software Minitab 16®. Each graphic summarizes the Anderson Darling Test, skewness and kurtosis measurement for all 40 performance indicators. Moreover, the mean and standard deviation are demonstrated in each figure for the 100 month time series.

These mean and standard deviation values are used in the optimization model, to calculate the standardized indicator values.

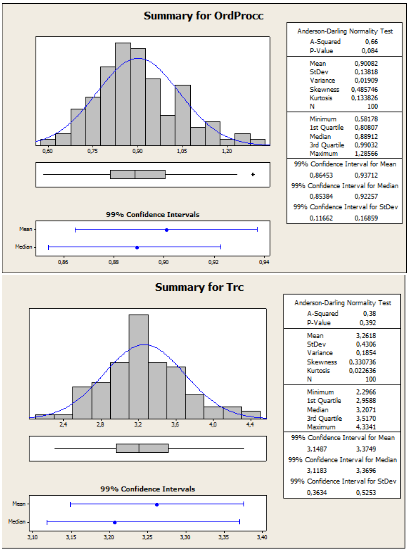


Figure G.1: Cost indicator data test.

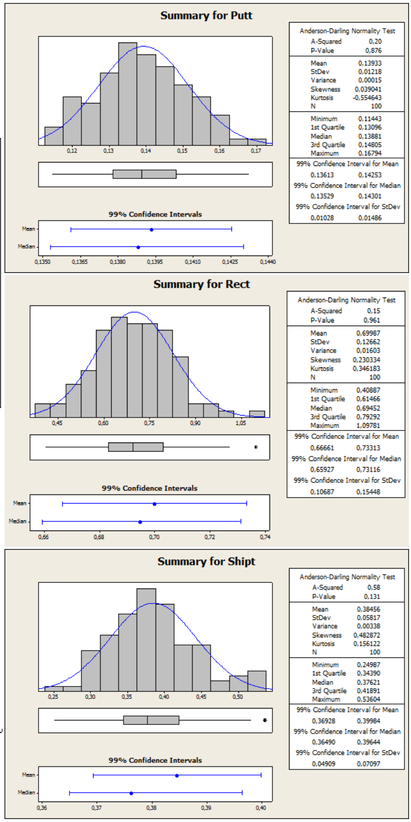


Figure G.2: Time indicator data test.

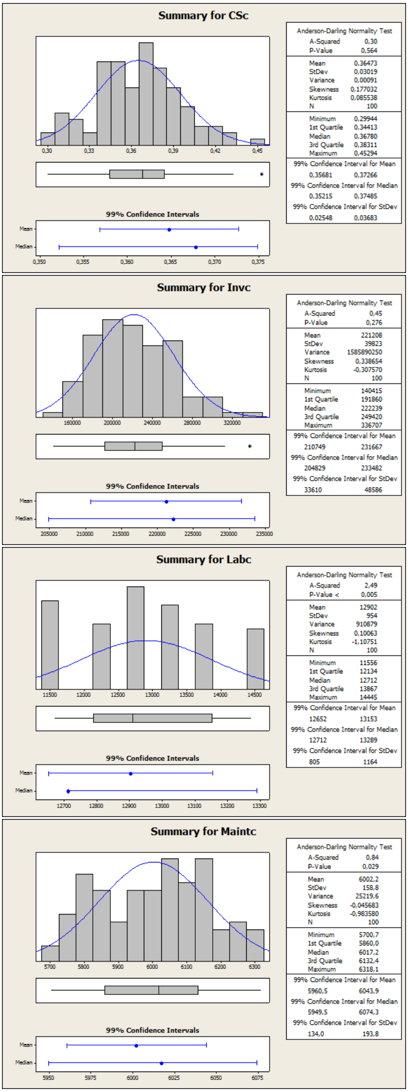


Figure G.3: Cost indicator data test.

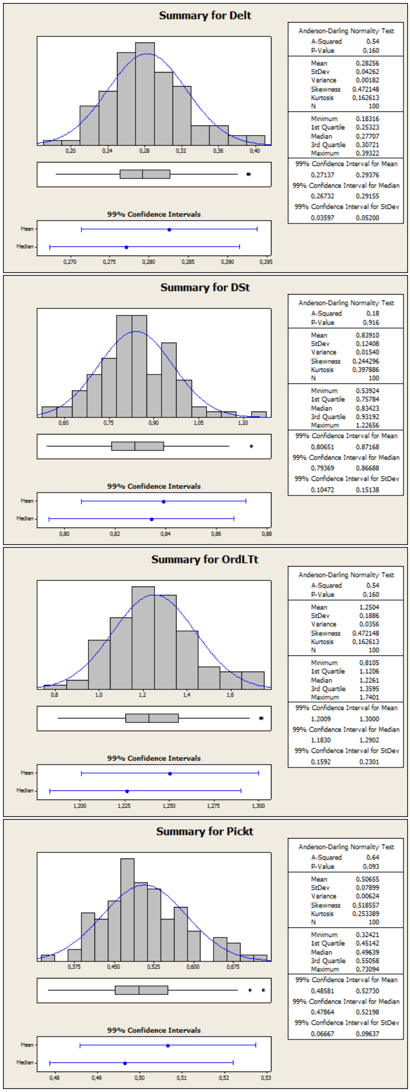


Figure G.4: Time indicator data test.

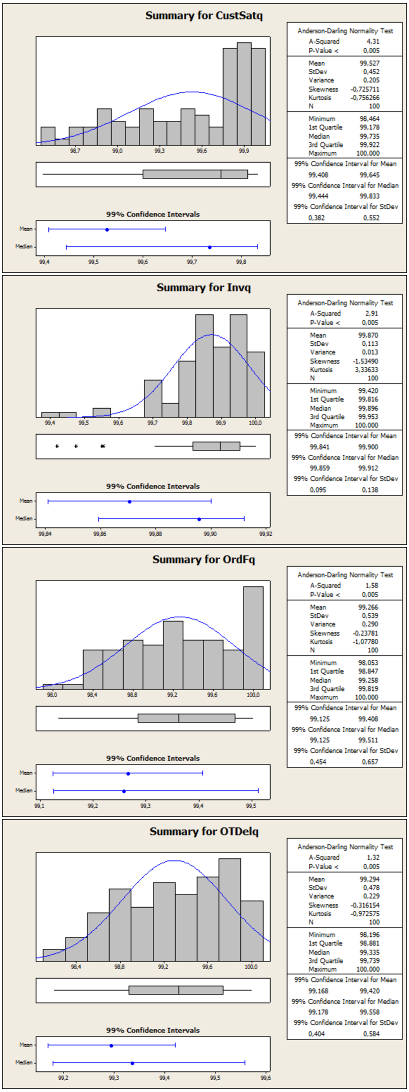


Figure G.5: Quality indicator data test.

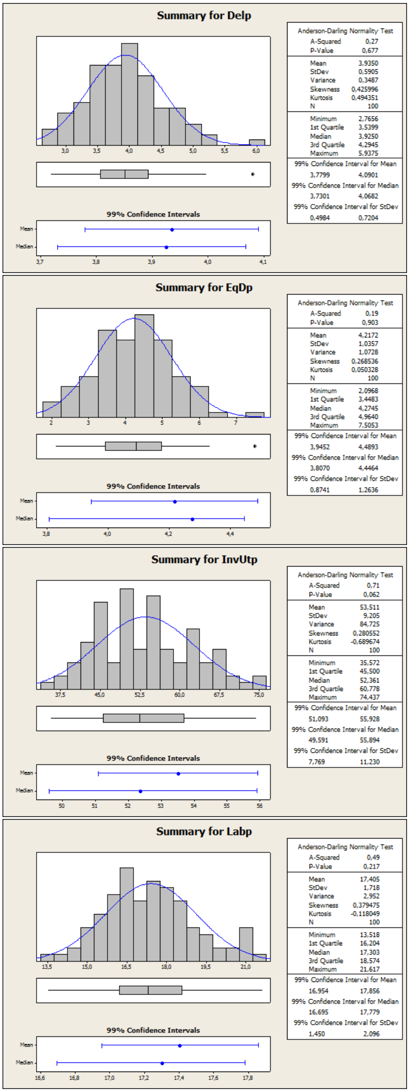


Figure G.6: Productivity indicator data test.

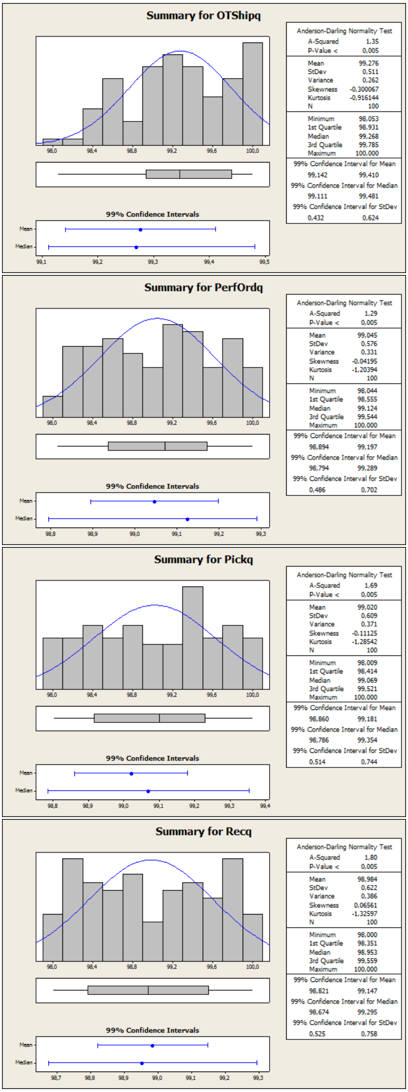


Figure G.7: Quality indicator data test.

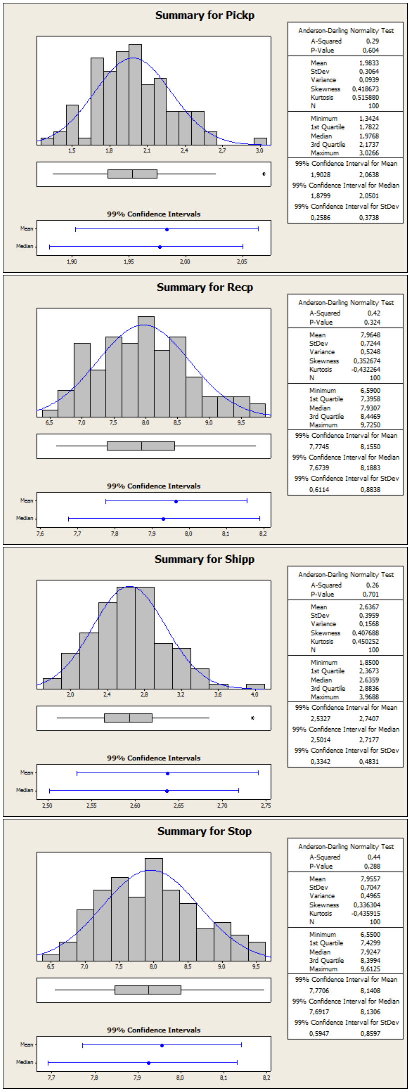


Figure G.8: Productivity indicator data test.

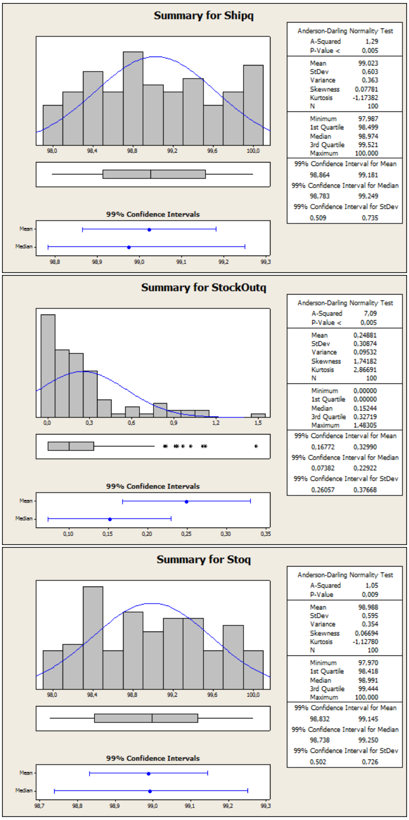


Figure G.9: Quality indicator data test.

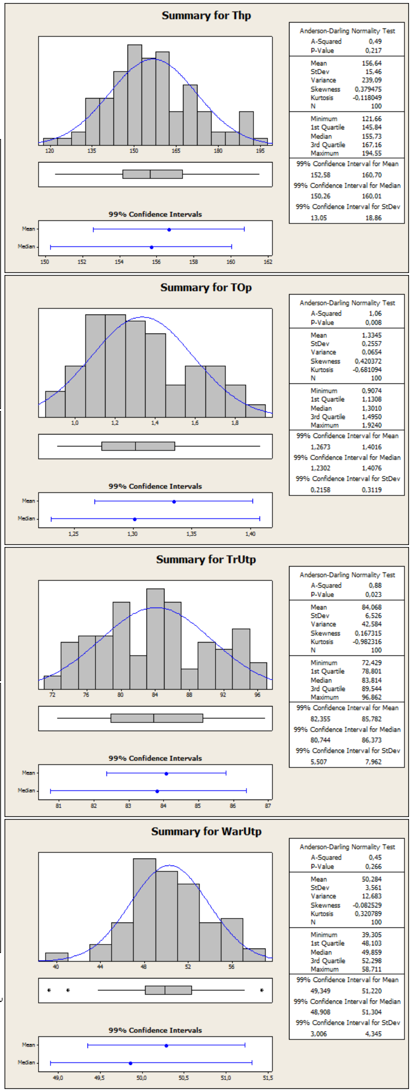


Figure G.10: Productivity indicator data test.

Appendix H

Optimization model

This appendix presents the optimization model coupled with *CADES Component Optimizer®*.

OBJECTIVE FUNCTION

GP = (1/N) * C1 + (1/N) * C2 + (1/N) * C3 + (1/N) * C4 + (1/N) * C5 + (1/N) * C6

COMPONENT EQUATIONS

C1 = -0.22 * CSc_NORM + 0.25 * Delp_NORM - 0.26 * Delt_NORM + 0.24 * Labp_NORM - 0.26 * OrdLTt_NORM - 0.24 * OrdProcc_NORM + 0.25 * Pickp_NORM -0.25 * Pickt_NORM + 0.24 * Repp_NORM -0.25 * Rept_NORM + 0.25 * Shipp_NORM -0.26 * Shipt_NORM + 0.24 * Thp_NORM -0.24 * Trc_NORM

C2 = - 0.24 * Labc_NORM - 0.37 * Putt_NORM + 0.36 * Recp_NORM + 0.37 * Stop_NORM + 0.29 * TrUtp_NORM

C3 = 0.22 * CustSatq_NORM - 0.43 * Invc_NORM -0.44 * InvUtp_NORM + 0.41 * TOp_NORM - 0.33 * WarUtp_NORM

C4 = 0.51 * OrdFq_NORM + 0.53 * OTShipq_NORM - 0.24 * Scrapq_NORM + 0.5 * Shipq_NORM

C5 = 0.4 * CustSatq_NORM + 0.46 * OTDelq_NORM + 0.51 *

PerfOrdq_NORM - 0.34 * Scrapq_NORM

C6 = -0.61 * DSt_NORM + 0.31 * Invq_NORM - 0.59 * Rect_NORM

STANDARDIZED INDICATOR EQUATIONS

intern Rect_NORM = (Rect - Mean_Rect)/STD_Rect
intern Putt_NORM = (Putt - Mean_Putt)/STD_Putt
intern DSt_NORM = (DSt - Mean_DSt)/STD_DSt
intern Rept_NORM = (Rept - Mean_Rept)/STD_Rept
intern Pickt_NORM = (Pickt - Mean_Pickt)/STD_Pickt
intern Shipt_NORM = (Shipt - Mean_Shipt)/STD_Shipt
intern Delt_NORM = (Delt - Mean_Delt)/STD_Delt
intern OrdLTt_NORM = (OrdLTt - Mean_OrdLTt)/STD_OrdLTt

intern Labp_NORM = (Labp - Mean_Labp)/STD_Labp
intern Recp_NORM = (Recp - Mean_Recp)/STD_Recp
intern Stop_NORM = (Stop - Mean_Stop)/STD_Stop
intern Repp_NORM = (Repp - Mean_Repp)/STD_Repp
intern Pickp_NORM = (Pickp - Mean_Pickp)/STD_Pickp
intern Shipp_NORM = (Shipp - Mean_Shipp)/STD_Shipp
intern Delp_NORM = (Delp - Mean_Delp)/STD_Delp
intern InvUtp_NORM = (InvUtp - Mean_InvUtp)/STD_InvUtp
intern WarUtp_NORM = (WarUtp - Mean_WarUtp)/STD_WarUtp
intern Thp_NORM = (Thp - Mean_Thp)/STD_Thp
intern TOp_NORM = (TOp - Mean_TOp)/STD_TOp
intern TrUtp_NORM = (TrUtp - Mean_TrUtp)/STD_TrUtp

intern Invc_NORM = (Invc - Mean_Invc)/STD_Invc
intern Trc_NORM = (Trc - Mean_Trc)/STD_Trc
intern OrdProcc_NORM = (OrdProcc - Mean_OrdProcc)/STD_OrdProcc
intern Labc_NORM = (Labc - Mean_Labc)/STD_Labc
intern CSc_NORM = (CSc - Mean_CSc)/STD_CSc

intern Invq_NORM = (Invq - Mean_Invq)/STD_Invq
intern Shipq_NORM = (Shipq - Mean_Shipq)/STD_Shipq
intern OTShipq_NORM = (OTShipq - Mean_OTShipq)/STD_OTShipq
intern OrdFq_NORM = (OrdFq - Mean_OrdFq)/STD_OrdFq
intern OTDelq_NORM = (OTDelq - Mean_OTDelq)/STD_OTDelq
intern PerfOrdq_NORM = (PerfOrdq - Mean_PerfOrdq)/STD_PerfOrdq
intern CustSatq_NORM = (CustSatq - Mean_CustSatq)/STD_CustSatq

intern Scrapq_NORM = (ScrapRate - Mean_ScrapRate)/STD_ScrapRate

EQUATIONS RELATING DATA

1. EQUATIONS ALREADY USED IN THE FIRST ANALYTICAL MODEL

intern WEfDel = beta_del * WHDel
intern WEfShip = beta_ship * WHShip
intern WEfPick = beta_pick * WHPick
intern WEfRep = beta_rep * WHRep
intern WEfSto = beta_sto * WHSto
intern WEfRec = beta_rec * WHRec
intern HAdmin_ord = beta_ord * WHAdmin
DeltaT_Insp = mean_Insp * nb_trucks
nb_trucks = Total_unlo / pal_truck
intern avepallet = aveinv / Prod_pal
intern Good_sold = (Total_del) * Prod_Ord
intern Kg_Tr = (Total_del) * Prod_Ord * kg_Prod
Product_Ship = (Cor_OrdLiShip + Prob_OrdLiShip)* Prod_Ord
WarCapUsed = (avepallet * pallet_area) + CapUsedAreas
aveinv = ((Total_sto * Prod_pal) + Remain_Inv) /2
Remain_Inv = Total_sto * Prod_pal - Total_pick * Prod_Ord
intern Sales = (ProductCost + Profit) * Good_sold
PalProcInv = Total_unlo + Total_sto + Total_rep
ErrorDataSystem = ErrorDataSystem1 + ErrorDataSystem2 + ErrorDataSystem3

2. EQUATIONS INCLUDED FOR OPTIMIZATION

Pal_Unlo = CorUnlo + ProbUnlo
ProbUnlo = Scrap_Unlo + ErrorDataSystem1 + Other_Prob_unlo
Pal_Sto = CorSto + ProbSto
ProbSto = Scrap_Sto + ErrorDataSystem2 + Other_Prob_sto
Pal_moved = CorRep + ProbRep
ProbRep = Scrap_Rep + ErrorDataSystem3 + Other_Prob_rep
Ord_LiPick = Cor_OrdLiPick + Prob_OrdLiPick
Prob_OrdLiPick = Scrap_Pick + ItemnoAvail_ord + Other_Prob_pick
ItemnoAvail = ItemnoAvail_ord * Prod_Ord
Ord_Ship = Cor_OrdLiShip + Prob_OrdLiShip
Prob_OrdLiShip = Scrap_Ship + No_OT_ship + NoComplet_OrdShip

+ Other_Prob_ship
Ord_Ship_OT = Ord_Ship - No_OT_ship
OTDel_ord = Ord_Del - No_OT_del
Ord_Del = CorDel + ProbDel
ProbDel = Scrap_Del + No_OT_del + Other_Prob_del
Ord_OT_ND_CD = CorDel
CustComplain = Ord_Del - NoComplain_ord

CONSTRAINTS

Ctrl_0_WHAdmin_and_SumAdmins = WHAdmin - WEfAdmin

Ctrl_1_TotalUnlo_and_TotalSto = Pal_Unlo - Pal_Sto

Ctrl_2_TotalOrder_and_TotalRep = ((Cust_Ord * Prod_Ord)/ Prod_pal) - Pal_moved

Ctrl_2A_TotalOrder_and_TotalRep = (Pal_Sto + (Remain_Inv/ Prod_pal)) - Pal_moved

Ctrl_3_Cust_Ord_and_Total_pick = Cust_Ord - (Ord_LiPick/ Line_Ord)

Ctrl_4_TotalShip_and_TotalPick = (Ord_LiPick/ Line_Ord) - Ord_Ship

Ctrl_4A_Product_Out_and_Prod_Ship = (Ord_LiPick * Prod_Ord) - Product_Ship

Ctrl_5_TotalDel_and_TotalShip = Ord_Ship - Ord_Del

Ctrl_6_OT_ND_DC_and_OTDel_ord = OTDel_ord - Ord_OT_ND_CD

TIME INDICATORS

Rect = (WEfRec + HAdmin_rec + DeltaT_QueueRec + DeltaT_Insp + DeltaT_Others1) / (CorUnlo + ProbUnlo)

Putt = (WEfSto + HAdmin_sto + DeltaT_QueueSto + DeltaT_Others2) / (CorSto + ProbSto)

DSt = (WEfRec + WEfSto + HAdmin_rec + HAdmin_sto + DeltaT_QueueRec + DeltaT_QueueSto + DeltaT_Insp + DeltaT_Others1 + DeltaT_Others2) / (CorUnlo + ProbUnlo)

Rept = (WEfRep + HAdmin_rep + DeltaT_QueueRep + DeltaT_Others3) / (CorRep + ProbRep)

Pickt = (WEfPick + HAdmin_pick + DeltaT_QueuePick + DeltaT_Others4) / (Cor_OrdLiPick + Prob_OrdLiPick)

Shipt = (WEfShip + HAdmin_ship + DeltaT_QueueShip + DeltaT_Insp2 + DeltaT_Others5) / (Cor_OrdLiShip + Prob_OrdLiShip)

Delt = (WEfDel + HAdmin_del + DeltaT_QueueDel + DeltaT_Others6) / (CorDel + ProbDel)

OrdLTt = (WEfPick + HAdmin_pick + DeltaT_QueuePick + DeltaT_Others4 + WEfShip + HAdmin_ship + DeltaT_QueueShip + DeltaT_Insp2 + DeltaT_Others5 + WEfDel + HAdmin_del + DeltaT_QueueDel + DeltaT_Others6 + HAdmin_ord) / (CorDel + ProbDel)

PRODUCTIVITY INDICATORS

Labp = Product_Ship / WH

Recp = (CorUnlo + ProbUnlo) / WHRec

Stop = (CorSto + ProbSto) / WHSto

Repp = (CorRep + ProbRep) / WHRep

Pickp = (Cor_OrdLiPick + Prob_OrdLiPick) / WHPick

Shipp = (Cor_OrdLiShip + Prob_OrdLiShip) / WHShip

Delp = (CorDel + ProbDel) / WHDel

InvUtp = (avepallet / palSpace)*100

TOp = Good_sold / aveinv

TrUtp = (Kg_Tr / (capTruck * nbTravel))*100

Thp = Product_Ship / WarWH

WarUtp = (WarCapUsed / WarCap)*100

COST INDICATORS

Invc = (aveinv * ProductCost * rate) + (ItemnoAvail * Profit)

Trc = (TruckMaint + (value_oil * liter_used_travel * nbTravel) + (value_h_del * WHDel) + alpha * (value_h_del * WHDel) + Deprec1 + Other1)/ (CorDel + ProbDel)

OrdProcc = ((beta_ord * WHAdmin * value_h_admin)+ alpha * (beta_ord * WHAdmin * value_h_admin) + Deprec2 + Other2)/ Cust_Ord

Labc = WHRec * value_h_rec + WHSto * value_h_sto + WHRep * value_h_rep + WHPick * value_h_pick + WHShip * value_h_ship + ((1-beta_ord)* WHAdmin * value_h_admin) + WHOthers * value_h_others + alpha * (WHRec * value_h_rec + WHSto * value_h_sto + WHRep * value_h_rep + WHPick * value_h_pick + WHShip * value_h_ship + ((1-beta_ord)* WHAdmin * value_h_admin) + WHOthers * value_h_others)

CSc = (((OrdProcc * Cust_Ord) + Labc + Maintc)/ Sales) *100

QUALITY INDICATORS

Invq = ((PalProcInv - ErrorDataSystem)/ PalProcInv)*100

Shipq = ((Cor_OrdLiShip) / (Cor_OrdLiShip + Prob_OrdLiShip))*100

OTShipq = (OTShip_ord / (Cor_OrdLiShip + Prob_OrdLiShip))*100

OrdFq = (((Cor_OrdLiShip + Prob_OrdLiShip) - NoComplet_OrdShip) /(Cor_OrdLiShip + Prob_OrdLiShip))*100

OTDelq = (OTDel_ord / (CorDel + ProbDel))*100

PerfOrdq = (OT_ND_DC_ord / (CorDel + ProbDel))*100

CustSatq = (((CorDel + ProbDel) - CustComplain) / (CorDel + ProbDel))*100

ScrapRate = ((((Scrap_Unlo + Scrap_Sto + Scrap_Rep) * Prod_pal) + ((Scrap_Pick + Scrap_Ship + Scrap_Del) * Prod_Ord))/ Product_Ship)*100

Appendix I

Mean and standard deviation values of indicators

A complete list of mean and standard deviation values for all indicators are described in this appendix, Table I.1. The input dataset to obtain this list are the 100 month time series of each indicator. These values are included as fixed variables in the optimization model.

Indicator	Mean	Standard deviation
CSc	0,36	0,02
CustSatq	99,53	0,39
Delp	3,93	0,46
Delt	0,28	0,03
DSt	0,84	0,10
Invc	221207,91	32507,65
Invq	99,87	0,08
InvUtp	53,51	7,66
Labc	12902,27	810,65
Labp	17,40	1,35
OrdFq	99,27	0,46
OrdLTt	1,25	0,15
OrdProcc	0,90	0,11
OTDelq	99,29	0,41
OTShipq	99,28	0,43
PerfOrdq	99,05	0,50
Pickp	1,98	0,24
Pickt	0,51	0,06
Putt	0,14	0,01
Recp	7,96	0,59
Rect	0,70	0,10
Repp	3,96	0,32
Rept	0,24	0,02
Scrapq	4,27	1,05
Shipp	2,64	0,31
Shipq	99,02	0,52
Shipt	0,38	0,05
Stop	7,96	0,57
Thp	156,64	12,19
TOp	1,33	0,21
Trc	3,26	0,34
TrUtp	84,07	5,43
WarUtp	50,28	2,81

Table I.1: The variable's mean and standard deviation.

Appendix J

Optimization results

The results of the optimization for the inputs and intermediate outputs are presented, respectively, in Table J.1 and Figure J.2.

Table J.1: Input results after maximization and minimization.

INPUT RESULTS

Time data [unit]	Limits in Hours	
	Maximization	Minimization
β_del	0,34	1,00
β_ord	0,30	0,30
β_pick	0,48	1,00
β_rec	0,53	1,00
β_rep	0,41	1,00
β_ship	0,48	1,00
β_sto	0,44	1,00
$Hadmin_{del}$ [hour]	4,9	1,0
$HAdmin_{pick}$ [hour]	1,0	1,0
$HAdmin_{rec}$ [hour]	1,0	1,0
$HAdmin_{rep}$ [hour]	1,0	1,0
$HAdmin_{ship}$ [hour]	1,0	1,0
$HAdmin_{sto}$ [hour]	2,6	141,9

Replenishment data [unit]	Limits	
	Maximization	Minimization
Cor Rep [pallet]	996	460
error data system 3 [pallet]	0	0
$scrap_3$ [pallet]	0	40
Other_Prob_rep [pallet]	4	0

Cost data	Limits in $	
	Maximization	Minimization
Maintc	R$ 1 000,0	R$ 1 000,0
Truck Maint C	R$ 50,0	R$ 200 000,0

Picking, Shipping and Delivery data [unit]	Limits	
	Maximization	Minimization
Prod noAvail [orders]	3000	0
No_OT_del [orders]	0	700
No_OT_ship [orders]	0	700
No Cust Complain [orders]	3000	0
NoComplet Ord Ship [orders]	0	0
Other_Prob_pick [orders]	2	0
Other_Prob_del [orders]	0	0
Other_Prob_ship [orders]	0	0
Cor OrdLi Pick [orders]	3000	660
Cor OrdLi Ship [orders]	3000	0
Cor Del [orders]	3000	0
$scrap_4$ [orders]	0	40
$scrap_5$ [orders]	0	0
$scrap_6$ [orders]	0	0

Unloading and Storing data [unit]	Limits	
	Maximization	Minimization
Cor Sto [pallet]	1000	340
Cor Unlo [pallet]	1000	340
$scrap_1$ [pallet]	0	15
$scrap_2$ [pallet]	0	18
Other_Prob_sto [pallet]	1,14	0
Other_Prob_unlo [pallet]	0,5	0
error data system 1 [pallet]	0	4,5
error data system 2 [pallet]	0	2

Other data [unit]	Limits	
	Maximization	Minimization
War WH [hour]	210	80
Prod Ord [product]	13,3	12,6
war used area [m2]	1000	4000
nb_Travel [travels]	80	300
mean_Insp [h]	0,27	0,5
Cust Ord [orders]	3000	1593

Table J.2: Intermediate output results after maximization and minimization.

INTERMEDIATE OUTPUT RESULTS

Constraints [unit]	Results	
	Maximization	Minimization
CTRL_0 [hour]	45	0,10
CTRL_1 [pallet]	0	0
CTRL_2 [pallet]	0	0
CTRL_2A [pallet]	0	0
CTRL_3 [order]	0	893
CTRL_4 [order]	0	0
CTRL_4A [product]	0	0
CTRL_5 [order]	0	0
CTRL_6 [order]	0	0

Component Equation	Results	
	Maximization	Minimization
C1	49,40	-184,56
C2	24,42	-29,05
C3	3,42	-50,04
C4	3,49	-193,39
C5	3,52	-282,76
C6	7,59	0,04

Data [unit]	Results	
	Maximization	Minimization
aveinv [product]	20000	10000
Prob Data [pallet]	0	6,24
Cust Complain [orders]	0	700
ΔT(Insp) [hour]	10,9	7,7
nb_trucks [trucks]	40	14,39
Prod noAvail [products]	0	0
Ord Del OT [orders]	3000	0
Ord OT, ND, CD [orders]	3000	0
Ord Ship OT [orders]	3000	0
PalProcInv [pallets]	3000	1219
Prob OrdLi Pick [orders]	2,3	40
Prob OrdLi Ship [orders]	0	700
Prob Del [orders]	0	700
Prod Proc [products]	40000	8790
Prob Rep [pallet]	4,3	40
Prob Sto [pallet]	1,2	20
Prob Unlo [pallet]	0,5	20
Remain_Inv [products]	0	5605
WarCapUsed	1600	4300
Pal Sto [pallet]	1000	360
Pal Unlo [pallet]	1000	360
Pal Moved [pallet]	1000	500
OrdLi Pick [orders]	3000	700
Ord Ship [orders]	3000	700
Ord Del [orders]	3000	700