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STATISTICAL SIMULATION MODELLING OF A WAREHOUSE PRODUCT RECEIVING PROCESS - A SCENARIO BASED ASSESSMENT

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Final thesis submitted as a requirement to obtain a Bachelor Degree in the Graduate Course of Transport and Logistics Engineering of the Joinville Technological Centre of the Federal University of Santa Catarina.

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This thesis paper has been judged and approved as a partial requirement for obtaining the Bachelor Degree of Transport and Logistics Engineering degree at the Federal University of Santa Catarina, Technological Centre of Joinville.

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Dedico este trabalho ao meu pai,
que partiu cedo sem o churrasco de despedida.

"Oh, you're the best
You're better than all the rest
Better than anyone
Anyone I've ever met"

Tina Turner

ABSTRACT

The receiving process in a warehouse serves as the initial step in fulfilling customer orders, and any delay or lack of information has the potential to undermine the overall company performance. This study examines a warehouse which reveals inefficiencies in the receiving process, mainly a delay in the adequacy of the products that are received. These issues are aggravated by a constant demand for consumption of the received items, leading to a decline in service level, and as a result, an increase in the total logistic cost. The main objective is to assess the performance of the receiving process via simulation modelling and queuing theory, using scenarios to propose possible implementations to reduce the overall receive time. The receiving process is mapped via interviews with the operators, on-site observations and collecting data through the WMS data base covering the each step of the process, from the arrival of the truck carrying the goods, the adequacy of each product and its final disposal inside the warehouse. Queuing theory enables the performance evaluation of each of the three steps of the receiving system, measuring its workload, utilisation and service rate. Additionally, queuing theory allows for the measurement of cost models for service level, representing the trade off between the cost of operating the receiving process and the waiting time for the products. As the receiving process itself and the queuing theory analysis are complex, the system is modelled as a DT, a simulation model that represents a real system, in a Discrete Event Simulation software called Plant Simulation, converting the concepts and mathematical relationships in a computer executable code to generate the output data. A methodology using statistical tools to calibrate the model is conducted, utilising probability distributions and fitting tests to calibrate the modelled simulation to the gathered and treated data from the WMS. The proposed scenarios include an RFID implementation, the addition of another operator in the receiving process, and a combination of these two. The results indicate that the process still generates infinite queues, even the combined scenario is insufficient to resolve the adequacy bottleneck, with a utilisation rate of 100.99%. Nevertheless, there is a mean 31.34% gain in efficiency compared to the base model scenario, and a significant mean 61.71% reduction in the Estimated Total Cost for the product arrival process in the RFID implementation scenario.

Keywords: Receiving. Queuing Theory. Simulation. RFID.

RESUMO

O processo de recebimento em um armazém é o primeiro passo para atender uma ordem de compra de um cliente, qualquer atraso ou falta de informação tem o potencial de detrimir o desempenho geral da empresa. Este estudo examina um armazém que revela ineficiências no processo de recebimento, principalmente um atraso na adequação dos produtos que são recebidos. Esses problemas são agravados por uma demanda constante pelo consumo dos itens recebidos, levando a uma queda no nível de serviço e, como resultado, um aumento no custo logístico total. O principal objetivo é avaliar o desempenho do processo de recebimento por meio de um modelo de simulação e teoria das filas, usando cenários para propor possíveis implementações para reduzir o tempo total de recebimento. O processo de recebimento é mapeado por meio de entrevistas com os operadores, observações no local e coleta de dados por meio do banco de dados do WMS, cobrindo cada etapa do processo, desde a chegada do caminhão transportando as mercadorias, a adequação de cada produto até sua disposição final dentro do armazém. Teoria de filas permite a avaliação de desempenho de cada uma das três etapas do sistema de recebimento, medindo sua carga de trabalho, utilização e taxa de serviço. Além disso, a teoria de filas permite a medição de modelos de custo para o nível de serviço, representando o equilíbrio entre o custo de operar o processo de recebimento e o tempo de espera pelos produtos. Como o próprio processo de recebimento e a análise da teoria das filas são complexos, o sistema é modelado como um DT em um software de DES chamado Plant Simulation, convertendo os conceitos e relações matemáticas em um código executável para gerar os dados de saída. Uma metodologia usando ferramentas estatísticas para calibrar o modelo é conduzida, utilizando distribuições de probabilidade e testes de aderência para calibrar a simulação modelada aos dados coletados e tratados do WMS. Os cenários propostos incluem uma implementação de RFID, a adição de outro operador no processo de recebimento e uma combinação destes ambos. Os resultados indicam que o processo ainda gera filas infinitas, o cenário combinado ainda é insuficiente para resolver o gargalo de adequação, com uma taxa de utilização de 100,99%. No entanto, há um ganho de eficiência de 31,34% em comparação com o cenário do modelo base e uma redução significativa de 61,71% no Custo Total Estimado para o processo de chegada no cenário de implementação de RFID.

Palavras-chave: Recebimento. Teoria de Filas. Simulação. RFID.

FIGURE LIST

FRAME LIST

TABLE LIST

SYMBOL AND ACRONYMS LIST

λ	Arrival Rate
μ	Service Rate
ρ	Utilisation rate
p	Stability Condition
Ω	Workload
A	Arrival Probability Distribution
B	Service Probability Distribution
m	Number of Service Stations
C	Queue Discipline
K	Maximum Number of Clients in a System
N	Total Population Size
C_1	Marginal Cost per Server
C_2	Waiting Time Cost per Awaiting Client
$\mu*$	Optimum Service Rate
χ^2	Person's Chi Square Test
DES	Discrete Event Simulation
DT	Digital Twin
EOC	Expected Cost of Operation
EWC	Expected Queuing Cost
ETC	Expected Total Cost
KS	Kolmogorov-Smirnov
AD	Anderson-Darling
DMAIC	Define, Measure, Analyse, Improve and Control

WMS	Warehouse Management System
RFID	Radio Frequncy Identification
K-W	Kruskal–Wallis
ITS	Intelligent Transportation Systems
EDI	Electronic Data Interchange
ANVISA	Agência Nacional de Vigilância Sanitária
AEO	Authorised Economic Operator

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1 INTRODUCTION

Supply chains are very important to service providers, not only for providing goods for the general population, but also for compiling valuable data on demand and consumption (YADAV, 2015; GATTUSO; CASSONE; PELLICANÒ, 2014). Also, supply chain success relies on effective coordination and integration of all involved entities, as an example, vendors, distributors, inbound and outbound transportation, third-party logistics companies, and information system providers (LENIN, 2014).

The receiving goods process is the first step for warehousing storage, starting on the arrival of goods until the release for internal consumption, and so, the flow of information and goods must be reliable and an effective coordination is indispensable for satisfactory results. Lack of standardization, staff shortage and mistakes, like missing information, may cause delays in every step of the process, forcing operators responsible for goods conference to review the information on several packages out of specification (BALLOU, 2006; MAGUIRE et al., 2010; SMITH; SRINIVAS, 2019).

Warehouses represent 15% to 20% of overall logistic costs for the company (GATTUSO; CASSONE; PELLICANÒ, 2014), and a high service level will result in a high logistic cost (BALLOU, 2006) and it has a direct relationship with the product waiting time. A conflict between the cost of operating the service facility and the cost of awaiting products is evident as an increase of one will automatically cause the reduction of the other (TAHA, 2008; SHARMA, 2016).

In this sense, the analysis of the receiving process in a warehouse and the implementation of better processes improves service level and overall logistics costs, reducing the waiting time for the products final disposal for consumption. Understanding the material handling dynamics involving the material arrival, adequacy and final storage is necessary, as the complexity of the dynamic flow of the process involves several entities and each step of the process has different impacts to the waiting time.

This case study examines the warehouse storage system of a company experiencing delays in its receiving process, leading to logistical costs primarily associated with the total waiting time from product arrival to disposal. The current process involves manual and labour-intensive checklists and data logging due to the complexity of the received products and procedures. While the implementation of automated data interchange methods such as Radio Frequency Identification (RFID) and Electronic Data Interchange (EDI) is considered as potential solutions, a comprehensive analysis of the impact of these technologies has not been conducted thus far.

Since the analysis of such complex system is intractable due to the intricate and large mathematical relationships with the physical structure (PETREAN, 1998;

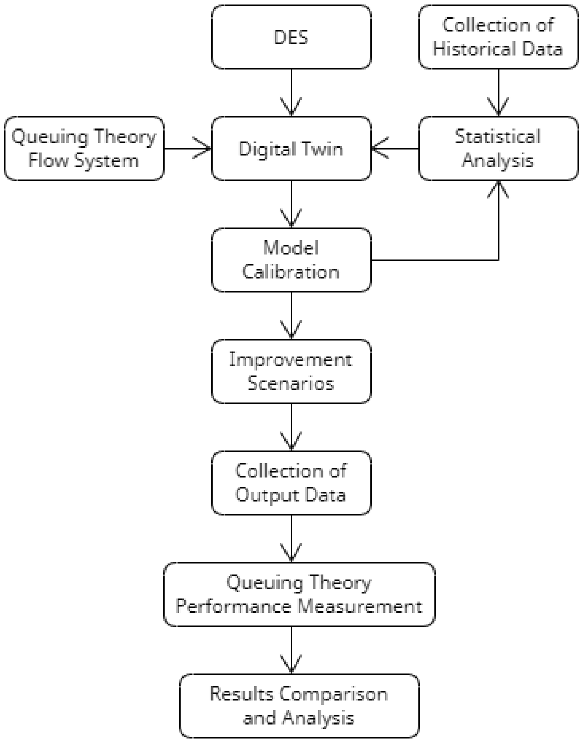
FISHMAN, 2001; FAWSETT; WALLER; FAWSETT, 2010) and receiving process operators, a Digital Twin (DT) of the warehouse is modelled, allowing for a computer executable code to simulate an over time representation of the receiving process (FISHMAN, 2001; LAW, 2016). DT are integrated simulations of complex physical models, generated using gathered data regarding the structure and processes inside a system (AGALIANOS et al., 2020).

The statistical analysis for the calibration of the DT base model is conducted gathering and fitting the frequencies of events to theoretical statistical probability distributions in a systematic methodology, using the available statistical tools of the chosen simulation software. As a performance measure of the inbound process a field of Stochastic Processes called Queuing Theory will be used, it studies the behaviour of queues with one or more service stations (KLEINROCK, 1975). Queuing theory also allows for the analysis of awaiting time costs and queue length.

The performance measurements are developed using Queuing Theory in a Discrete Event Simulation (DES) in a software that simulates the interactions between the supply chain agents, transporters trucks arriving with goods, forklifts unloading pallets and operators responsible for the arrival processes are examples of these agents. The chosen software is Plant Simulation, developed by Siemens Product Lifecycle Management Software Inc. Siemens PLM (2023), allowing for the simulation modelling, data and statistical analysis.

The structure of this study is demonstrated by Figure 1.

Figure 1 – Study Structure Flowchart



Source: Author (2023).

1.1 OBJECTIVES

To simulate and suggest improvements to a warehouse receiving process are proposed:

1.1.1 General Objective

Assess the receiving process performance of a warehouse using queuing theory and DES, proposing scenarios for improving system efficiency and reducing costs.

1.1.2 Specific Objectives

- Model and calibrate a DT of the warehouse receiving process, using statistical tools and gathered data;
- Design scenarios to improve the overall receiving performance, based on similar warehouse simulation studies;
- Measure and compare the efficiency and the logistical cost of each process step;
- Propose an implementation that can improve the receiving process performance.

2 THEORETICAL FRAMEWORK

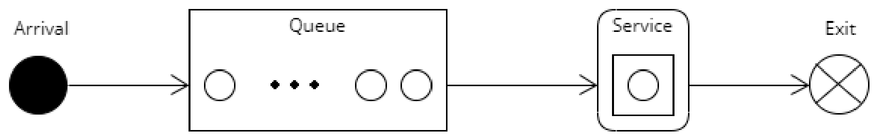
In this chapter a theoretical framework is built that describes topics in queuing theory and simulation concepts.

2.1 QUEUING THEORY

For improvements and performance measurement of the receiving process a field of Stochastic Processes, the description of how a system behaves in a determined time period, called Queuing Theory is used, where statistical functions and dynamic processes are used to quantify the phenomenon of average queue length, awaiting times and utilisation (TAHA, 2008; HILLIER; LIEBERMAN, 2010). These processes can be built and analysed using different scenarios in a simulation model, and then compared, to arrive at a solution.

Queuing Theory represents one of several other dynamic systems fields, called *flow systems*, as described by KLEINROCK (1975), a flow system is where a object flows, moves, or is transferred in one or more channels of finite capacity in order to go from a point to another, like vehicles in a traffic network, the transfer of goods in a rail terminal or the flow of water in a dam. The Figure 2 illustrates in a dynamic system the flow of clients, represented by hollow circles, being pilled in a queue and then serviced.

Figure 2 – Flow System in with one Channel, one Queue and Infinite Population



Source: Adapted from TAHA (2008), HILLIER and LIEBERMAN (2010).

Client arrival flow can be defined by various statistical distribution functions (FILHO, 2008; ARENALES, 2015), Equation 1 describes the arrival rate per unit of time of a client and, as described by Equation 2, the probability distribution between arrivals describes the statistical function dependant of the arrival rate given in Equation 1. Arrivals of more than one client are not possible, if so desired, it must be considered that the arrival is determined by batches, like the arrival of a couple in a restaurant (ARENALES, 2015).

$$\lambda = \frac{1}{time\ unit\ of\ arrival} \tag{1}$$

$$A(\lambda) = P[Arrivals \leq \lambda] \tag{2}$$

Similarly to Equation 1, Equation 3 describes the service rate per unit of time and Equation 4 describes the probability distribution for the service time between clients (FILHO, 2008; ARENALES, 2015), as a function of the service rate given in Equation 3. The same concept of batches, of the arrival distribution, must be applied to the service time if the release of the clients occurs in groups, like an elevator that opens its doors for several people to exit (ARENALES, 2015).

$$\mu = \frac{1}{time\ unit\ of\ service} \tag{3}$$

$$B(\mu) = P[Service \leq \mu] \tag{4}$$

Queuing Theory also states a stability condition (Equation 5) where the arrival rate should never be higher than the service rate, if so causing an infinite queue:

$$\lambda < \mu \tag{5}$$

System parameters are queue buffering capacity K, in general considered as infinite, the number of arrivals N and service channels m, with different A(λ) and B(μ) if necessary, the queuing service discipline C, which can be First In First Out ($FIFO$), Last In First Out ($LIFO$), Service In Random Order ($SIRO$), Shortest Processing Time (STP), with a set priority for each client or allocation algorithm (TAHA, 2008; ARENALES, 2015).

After these parameters are defined, it is possible to measure the performance of the system using the formulas in Table 1 for so called Steady-State systems, that is, the system behaves in the same way in a long period of time, and invariably, the arrival and service rates do not alter in the period of study (TAHA, 2008; ARENALES, 2015):

Table 1 – Steady-State measures of performance

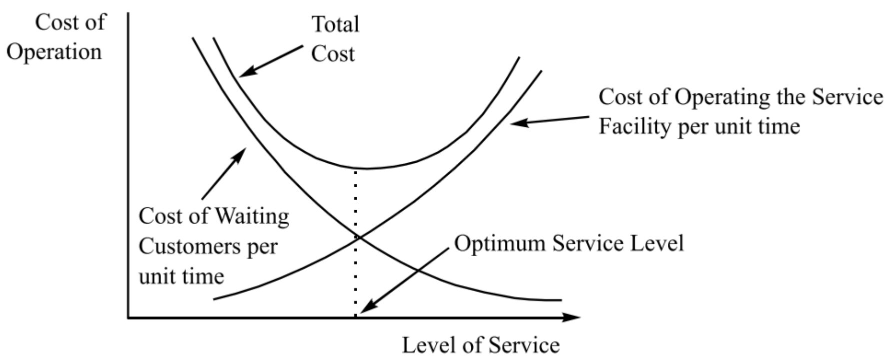
Description	Formula
Ω workload in the system	$\Omega = \lambda * time\ unit\ of\ service$
ρ utilisation rate	$\rho = \frac{\lambda}{m\mu} = \frac{\lambda * \Omega}{m}$
L_q number of clients in queue	$L_q = \sum_{N=C+1}^{\infty}(N - C) * p$
L_s number of clients in the system	$L_s = \sum_{N=1}^{\infty}(N * p)$
W_q client wait time in queue	$W_q = W_s - \frac{1}{\mu}$
W_s client wait time in the system	$W_s = W_q + \frac{1}{\mu}$
$\bar{c}$ number of busy servers	$\bar{c} = L_s - L_q$
ρ utilisation rate can also be	$\rho = \frac{\bar{c}}{m}$

Source: Adapted from TAHA (2008) and ARENALES (2015).

2.1.1 Cost Model and Service Level

Queue systems have two conflicting costs, the cost of operation (EOC) and the queuing cost (EWC), where its sum is the expected total cost (ETC) of the model per time unit (TAHA, 2008; SHARMA, 2016). The EOC is proportional to the structure available to offer the service to a client and the EWC represents the cost of clients waiting for service, an increase in service facilities reduces client waiting times and the decrease in the level of service results in longer queues (SHARMA, 2016), as shown in Fugure 3.

Figure 3 – Trade off between Cost of Operation and Level of Service



Source: SHARMA (2016).

Equation 6 defines the ETC based on the EOC and the EWC described by the Equations 7 and 8 respectively, where μ is the service rate, C_1 is the marginal cost per unit of m and C_2 is the waiting time cost per awaiting client (both per time unit):

$$ETC(\mu) = EOC(\mu) + EWC(\mu) \tag{6}$$

$$EOC(\mu) = C_1 * \rho \tag{7}$$

$$EWC(\mu) = C_2 * L_s \tag{8}$$

An optimum service level, the efficiency of the queuing system, is obtained by determining an optimum level of service rate (μ^*), that is, an rate in which a certain number of service stations m avoids an excessive delay in offering the service to its clients. An optimum service rate μ^* can be obtained using the Equation 9 (SHARMA, 2016).

$$\mu^* = \lambda + \sqrt{\frac{\lambda * C_2}{C_1}} \tag{9}$$

2.1.2 Probability Distributions

In various queue systems, client arrival occurs in a random manner, that is, the arrival of one client is not influenced by the time between the arrival of other client or its service (ARENALES, 2015), in a pure birth system, that is the arrival process, a time interval that follows an exponential distribution and the arrival rate is λ clients per time unit, client arrivals can be described by the Poisson distribution, that is, if the time between arrivals follows an exponential distribution with an $\frac{1}{\lambda}$ mean, then the number of arrivals in a time unit t follows a Poisson distribution with a $\lambda * t$ mean (TAHA, 2008; SHARMA, 2016; ARENALES, 2015).

In a pure death system, that is the service or departure process, the system starts with one client at time equals zero and new arrivals are denied, since the service is provided following a rate of μ clients per unit of time t (TAHA, 2008; SHARMA, 2016). According to ARENALES (2015), an example of a pure death system is the outbound segment of a warehouse, were products are shipped but not replenished.

2.1.2.1 Continuous Distribution Functions

Continuous distribution functions are used to describe the probability of a random variable in an interval, as an example, the chance of a number of defects in a length of copper wire, or so the number of a determinate event in a set interval (MONTGOMERY; RUNGER, 2009). These distributions can also be used to describe stochastic events such as the probability of arrival of a client in a shop during a day, and in this study, they are set as parameter functions to fitting tests, describing various stochastic events in a warehouse simulation model.

Some Continuous Distribution Functions are described below, on Frame 1:

Frame 1 – Continuous Distribution Functions

Distribution	Formula	Considerations
Uniform	$F(x_i) = 1/(b-a)$	$a \leq x \leq b$
Normal	$\frac{1}{\sqrt{2\pi}\sigma}e^{\frac{-(x-\mu)^2}{2\sigma^2}}$	None.
Exponential	$F(x) = \lambda e^{-\lambda x}$	$0 \leq x \leq \infty$
Gamma	$F(x) = \frac{\lambda^r x^{r-1} e^{-\lambda x}}{\Gamma(r)}$	$\Gamma(r) = \int_0^\infty x^{r-1}e^{-x}$ r > 0 x > 0
Erlang	$F(x) = \frac{\lambda^r x^{r-1} e^{-\lambda x}}{\Gamma(r)}$	r > 0, r is an integer x > 0
Weibull	$F(x) = 1 - e^{-(\frac{x}{\delta})^\beta}$	$0 \leq x \leq \infty$
Lognorm	$F(x) = \frac{1}{x\omega\sqrt{2\pi}}exp[-\frac{(lnx-\theta)^2}{2\omega^2}]$	$\theta = mean, \omega^2 = variance$
Beta	$F(x) = \frac{\Gamma(a_1+a_2)}{\Gamma(a_1)\Gamma(a_2)}x^{a_1-1}(x-1)^{a_2-1}$	$0 \leq x \leq \infty$
Cauchy	$F(x) = \frac{1}{2} + \frac{1}{\pi}atan\frac{x-\mu}{\theta}$	$\mu > 0, \theta > 0$
Frechét	$F(x) = exp(-(x\theta)^\alpha)$	$\mu > 0, \theta > 0$
Gumbel	$F(x) = exp(-(exp(\frac{x-\mu_0}{\theta})))$	$\mu > 0, \theta > 0$
Laplace	$F(x) = \frac{1}{2}exp(\frac{x-\mu}{\beta})$	$\mu > 0, \theta > 0$
Logistic	$F(x) = \frac{1}{1+exp(-\frac{x-\mu}{\beta})}$	$\mu > 0, \theta > 0$
LogLogistic	$F(x) = (\frac{1}{1+\frac{x}{a}})^{-\beta}$	$a > 0, \beta > 0$
Triangular	$\frac{2(x-a)}{(c-a)(b-a)}$ $\frac{2(x-a)}{(c-a)(b-a)}$	a $\leq$ x $\leq$ c c $\leq$ x $\leq$ b

Source: Adapted from MONTGOMERY and RUNGER (2009), Siemens PLM (2023).

2.2 FITTING TESTS

Fitting tests are used to verify if the collected data fits (or follows) a certain theoretical distribution (FILHO, 2008), these kind of distributions represent the behaviour of a certain event in function of its frequency (LEOTTI; BIRCK; RIBOLDI, 2005). From a completely specified probability distribution, the probability of a random variable can be calculated assuming a given range (LEOTTI; BIRCK; RIBOLDI, 2012), and so it is possible to analyse a set of data and using several distributions to find functions and parameters that can represent a system, or one element of a system.

Analysing distributions that fits in a data set as a good description of an event is done using several tests that can be parameterised and not parameterised (FILHO, 2008; LEOTTI; BIRCK; RIBOLDI, 2005), parameterised tests such as Student t requires a specific probabilistic distribution to its random variable, the Normal distribution, and other parametric methods supports other probability distributions. Non-parametric methods such as Mann-Whitney, Kolmogorov-Smirnov, Cramer-von Mises, Anderson-Darling and Shapiro-Wilk (LEOTTI; BIRCK; RIBOLDI, 2005) can be used on data sets that are not normalised and do not presume a probability distribution to the data set (LEOTTI; BIRCK; RIBOLDI, 2012; FILHO, 2008).

2.2.1 Pearson Chi-Square Test

The hypothesis that a sample of data O $(O_1, ..., O_n)$ has the distribution $F(x)$, a range of O_i samples is partitioned in a set $(E_1, ..., E_M)$, if a set of N (that is $N_1, ..., N_M$) values are observed of O_j, then N_i has the binomial distribution with parameters n and, Equation 10, when the null hypothesis is true (D'AGOSTINO; STEPHENS, 1986).

$$P_i = P(X_j \ falls \ in \ E_i) = \int_{E_i} dF(x) \tag{10}$$

Pearson has set three stages:

- First: The quantities $N_i - npi$ have in large samples approximately a multivariate normal distribution, and this distribution is non singular if only $M - 1$ of the cells are considered;
- Second: If $Y = (Y_i, ..., Y_p)'$ has a non singular p-variate normal distribution $Np(\psi, \sum)$, then the quadratic form $(Y - \psi)' \sum^{-1} (Y - \psi)$ appearing in the exponent of the density function has the $\chi^2(p)$ distribution as a function of Y;
- Third: Computation shows that if $Y = (N_1 - np_1, ..., N_{M-1} - np_{M-1})$‘, this quadratic form is given by Equation 11, which therefore has approximately the $\chi^2(M - 1)$ null distribution in large samples:

$$\chi^2 = \sum_{i=1}^{M} \frac{(N_i - np_i)^2}{np_i} \tag{11}$$

Its use has been discouraged for continuous distributions, but has a good advantage for dealing with parameter estimations (ROLKE; GONGORA, 2021). Rolke and Gonora (2021) also states that other methods have been developed over time, Kolmogorov-Smirnov and Anderson-Darling are the most commonly used.

2.2.2 Kolmogorov-Smirnov Test

The Kolmogorov and Smirnov methods compares cumulative distribution functions, letting G_t be a empirical, that is the collected data, and $F(t)$ the theoretical function, containing a Normal with a mean ι and variance σ^2, the Kolmogorov–Smirnov test statistic takes one of theses forms represented by Equations 12, 13 and 14, (BERGER; ZHOU, 2014):

$$D_k = max|F(t) - G_n(t)|, min(x) \leq t \leq max(t) \tag{12}$$

where the alternative hypothesis is that $F(t) \neq G(t)$,

$$D_k^+ = max|F(t) - G_n(t)|, min(x) \leq t \leq max(y) \tag{13}$$

where the alternative hypothesis is that $F(t) > G(t)$ for some value(s) of t, and

$$D_k^- = max|G_n(t) - F(t)|, min(x) \leq t \leq max(x) \tag{14}$$

where the alternative hypothesis is that $F(t) < G(t)$ for some value(s) of t. Berger and Zhou also states that the Kolmogorov–Smirnov test has an exact null distribution for the two directional alternatives but the distribution must be approximated for the non directional case. Regardless of the alternative, the test is less accurate if the parameters of the theoretical distribution have been estimated from the sample.

2.2.3 Anderson-Darling Test

Anderson and Darling describes a goodness of fit method, Equation 15:

$$A_m^2 = m \int_{-\infty}^{\infty} \frac{[F_m(x) - F_0(x)]^2}{F_0(x)[1 - F_0(x)]} dF_0(x) \tag{15}$$

The Anderson-Darling method is a test which does not involve a subjective grouping of the data, like the Pearsons χ^2 method, it consists of comparing the empirical cumulative distribution function with the hypothetical distribution function (ANDERSON; DARLING, 1952). Let a sample of data O $(O_1, ..., O_n)$, with empirical distribution $F_m(x)$, with distribution function $F(x)$ where $F(x) = F_0(x)$ for some completely specified distribution function $F_0(x)$, where $F_m(x)$ is defined as a proportion of sample O, which is not greater than x (ANDERSON; DARLING, 1952; SCHOLZ; STHEPENS, 1986).

As described by Anderson and Darling, the test wishes to consider a convenient measure of the discrepancy or "distance" between two distribution functions. The authors also stated that this test is more appropriated for smaller data samples, for which larger samples the Kolmogorov-Smirnov and Cramer-Von Misses should be considered, reducing the problems to straight-foward considerations in the theory of Gaussian stochastic processes.

The innovation of this method is that a weighting function, $w(x)$, Equation 16, which provides flexibility in the test (ANDERSON; DARLING, 1952).

$$w(x) = [F_0(x)(1 - F_0(x))]^{-1} \tag{16}$$

2.3 SIMULATION OF PROCESSES

2.3.1 Discrete Event Simulation

Petrean (1998) concludes that the more complex the queuing systems get, the mathematics involved becomes intractable, that happens because of the complexity of the formulas involved in the analytical treatment of the system using queuing theory models, so it is more convenient to apply simulation techniques.

Discrete Event Simulation (DES) is a collection of techniques that are used to study a discrete-event dynamical system, FISHMAN (2001) describes these collections as modelling concepts for abstracting the essential features of a system in a set of precedence and mathematical relationships, the use of computer software to convert these concepts into computer executable code to generate data, converting this data into estimates of system performance and the use of methods for assessing how these estimates approximate true, but unknown, system behaviour. LAW (2016) defines DES as the modelling of a system as it evolves over time by a representation in which the state variables change instantaneously at separate points in time.

2.3.1.1 Discrete Event Simulation Software

DES softwares are computer programs that allow the modelling of processes in a virtual environment. Agalianos et al. (2020) describes that Digital Twins (DT) as DES models that are used in real time to improve processes, including real-time decision making, recognise trends and limitations in warehouses. These DT models are integrated complex simulations of complex physical models, using data gathered from sensors and other real-time acquiring data devices (AGALIANOS et al., 2020).

Some state-of-the-art DES Software are listed below on Frame 2:

Frame 2 – Discrete Event Simulation Softwares

Software	Distributor	General Description
Anylogic	The AnyLogic Company	AnyLogic allows for DES, Agent-Based, and system dynamics modelling, focusing in a visual modelling language.
Arena	Rockwell Automation	Arena allows for DES, Flow and Agent-Based modelling methods, to create a DT using historical data to to analyse system results.
Flexsim	FlexSim Software Products, Inc.	Software that enables the simulation and optimisation of production systems and processes.
Siemens Plant Simulation	Siemens PLM Software	Using object-oriented architecture and the support of multiple interfaces and integration to model and assess system performance.

Source: Author (2023).

2.3.2 Other Warehouse Simulations

In a study Smith and Srinivas (2019) used a simulation-based evaluation for improving inbound logistics operations and reducing truck detention fees in one of the major costumer goods in the United States, proposing different check-in policies such as staging areas, dynamic dispatching rules and automation. The main key performance indicators are the processing time, truck awaiting time and queue length, the main bottlenecks are delays generated by traffic congestion at the facility entrance, mainly during peak hours when the arrival rate succeeds the service rate.

The methodology used to tackle the issue is defined in five stages: Define, Measure, Analyse, Improve and Control (DMAIC), being composed mainly of: Process mapping and the creation of flow charts, collection of historical data, the fitting of the analysed data into statistical distributions and baseline model development. For data analysis for use in the simulation models, nine weeks where extracted from the Warehouse Management System (WMS) (SMITH; SRINIVAS, 2019).

Defining the sequence of events enabled an easier understanding of the check-in process, resulting in a flowchart containing the unique characteristics of the flow of material and trucks. Such characteristics includes that different types of trucks enter thought entrances, one of them has an RFID (Radio-Frequency Identification) technology for automatic and faster check-in processing, but has only one server and queue. In case a RFID check-in fails, the truck has to re-route to the main entrance and redo its identification manually.

Smith and Srinivas (2019) then uses the collected data to determine the arrival and service rates for use in the simulation model, after outlier treatments, a Kruskal–Wallis (K-W) test was conducted to to assess the homogeneity of the arrival rates of the three busiest days, the test resulted in a combined data sheet for these days. After the K-W test, a Persons χ^2 test was used for the fitting test, resulting that a Poisson distribution with a time-varying arrival rate to be a good fit for modelling truck arrivals.

To simulate a warehouses modular conveyor system Ashrafian (2019) used a three dimensional DES model and other statistical models to capture the randomness and the complexity of the whole system. The focus of the study is to show how a DES can help the design and optimisation of warehouse systems, using a Digital Twin as a tool for decision making and optimisation.

Data of various time-dependant operations regarding one week of operation amounting near 500000 products was collected. A Statistical analysis was used to model statistical distributions for the inputs, such as supplier feeding rates, storage feeding rates, processing times at pickup stations and decision points that distributes the products (ASHRAFIAN, 2019).

The outcomes of the suggested solution scenarios reveal that implementing a new loop parallel to the conveyor highway effectively enhances the availability of products at pickup stations. This, in turn, reduces the average product quantity on the highway, thereby preventing congestion. The overall product quantity within the system decreased by 8%, and the number of products passing through decision points saw a 28% reduction. These metrics represent the most significant Key Performance Indicators (KPIs) for this particular scenario(ASHRAFIAN, 2019).

In other study Gattuso, Cassone and Pellicanò (2014) simulates the receiving process of a logistics centre warehouse for food and household goods distribution using the software Witness, generating models for the treatment and handling of goods utilising Intelligent Transportation Systems (ITS), Radio Frequency Identification (RFID) implementations and automation. The main objective is to reduce the time costs of receiving goods using a DES implementation.

Gattuso, Cassone and Pellicanò (2014) points out that RFID technologies, together with a Electronic Data Interchange (EDI) communicating the relevant documentation data reducing the human interaction, grants a 15% to 20% reduction to the checking phase of the unloading of cargo, leading also to saving time on the following phases of storing, picking and shipping. This resulting data regarding the reduction of time in the receiving process is also shown in a study done by Sooksaksun and Sudesertsin (2014), where a similar warehouse context regarding the implementation, but in this case an actual implementation, has reduced the receiving process in 28,79% using RFID.

Other advantages are for the usage of RFID technology is its use in inventory management, location of products in real time, routing inside the warehouse (optimising travel time) and product backtracking. The main disadvantages are its cost for implementation, consisting in the tags for each product, the antennas for receiving the radio signal, software needed to transform the relayed data (EDI) and adaptations to the existing system inside the warehouse (GATTUSO; CASSONE; PELLICANò, 2014; SOOKSAKSUN; SUDSERTSIN, 2014).

Leveraging the established theoretical framework on measuring the performance and costs of queuing systems, understanding the utilisation of probability distributions in determining process arrival intervals, discerning how to statistically fit probability distribution functions to collected data, and recognising how DES simplifies the analytical complexity of queuing system analysis, this case study will now proceed to demonstrate and discuss its construction and analysis. The following chapters will detail the mapping of the receiving process, the collection of data, the construction and calibration of the DT model, the configuration of simulation parameters, and the development of proposed improvement scenarios, involving modifications to a base model.

3 METHODOLOGY

In this chapter the method in which the main bulk of the study is described, using a methodology as stated by Smith and Srinivas (2019), Define, Measure, Analyse, Improve and Control (DMAIC). The Define step consists of the process mapping and the construction of the DT model of the warehouse inside Plant Simulation, the chosen DES software for this study, the Measure step comprises the data collection regarding the define processes and also establishes the baseline values for evaluation, then Analyse involves the data fitting for the distribution functions and the calibration of the base model scenario.

Once the base model scenario is calibrated, the resulting simulation replicates dynamic behaviours observed in historical data, enabling the modelling of potential Improvements and scenarios (XIE; ZHANG; ZHANG, 2017). The proposed changes can be clearly defined, measured, and analysed in comparison to the base model scenario, facilitating the identification of potential improvements. These proposed improvements can then be Implemented and Controlled in subsequent iterations.

3.1 OBJECT OF STUDY

This study focuses on a warehouse belonging to a company in southern Brazil, this company imports products for two main purposes: direct resale and assembly within this facility. The choice to locate the warehouse here is strategic, benefiting from its proximity to sea cargo ports, major national highways and capital cities.

The company also procures products from domestic suppliers, using them for both resale and internal consumption within its assembly processes. These items are stored and subsequently sold alongside the primary product.

As these are healthcare materials, ANVISA (Agência Nacional de Vigilância Sanitária), the Brazilian Health Regulatory Agency, imposes numerous procedures and restrictions to ensure compliance (ANVISA, 2021). Furthermore, some of these products are intricate, consisting of a primary volume along with various accessories or complementary volumes, which necessitate the assembly of multiple components to create the final product, and some of these products are only assembled inside the clients site.

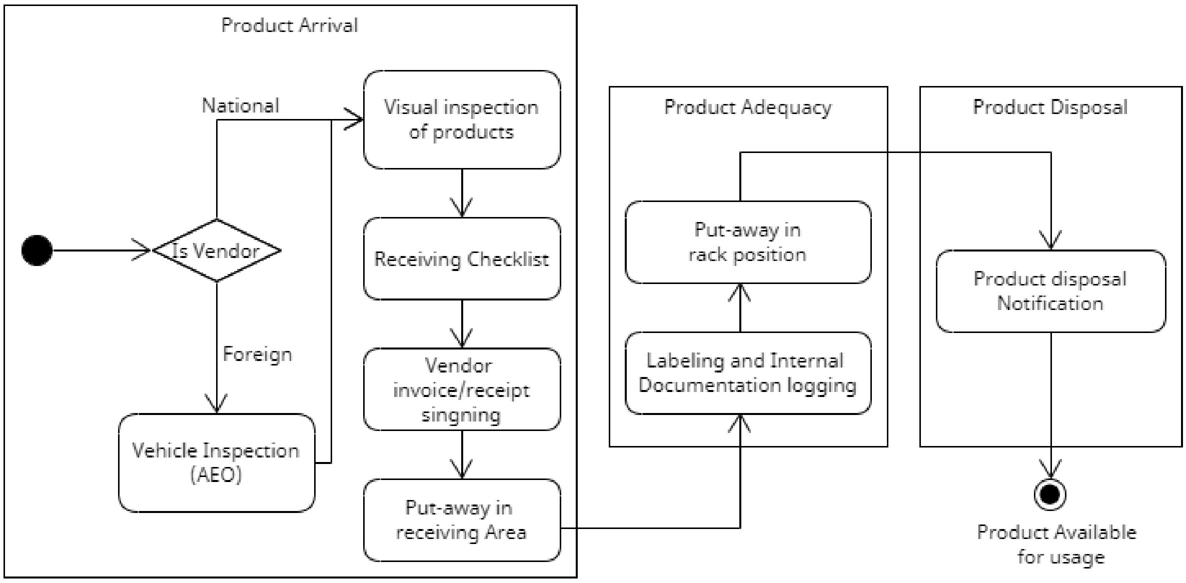
The central issue associated with the receiving process is the delay between the arrival of products and their disposal, that is the availability for consumption in the assembly process or direct sale. This delay is particularly attributed to the process of labelling and documentation logging. Currently, crucial information is solely obtained from product invoices and import documentation, involving the use of spreadsheets and manual data logging into the WMS.

As the information used on this study is highly sensible to the company, all data shown is camouflaged by multiplying all values by a constant X.

3.2 PROCESS MAPPING AND MODEL CONSTRUCTION

The process mapping was conducted via interviews with the warehouse operators, internal processes procedure documentation and on-site observations. Figure 4 illustrates a flowchart detailing the Receiving Process of the warehouse, covering the entire process from the arrival of the truck carrying the goods to their disposal.

Figure 4 – Mapped Receiving Process



Source: Author (2023).

The first procedure to be enrolled is to inspect the vehicle in which the products have been transported, if the product is imported, that is, the vendor is from a foreign country, a procedure following the Authorised Economic Operator (AEO), an European Union program of internationally recognised standards (EC, 2023), must be conducted, if the product has a national vendor origin the vehicle inspection procedure is skipped.

Subsequently, a visual quality inspection is carried out to check for any signs of damage and to verify whether any tilt or shock sensors have been activated. A checklist is completed, including details such as the quantity of volumes received, the presence of a purchase order reference on the invoice, the type of material, any observed damage or triggered sensors, and the products suitability for acceptance. Once the checklist is completed, the invoice (or receipt) is signed, and the product is then placed in the receiving area.

This first set of actions are represented in the simulation with a buffer block, representing the warehouse unloading dock, named "Receiving Buffer", with a triangular distribution with parameters a = 1 minute, b = 20 minutes and c = 5 minutes for the unloading time on the workplace, then two store blocks called "Store National received"and "Store Import received", with triangular distributions with parameters a = 1 minute and 15 seconds, b = 1 minute and c = 1 minute and 30 seconds.

After storing the material in the receiving area, its adequacy phase begins with the upload of the invoice reference and arrival data to the WMS and the office operators are notified, so that the product can then be labelled following the procedures and internal documentation. A random location on one of the racks is determined by the WMS software, and then the product can be stored at that location and is available for use upon notification of the office operation.

Then for the removal from the receiving areas and storage of the product in its final warehouse position, the workplaces for the storage blocks have a triangular distribution with parameters a = 5 minutes, b = 3 minutes and c = 10 minutes for the unloading and, depending on the final position of the product in the storage rack, the equation 17 is used to set the time for storage in the rack, where i is the horizontal position and j is the vertical position on the rack:

$$Time\ to\ storage\ on\ rack = i * 1.33 + j * j * 10 \tag{17}$$

The processes of transfer and expedition of products was not mapped as they are not the focus of this study, only its impact regarding the availability of the rack positions was considered using a simple logic to delete the material and clear the rack position. The data regarding the quantities and timings where considered, as to emulate the internal dynamic of position availability.

After the process mapping the flow system for analysis using Queuing Theory can be established, Figure 5:

Figure 5 – Flow System of the Receiving Process

Source: Author (2023).

The DT is modelled using the layout blueprints for the warehouse, comprising all measurements of the physical structure (including rack sizes, locations, available stocking positions, receiving, transfer and expedition areas, office spaces, entrances, etc). These objects are then modelled to a one-to-one scale, allowing the simulated workers to route inside the warehouse.

In this study, the chosen time span for modelling the receiving process spans two weeks, and two months of data were used to generate the fitted distributions. This time frame was selected because a larger span would undermine the data set by high variability, giving poor statistical results for the fitting tests, particularly given the inconsistency in the demand for products and receiving quantities. The two weeks of simulation time is set as the mean time of completion of the receiving process is three days, giving enough time to several products to be processed and the output data collected.

3.3 COLLECTION OF HISTORICAL DATA

Data spanning two months was collected from reports provided by the warehouse operator manager, and its accuracy was verified using the internal Warehouse Management System (WMS). This data encompasses information on the enrolled times and quantities related to the receiving, transfer, and expedition processes, totalling 8,751 rows of data. The specific data elements included are outlined in Frame 3:

Frame 3 – Collected Data

Process	Data	Data Quantity
Receiving	Date and Time of Arrival Date and Time of Notification Internal Material Reference Material Serial Number Quantity of Volumes	2504
Internal Transfer	Date and Time of the Order Internal Material Reference Material Serial Number Date and Time of delivery Quantity of Volumes	4073
Expedition	Date and Time of the Order Internal Material Reference Material Serial Number Date and Time of Picking Date and Time of Packing Date and Time of Expedition Quantity of Volumes	2174

Source: Author (2023).

3.4 BASE MODEL CALIBRATION

For the calibration of the proposed DES some literature was reviewed regarding the impacts of the number of runs, warm up time, transient and steady state and also the statistical analysis for the collected data.

3.4.1 Simulation Parameters

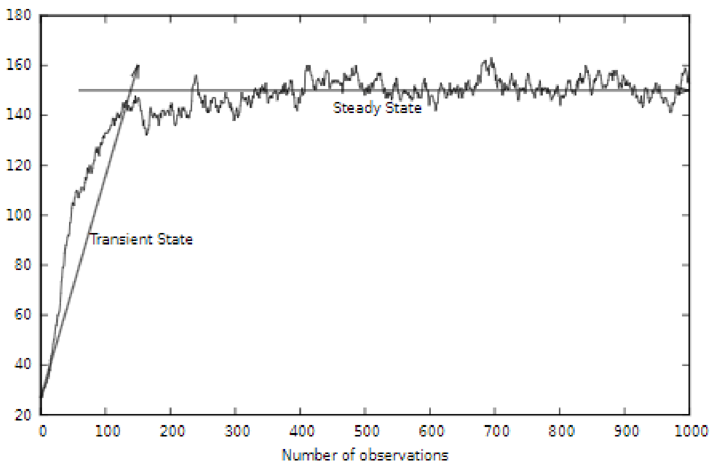
For a simplified simulation model Xie, Zhang and Zhang (2017) utilises the service rates μ of a queue where the arrival times ate exponentially distributed with an average of $\frac{1}{\lambda}$, and service times are exponentially distributed as an average of $\frac{1}{\mu}$, representing a bottleneck at workstations, with the output of the dynamic behaviours being the order cycle times, adjusting the variables so the output samples match with the historical data under the same conditions.

On the study done by Gattuso, Cassone and Pellicanò (2014) the calibration is conducted by first identifying the theoretical probability distribution that represents the phenomena using the minimum square, or the maximum likelihood, methods then verifying its statistical tests via the Pearson χ^2 and Kolmogorov-Smirnov tests. The authors then demonstrates how the fitted data adheres to the historical data using graphical representations and also describes the fitting test results and the parameters for the fitted distributions.

Both of the studies (by Xie, Zhang and Zhang (2017) and Gattuso, Cassone and Pellicanò (2014)) do not consider any warm up times and number of runs. Borges et al. (2014) defines the importance of warm up times as the transient stage, the time of initialisation of the simulation that is not steady, generates values that should not be considered in the output analysis. Borges et al. (2014) also states that one method to overcome this phase in the simulation run time for DES is to ignore the data generated, and so the resulting treated data is statistically reliable.

The steady stage of the simulation is defined by the immediate end of the transient stage of the simulation (BORGES et al., 2014). Borges et al. (2014) suggest a heuristic for determining the steady state of a simulation, using a linear regression of the range of results of the simulation, where the coefficient is near zero for the specified range of observations. If the specific data has a incline represented by the R^2 value of the linear regression, the simulation run time is still in its transient state, as represented by Figure 6:

Figure 6 – Transient and Steady State

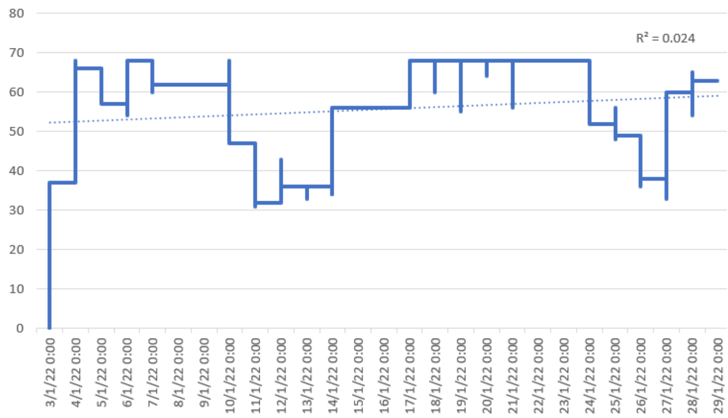


Source: Adapted from Borges et al. (2014).

For the model that is constructed in this study, a warm up time of 2 days is considered, using the heuristic proposed by Borges et al. (2014). For analysing this behaviour of the simulation, a one hour interval pooling of data from the receiving area stock is collected the analysed its linear regression R^2 values, as the stock quantity is not defined directly by the modeller.

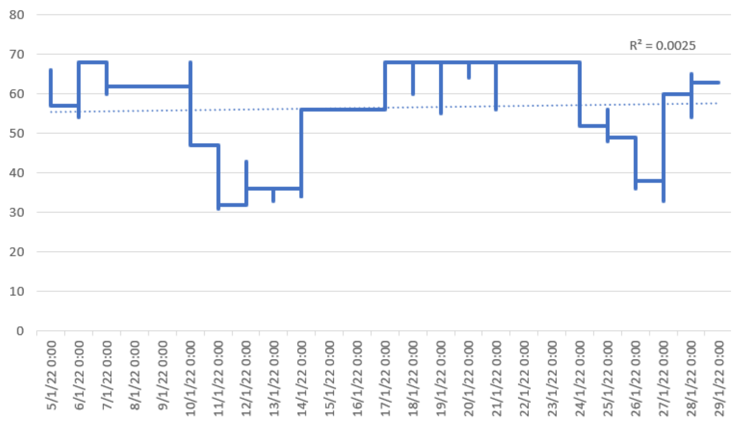
The R^2 value for the linear regression considering an entire run is 0,024 with a ramp in its initial values. The steady state is reached at the third simulated day, with an R^2 value of 0,0025, from this point the simulation is then considered at the steady state.

Figure 7 – Pooled data for an entire simulation run with the R^2 value



Source: Author (2023).

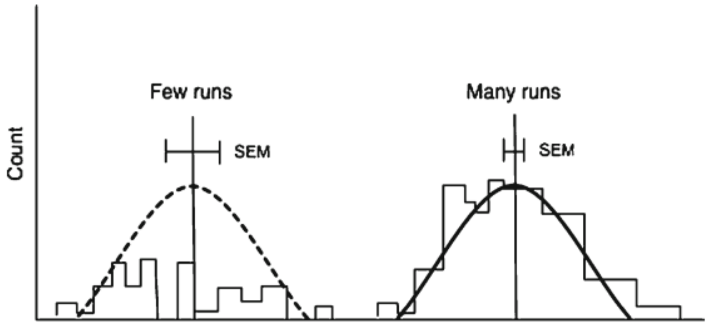
Figure 8 – Pooled data without the warm up time for a simulation run with the R^2 value



Source: Author (2023).

For the number of runs, a study done by Ritter et al. (2011) on simulating tasks where humans are involved, or Human-on-the-Loop simulations, describes that these simulations should not be sampled, but run enough times to provide reliable results. Ritter et al. (2011) then describes the modellers dilemma of how many simulations should be run for comparing experimental and gathered historical data, citing that other researchers use a range of methods, from one run up to 1000 simulation runs.

Figure 9 – Performance Distribution



Source: Adapted from Ritter et al. (2011).

Ritter et al. (2011) proposes a heuristic for determining the number of runs if the simulations are easy to obtain, that is, the simulation time and resources used are not a problem for the modeller, using a simple criterion: the Standard Error of the Mean (SEM), representing the error in predicting the mean of the distribution of results. The equation 18 represents the SEM, where κ is the number of runs:

$$SEM = Variance/\kappa = Standard\ Deviation/\sqrt{\kappa} \tag{18}$$

As an example, Ritter et al. (2011) demonstrates that for a simulation with a confidence of 95% and a standard error of 0,5, the SEM value is $0,5/1,96$, or 0,255, for a 95% confidence limit, where the 1.96 value is the approximate value for the 97.5 percentile point of the normal distribution. If the standard deviation is 3.6 then using Equation 18, it is solved the value of κ as 199 runs.

For this study, the number of runs is determined by using an 85% confidence interval with value 1,282 (MONTGOMERY; RUNGER, 2009), the standard error for the receiving area stock (which represents the number of clients in the queue) is 11,83 and its variation is 140,04. Solving the value κ, with a SEM value of 9,22, the number of runs is set as 231 runs.

3.4.2 Fitting of the Analysed Data

For the data fitting tests the following methodology was established:

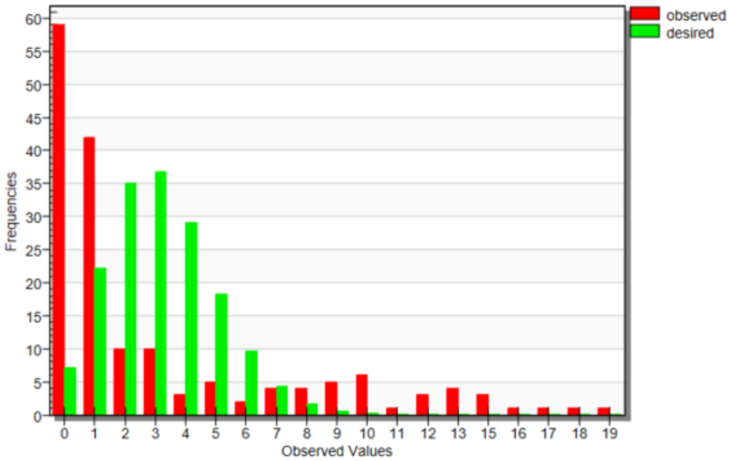
1. Gather the desired data subject from the database;
2. Removal of outliers using the data visualiser, inside Plant Simulation;
   a) Where considered outliers any data that has an abnormal distance from the other values;
3. Input the treated data in the DataFit block;
   a) Set the data input type as Continuous or Discrete;
   b) Set the recommended number of classes for the χ^2 test;

c) Set the distributions to be evaluated;
d) Visualise the fitted data and the results of the fitting tests;

4. Set the four most fitted distribution and its defined parameters into the subjects process block;
5. Run 231 simulations using the ExperimentManager block, with random seeds (SIEMENS PLM, 2023);
6. Get the average value for the the desired data subject;
7. Compare and set the best distribution (that has the lower error percentage compared to the actual data) for the subject.

Following Figure 5, the distributions used to describe the various flow items are now described. As an example, starting with the frequency of truck arrivals, it is assumed that a Poisson distribution should be a good distribution to define this arrival process, but the analysed data and the fit results shows an unsatisfactory result as in Figure 10:

Figure 10 – Observed data versus Poisson distribution for truck arrivals (in hours)



Source: Author (2023).

The average number of arrivals for the simulated time frame is 35 trucks per week, the resulting λ value output from the DataFit block is 3.1416 with a χ^2 statistic of 582.9027 (better if lower), giving a total of 15 arrivals and a 43.86% error. Considering other distributions and the methodology proposed, Frames 4 and 5 describes the new fitted distributions for this step of the receiving process:

Frame 4 – KS test for distributions for the Truck Arrivals and its corresponding error

Distribution	KS Statistic	KS test	Arrivals	Error
Weibull	0.8998	true	33	5.7%
Lognorm	0.9862	true	25.3	28.57%
Erlang	0.9962	true	25.4	28.57%
Gamma	1.0160	true	23.7	34.28%

Source: Author (2023).

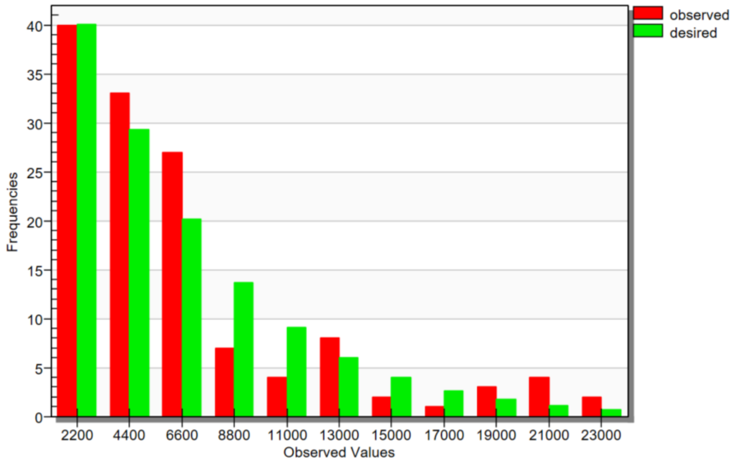
Frame 5 – AD test for distributions for the Truck Arrivals and its corresponding error

Distribution	AD Statistic	AD test	Arrivals	Error
Weibull	0.5967	true	33	5.7%
Gamma	0.9215	false	23.7	34.28%
Erlang	1.4013	false	25.4	28.57%
Lognorm	1.5801	false	25.3	28.57%

Source: Author (2023).

The truck Arrivals, resulting in a Weibull distribution with parameters α = 1.05378 and β = 5599.55361 (seconds) fitted considering the AD test, graphed in Figure 11:

Figure 11 – Fitted Weibull Distribution for Truck Arrivals (in seconds)



Source: Author (2023).

The next distribution to be calibrated is the quantity of products in the trucks containing products from national origin. On average, the number of volumes received is 107 per week, the DataFit block provides the following results for the fitting tests in Frames 6 and 7:

Frame 6 – KS results for National Product Quantity Arrival in Trucks and its corresponding error

Distribution	KS Statistic	KS test	Quantity	Error
Weibull	3.2208	false	88.5	17.76%
Pareto	3.3350	false	102.7	4.09%
Gumbel	3.4568	false	96.3	10%
Lognorm	3.6574	false	68.9	36.45%

Source: Author (2023).

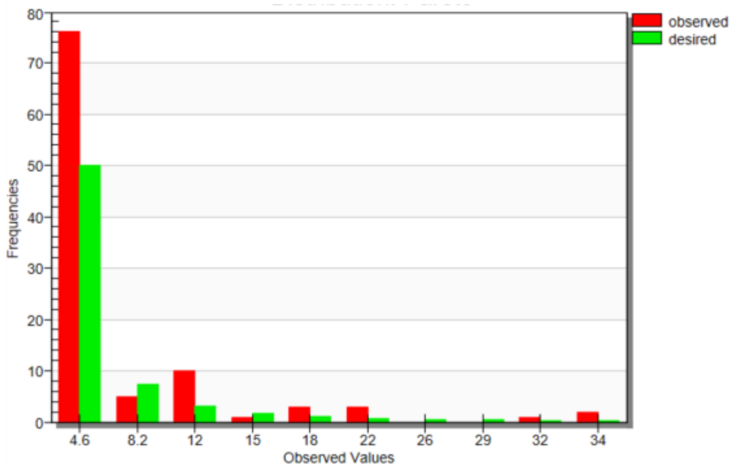
Frame 7 – AD results for National Product Quantity Arrival in Trucks and its corresponding error

Distribution	AD Statistic	AD test	Quantity	Error
Pareto	11.0339	false	102.7	4.09%
Weibull	13.6404	false	88.5	17.76%
Lognorm	14.1633	false	68.9	36.45%
Gumbel	15.1805	false	96.3	10%

Source: Author (2023).

Quantity of volumes for national products fitting results in a Pareto distribution with parameters α = 0.86060 and β = 0.64106, graphed in Figure 12:

Figure 12 – Fitted Pareto Distribution for National Product Quantity Arrival in Trucks



Source: Author (2023).

The quantity of products in the trucks containing products from foreign origin is now calibrated. The average number of volumes per truck received is 68, the DataFit block outputs the following results for the tests and proposed distributions in Frames 8 and 9:

Frame 8 – KS results for Foreign Product Quantity Arrival in Trucks and its corresponding error

Distribution	KS Statistic	KS test	Quantity	Error
Normal	1.5824	false	90.2	32.72%
Gamma	1.5590	false	83.2	22.35%
Weibull	1.5684	false	75.2	10.59%
Gumbel	1.6239	false	91.6	34.78%

Source: Author (2023).

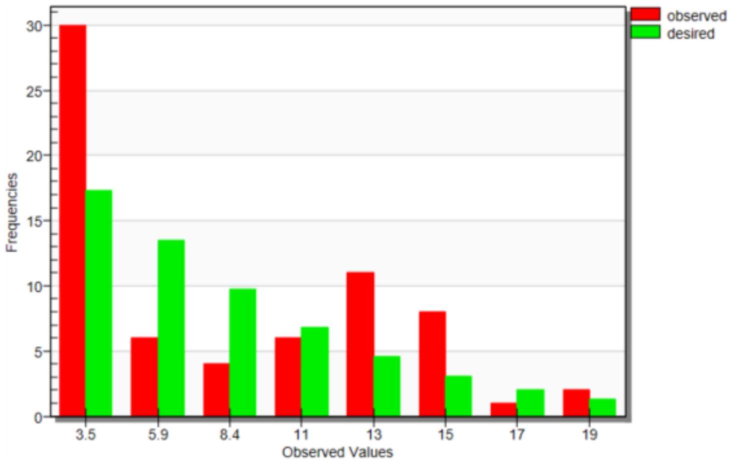
Frame 9 – AD results for Foreign Product Quantity Arrival in Trucks and its corresponding error

Distribution	AD Statistic	AD test	Quantity	Error
Normal	3.4364	false	90.2	32.72%
Gamma	3.4987	false	83.2	22.35%
Weibull	3.5815	false	75.2	10.59%
Gumbel	3.9397	false	91.6	34.78%

Source: Author (2023).

Quantity of volumes for imported products fitting results in a Weibull distribution with parameters α = 1.13321 and β = 6.84269, graphed in Figure 13:

Figure 13 – Fitted Pareto Distribution for Imported Product Quantity Arrival in Trucks



Source: Author (2023).

As for the times between the product placement at the adequacy area and the final disposal notification, for national products, the mean time lost awaiting is 69 hours and 32 minutes. And so the fitted distribution for the release of the products in the receiving area is given by the following Frames 10 and 11:

Frame 10 – KS results for National Product Adequacy time and its corresponding error

Distribution	KS Statistic	KS test	Average Time	Error
Lognorm	1.7702	false	66:40	4,32%
Gamma	2.0606	false	84:23	17,66%
Erlang	2.2686	false	95:56	27,50%
Weibull	2.3805	false	88:49	21.69%

Source: Author (2023).

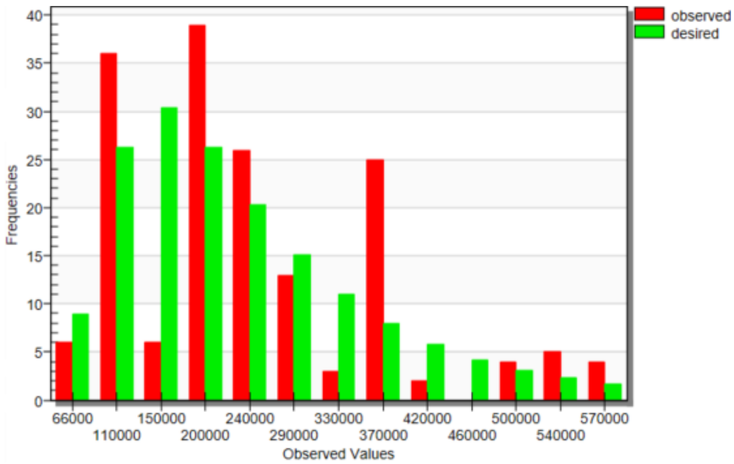
Frame 11 – AD results for National Product Adequacy time and its corresponding error

Distribution	AD Statistic	AD test	Average Time	Error
Gamma	2.6116	false	84:23	17,66%
Erlang	2.7770	false	95:56	27,50%
Lognorm	3.0282	false	66:40	4,32%
Weibull	3.0652	false	88:49	21.69%

Source: Author (2023).

For the time enrolled between the product placement at the adequacy area and the final disposal notification, for national products, the fitted distribution with best error is a Lognorm distribution with parameters μ = 2:14:40:04 and σ = 1:20:33:38, graphed in figure 14:

Figure 14 – Fitted Lognorm Distribution for National Product Enrolled Time



Source: Author (2023).

As for the times between the product placement at the adequacy area and the final disposal notification, for foreign products, the mean time lost awaiting is 111 hours and 43 minutes. And so the fitted distribution for the release of the products in the receiving area is given by the following Frames 12 and 13:

Frame 12 – KS results for Foreign Product Adequacy time and its corresponding error

Distribution	KS Statistic	KS test	Average Time	Error
Normal	3.7603	false	137:50	18,94%
Weibull	4.2436	false	142:27	21,57%
Gamma	5.0176	false	131:09	14,81%
Gumbel	5.0282	false	143:06	21.92%

Source: Author (2023).

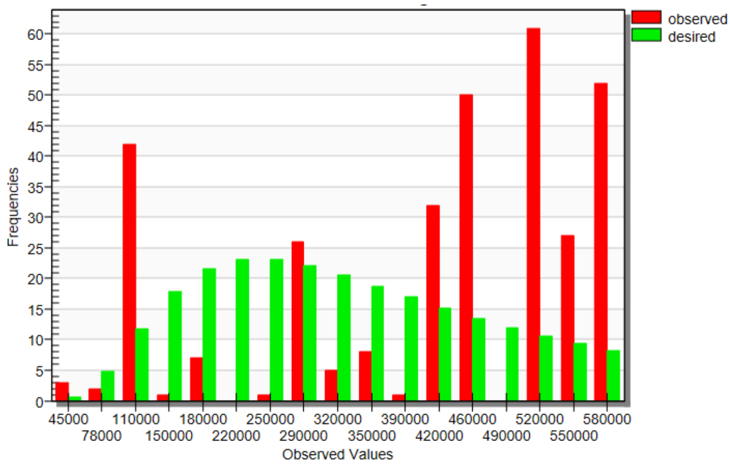
Frame 13 – AD results for Foreign Product Adequacy time and its corresponding error

Distribution	AD Statistic	AD test	Average Time	Error
Normal	15.4390	false	137:50	18,94%
Weibull	21.9323	false	142:27	21,57%
Gamma	26.9111	false	131:09	14,81%
Lognorm	32.4728	false	128:20	12.94%

Source: Author (2023).

For the time enrolled between the product placement at the adequacy area and the final disposal notification, for imported products, the fitted distribution with best error is a Lognorm distribution with parameters μ = 5:00:40:05.44 and σ = 3:21:39:12.97, graphed in figure 15:

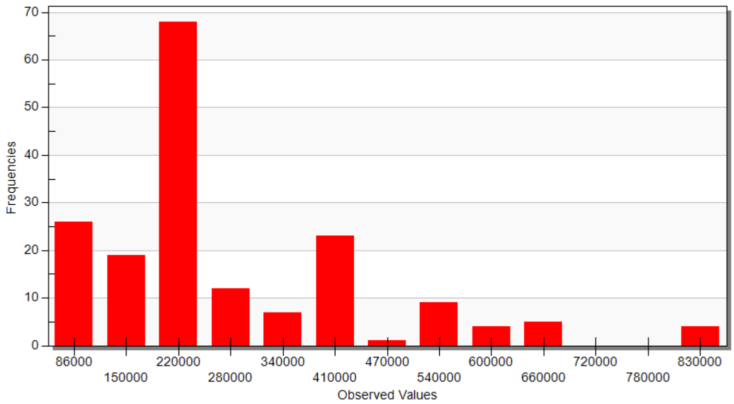
Figure 15 – Fitted Lognorm Distribution for Imported Product Enrolled Time



Source: Author (2023).

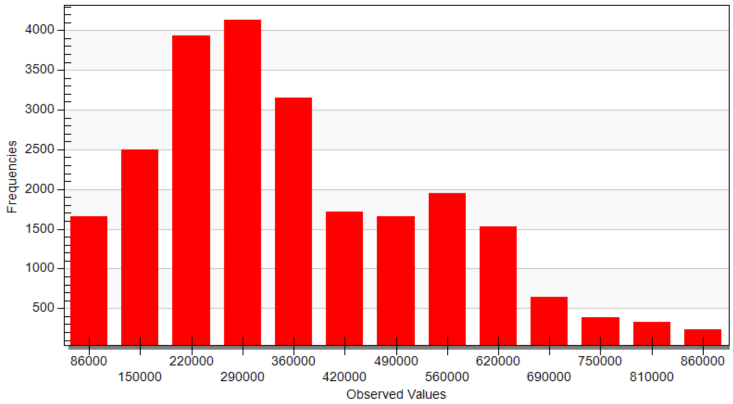
The final mean time values for the arrival process, from the unloading of the truck up to the storage and notification, for national products is 87 hours and 47 minutes, and for products from foreign origin 125 hours and 55 minutes, resulting in a mean error of 15,4% and 6,4% respectively. The following figures illustrates the generated frequencies for the sets of products, for 231 runs, starting with national products in figures 16 and 17:

Figure 16 – Distribution of frequencies for collected data on national products



Source: Author (2023).

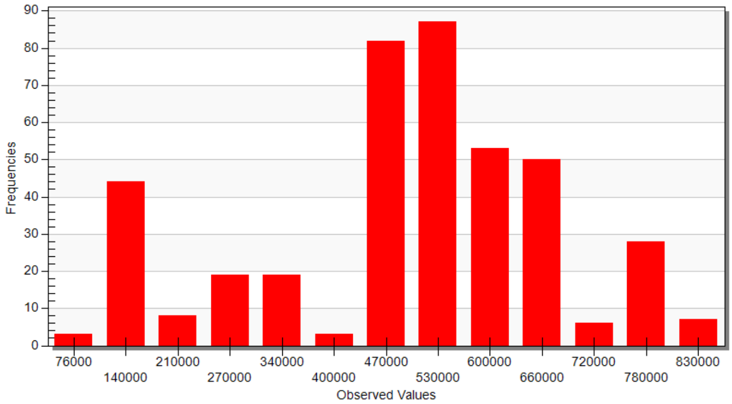
Figure 17 – Resulting distribution of frequencies for simulated data on national products



Source: Author (2023).

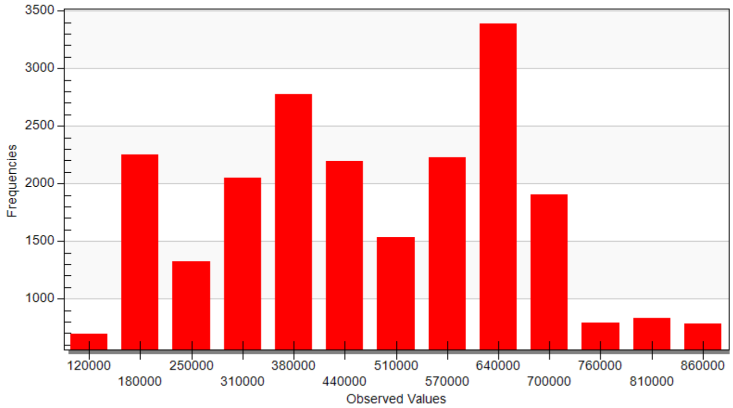
And for products that are imported, figures 16 and 17:

Figure 18 – Distribution of frequencies for collected data on imported products



Source: Author (2023).

Figure 19 – Resulting distribution of frequencies for simulated data on imported products



Source: Author (2023).

3.5 PROPOSED SCENARIOS

Following the studies of Gattuso, Cassone and Pellicanò (2014) and Sooksaksun and Sudsertsin (2014) the first proposed scenario to be compared to the base model scenario is the implementation of a RFID capability to the process, as stated by the authors, this technology promotes gains in efficiency for the receiving process with a theoretical range of 15% up to 20%, but with an real example of an 28,79% reduction on the receiving time. Due to the characteristics of the operation inside the warehouse that is the object of this study, only the imported products will receive the RFID capability, as all imported products are from an internal supplier.

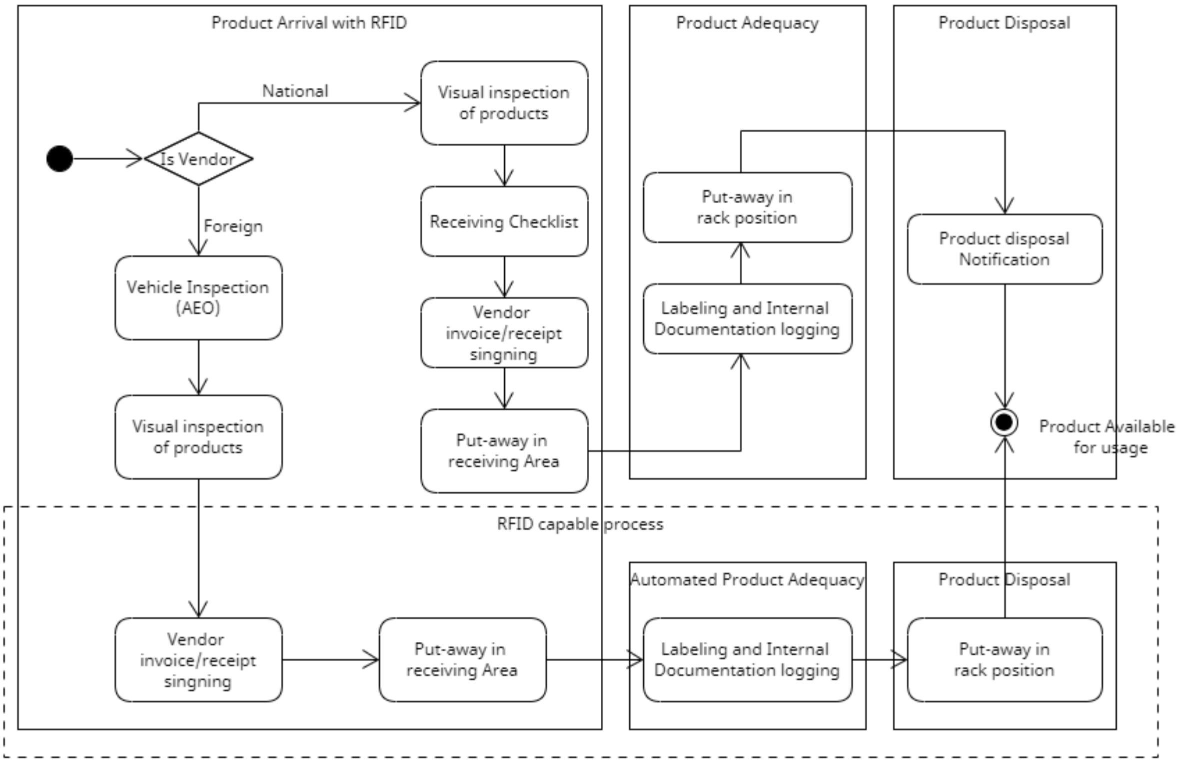
With the implementation of RFID and EDI, enabling automated data transfer, the internal WMS gains the capability to automatically transmit relevant data. Each imported product, equipped with an RFID tag, facilitates the seamless transfer of information, encompassing details such as the product invoice (and its signing), as well as the checklist containing quantities, purchase order, type of material, internal material identification, and other pertinent data.

This significantly impacts the primary bottleneck in the process, namely the labelling and internal documentation logging. With automation at this stage, the product can be directly allocated to its predetermined final position, complete with automated position verification and routing.

The actual data regarding the receiving process for the imported goods is then reduced by 20%, as a proposed gain in efficiency with the RFID technology. A new fit test to the data is conducted, giving a new probability distribution for the time enrolled between the product placement at the adequacy area and the final disposal notification: a triangular distribution with parameters c = 4:21:24:20.18, a = 2:28:48 and b = 7:23:32:48. The maximum time for the distribution of the "Receiving Buffer"is also reduced by 20%, with a new value for c of 16 minutes.

Figure 20 illustrates the applied RFID capability to the receiving process:

Figure 20 – RFID capable receiving process



Source: Author (2023).

The second scenario is to increase the number of operator available to receive products (from one to two operators). This model will be useful to compare the impact of a greater workforce versus the RFID implementation, being that the implementation of the technology is expensive, time consuming and needs the training of the staff. At last, a third scenario combining both the RFID and the additional staff is proposed.

4 RESULT ANALYSIS

The result analysis compares the results of the performance measures for the steady state of a queuing system (Table 1) and the cost model and service level trade offs (Figure 3). The $C1$ and $C2$ values found in equations 7 and 8 where considered as $C1$ = 1 monetary unit and $C2$ = 3 monetary units, to hide the true values considered by the company.

First, the receiving buffer that represents the product arrival in the mapped receiving process (Figure 4) has its results described in Frame 14 for the Base Model Scenario and Frame 15 for the proposed alternative scenarios:

Frame 14 – Results for the Base Model Scenario for Product Arrival

Measurement	Value	Unit
Utilisation Rate	75,10%	None
Busy Servers	100%	None
Mean time between arrivals	0:49:48	hours
Mean client waiting time	0:37:24	hours
Workload	1,2048	None
Service Rate	1,6043	Clients per hour
Arrival Rate	1,2048	Clients per hour
EOC	0,7510	Monetary unit
EWC	9,0480	Monetary unit
ETC	9,7990	Monetary unit
Optimum Service Rate	3.1060	Clients per hour

Source: Author (2023).

Frame 15 – Results for the Proposed Scenarios for Product Arrival

Measurement	RFID	Two Operators	Combined	Unit
Utilisation Rate	51,87%	64,24%	74,85%	None
Busy Servers	100%	100%	100%	None
Mean time between arrivals	0:58:38	0:58:13	0:57:46	hours
Mean client waiting time	0:30:25	0:37:24	0:43:14	hours
Workload	1,0233	1,0306	1,0387	None
Service Rate	1,9726	1,6042	1,3878	Clients per hour
Arrival Rate	1,0233	1,0306	1,0387	Clients per hour
EOC	0,5187	0,6424	0,7485	Monetary unit
EWC	3,2331	5,3892	8,9283	Monetary unit
ETC	3,7518	6,0316	9,6768	Monetary unit

Source: Author (2023).

In Frame 16 the comparison is displayed:

Frame 16 – Comparison of the Results with the Base Model Scenario for Product Arrival

Measurement	RFID	Two Operators	Combined
Utilisation Rate	69,07%	85,54%	99,97%
Busy Servers	100%	100%	100%
Mean time between arrivals	117,74%	116,90%	116%
Mean client waiting time	81,32%	100%	115,58%
Workload	84,94%	85,54%	86,62%
Service Rate	122,96%	100%	86,50%
Arrival Rate	84,94%	85,54%	86,62%
EOC	69,07%	85,54%	99,97%
EWC	35,73%	59,56%	98,68%
ETC	38,29%	61,55%	99,75%

Source: Author (2023).

As indicated by the results, introducing an extra operator to the Product Arrival step and incorporating RFID capabilities to imported products simultaneously does not necessarily ensure a higher Service Rate for the initial stage of the process. The noteworthy outcome is that the RFID implementation is solely enough to improve the effectiveness of this phase of the process, with an significant decrease in the ETC for the operation, as a reflex of the reduction in the client waiting time.

An improvement in the efficiency of the system was expected for the Combined Scenario, where both the implementation of the RFID technology and the addition of another staff member are implemented, but the results show a undermined waiting time and a comparable running cost. This happens as the L_q and L_s are similar to the Base Model Scenario, as for the scenario considering only the implementation of the RFID capability has significantly lower values, as shown by Frame 17:

Frame 17 – Comparison of the Results for Queue Length for Product Arrival

Measurement	Base	RFID	Two Operators	Combined
L_q	2,265	0,559	1,1540	2,2276
L_s	3,016	1,0777	1,7964	2,9761

Source: Author (2023).

These results show that a implementation of the RFID capability can increase the efficiency of the first step of the receiving process, before the product adequacy. A mean reduction of 18,68% in Utilisation Rate could be reached with a 61,71% reduction in the ETC for this step of the process.

As for the following step, Product Adequacy, the Base Model Scenario and two of the proposed scenarios show a violation of the stability condition 5, with an Arrival Rate superior to the Service Rate, generating infinite queues. Even with the considerable reduction of 20% to the first step of the receiving process on the RFID capable Scenario or the increase of available staff, the Service Rates for the base, additional staff and the RFID Capable Scenario show no significant reduction in the client waiting time, as shown by Frames 18, 20 and 19:

Frame 18 – Results for the Base Model Scenario Product Adequacy

Measurement	Value	Unit
Utilisation Rate	156,12%	None
Busy Servers	100%	None
Mean time between arrivals	36:55:11	hours
Mean client waiting time	57:43:25	hours
Service Rate	0,0173	Clients per hour
Arrival Rate	0,0270	Clients per hour

Source: Author (2023).

Frame 19 – Results for the RFID Capable Scenario Product Adequacy

Measurement	Value	Unit
Utilisation Rate	136,23%	None
Busy Servers	100%	None
Mean time between arrivals	39:06:52	hours
Mean client waiting time	53:15:00	hours
Service Rate	0,0187	Clients per hour
Arrival Rate	0,0256	Clients per hour

Source: Author (2023).

The only significant result for the Product Adequacy phase, in the isolated scenarios, is presented by the Additional Staff Scenario (Figure 20), where the utilisation Rate is decreased by 31,34%. This means that the additional staff has increased the efficiency of the process, but not enough to suffice the Arrival Rate and still generating an infinite queue, as shown by Frame 20:

Frame 20 – Results for the Additional Staff Scenario for Product Adequacy

Measurement	Value	Unit
Utilisation Rate	124,78%	None
Busy Servers	100%	None
Mean time between arrivals	41:58:10	hours
Mean client waiting time	52:22:57	hours
Service Rate	0,01909	Clients per hour
Arrival Rate	0,02382	Clients per hour

Source: Author (2023).

The final simulation result for the Product Adequacy step of the process, the Combined Scenario, also demonstrates a great decrease in utilisation rate, as shown by Frame 21, but just not enough to solve the bottleneck at the process:

Frame 21 – Results for the Combined Additional Staff and RFID Capable Scenario Product Adequacy

Measurement	Value	Unit
Utilisation Rate	100,99%	None
Busy Servers	100%	None
Mean time between arrivals	45:36:02	hours
Mean client waiting time	46:01:19	hours
Service Rate	0,0217	Clients per hour
Arrival Rate	0,0219	Clients per hour

Source: Author (2023).

As this is the main bottleneck reported by the company, the ideal Service Rate shown by the Equation 9 should be reached at this step to severely reduce the ETC of the process and decrease the number of products awaiting in queue for its adequacy and final placement inside the warehouse. As the condition p is still violated, the ETC cannot be calculated and is considered infinite also.

The optimum Service Rate for this step of the process is 0,3116, an increase of 14,36 times of the Service Rate presented by the Combined Scenario should be reached to optimise the ETC and the service level for this step of the process. The ETC if considered the optimal Service Rate is 0,2271 Monetary Units.

As for the final step of the receiving process, the Product Disposal at the final position and notification for the office operators, the Frame 22 shows the results for the Base Model Scenario:

Frame 22 – Results for the Base Model Scenario for Product Disposal

Measurement	Value	Unit
Utilisation Rate	101,17%	None
Busy Servers	100%	None
Mean time between arrivals	57:43:25	hours
Mean client waiting time	58:19:00	hours
Service Rate	0,0171	Clients per hour
Arrival Rate	0,0173	Clients per hour

Source: Author (2023).

A similar occurrence for the Combined simulated Scenario for the Product Adequacy is presented, as the Service and Arrival Rates are practically the same, resulting again in an infinite queue, as the utilisation rate is is still higher than 100%.

As for the proposed scenario, the scenario with the RFID implementation, the additional staff and the combined scenarios has its results in Frame 23:

Frame 23 – Results for the Proposed Scenario for Product Disposal

Measurement	RFID	Two Operators	Combined	Unit
Utilisation Rate	101,17%	101,63%	100,05%	None
Busy Servers	100%	100%	100%	None
Mean time between arrivals	53:15:00	52:22:57	46:01:19	hours
Mean client waiting time	58:19:00	54:17:27	46:17:07	hours
Service Rate	0,0171	0,0187	0,0216	Clients per hour
Arrival Rate	0,0173	0,0184	0,0217	Clients per hour

Source: Author (2023).

As demonstrated by the Combined Scenario for the Product adequacy and all the scenarios on Product Disposal, the current and proposed processes solutions were not sufficient for attending all the Arrival Rates of the process steps, generating infinite queues. This aligns with on-site observations at the company warehouse during the time frame of the collected data. The consequence is the incurring of additional costs for extra staff, external storage, and an operation running on overtime to mitigate the impacts of the demand.

As the overtime work and external storage was not considered for the scenarios, the simulations where spectated to show infinite queues on some scenarios, but as demonstrated by the results, all the measures implemented do not attend the Arrival Rates. Since the best results where attributed to the Combined Scenario, it is assumed that the implementation of the RFID technology, along with the addition of one employee as another operator dedicated to the receiving process, and considering some overtime working hours, the company should reduce the costs related to the client waiting times and ETC.

5 FINAL CONSIDERATIONS

This case study, along with the cited articles, demonstrates the widespread applicability of simulations for warehouse processes and their significant potential for implementation across various stages of the product supply chain. The primary challenge lies in the process mapping and the creation of a model capable of accurately replicating the real process within a software environment.

Once the base model is constructed and calibrated, the modeller can then introduce modifications, creating various scenarios to test, validate, and explore hypotheses. This approach opens up a vast array of possibilities, and if the implemented modifications to the base model prove to be reasonable and effective, the actual process can be adjusted based on what has been simulated, with an anticipated outcome.

Each step involved in modelling a simulation must be thoroughly researched, discussed, and implemented. Rushing or cutting corners in any of these steps can compromise the validity of the final simulation, potentially leading to the accumulation of errors. A dilemma arises as the modeller aims to incorporate the maximum level of detail and fidelity into the simulation, this is because limitations in software, available data, human and computational resources can impede the desired outcome or extend the development time. Balancing these considerations becomes crucial for achieving a meaningful and practical simulation as some premises have to be considered.

The applied heuristics for finding the steady state and run quantity have proven to be an effective tool for setting the simulation parameters considering the statistical significance of the output data, giving an 85% confidence that the 231 runs considering at the steady state will result in a reliable data source for the analysis for the performance of the scenarios. As stated by Ritter et al. (2011), the number of runs should maximise the results and not waste resources, then a heuristic based on a statistical method to determine the population (number of runs) of a sample (output) has solved this part of the modellers dilemma for this case study, and if a higher statistical confidence is needed then it should reapply Equation 18 for the desired confidence limit.

The fitting tests for the enrolled time between placement in the adequacy area for imported products (Figure 15) exhibited the most significant error in the fitted distributions compared to the actual data collected, amounting to 12.94%, and a final mean error of 15,4% for the whole process involving imported products. This discrepancy is attributed to the considerable variability associated with the type of product being received. As a limitation in this case study arises from the aggregation of different product subgroups, the combined gathered data shuffles values, making it challenging to fit the theoretical distribution to a specific frequency distribution accurately.

Another limitation is that the queuing theory is more adequate for exponentially distributed statistical distributions and for some of the fitted, and the overall simulation models, do not follow the frequency behaviour of these distributions. But at the same time, as Petrean (1998) pointed out, if only considered the strict queuing theory exponentially distributed statistical distributions the complexity of the analytical treatment of the system will become intractable.

For the DT construction and data collection, the surveys only indicated the perceived experience of the operators, if the warehouse had automated data collection mechanisms, such as EDI directly with vendors or an existing RFID implementation, relevant data concerning human interactions would have been systematically documented in a structured data set and would be easily extracted and analysed in real time by the WMS manager and any party. A reasonable future improvement to the process is the implementation of an EDI capability, not necessarily using RFID, but a system that can at least reduce the manual labour of referencing, labelling, and structuring the data relevant to the receiving process and its communication.

The simulation results reveal that the proposed scenarios are insufficient to meet the Arrival Rates within the specified time frame. However, if overtime hours, dynamically allocated staff, and external storage were taken into consideration in the proposed scenarios, it might be possible to achieve a practical solution using the methodology outlined in this case study. Further investigation is necessary to gather the relevant data regarding the overtime hours, how the dynamically allocated staff works and which criteria is used to send products for external storage, as these impact severely in the overall cost of operation for the warehouse.

Finally, as a recommendation to future studies, the collection of data must follow a well structured methodology and consider a time window much greater than the desired to the simulation model. Data sets that are already well documented in WMS data bases are extremely useful but must be validated, and any type of data collected regarding human interactions should be considered with uttermost care and consideration. As for the simulation model and scenarios, understanding the limitations of the modeller and the software are essential, the emphasis on research and calibration should also treated with care, as any premises, mistakes and overlooks can be catastrophic to the final simulation results.

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