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Abordagem Preditiva e Adaptativa de Gestão Operacional Aplicada à Cadeia de Suprimentos do Varejo Omni-Channel

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O presente trabalho em nível de doutorado foi avaliado e aprovado por banca examinadora composta pelos seguintes membros:

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Este trabalho é dedicado a Deus e a minha família

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"O êxito da vida não se mede pelo caminho que você conquistou, mas sim pelas dificuldades que superou no caminho.”. (LINCOLN, Abraham)

RESUMO

A evolução tecnológica e a digitalização possibilitam a comercialização de produtos através de múltiplos canais e plataformas de forma integrada, propiciando a gestão de varejo omni-channel. Esse processo contínuo de integração das tecnologias digitais/virtuais aos processos gerenciais físicos dos diversos canais influencia na interação das organizações com os clientes. O comportamento de consumo dos clientes é influenciado em decorrência do aumento da conveniência, tornando, contudo, a gestão operacional das cadeias de suprimentos do varejo mais complexa. Para a gestão da cadeia de suprimentos de varejo omni-channel a complexidade reside na incerteza, oscilações no volume de vendas e incompatibilidade entre oferta e demanda. Para lidar com essa complexidade é necessária a adoção de abordagens inovadoras relacionadas a tecnologias de informação e métodos de decisão inteligentes, destacados pela indústria 4.0. No entanto, ainda faltam pesquisas sobre a conexão entre os mundos digital e real, principalmente quando se trata de cadeias de suprimentos de varejo omni-channel, que se baseiam na integração de fluxos e atividades multicanais para melhor atender ao consumidor. Neste contexto, esta pesquisa tem como objetivo propor uma abordagem preditiva e adaptativa para a gestão operacional combinando aprendizado de máquina para minimizar a incerteza, e otimização baseada em simulação para lidar com a sincronização entre oferta e demanda, aplicada à cadeia de suprimentos do varejo omni-channel. Para isso foram identificados os métodos de aprendizado de máquina, de simulação e de otimização aplicados à cadeia de suprimentos e a indústria 4.0 com o intuito de apoiar a escolha do método de redes neurais e da otimização baseada em simulação por meio do algoritmo genético. O método de redes neurais e a otimização baseada em simulação foram analisados por meio de aplicação de um caso teste, visando identificar a aplicabilidade do método levantado na literatura, na gestão operacional da cadeia de suprimentos varejista omni-channel. Em seguida, a abordagem preditiva e adaptativa é aplicada a uma empresa varejista brasileira e como resultado um modelo de gerenciamento operacional de demanda e suprimentos é proposto para a cadeia de suprimentos varejista omni-channel. Os resultados da aplicação do modelo evidenciaram uma redução dos custos da cadeia de suprimentos, do tempo de entrega dos produtos e da quantidade de pedidos provenientes da incompatibilidade de oferta-demanda. Dessa forma, a tese possibilitou a redução das incertezas proveniente da previsão de demanda, redução da falta de produtos na cadeia, e consequentemente um melhor gerenciamento da distribuição da cadeia de suprimentos.

Palavras-chave: Varejo Omni-channel. Gestão da Cadeia de Suprimentos. Indústria 4.0. Aprendizado de Máquina. Otimização baseada em Simulação.

ABSTRACT

Technological evolution and digitalization enable the commercialization of products through multiple channels and platforms in an integrated way, providing omni-channel retail management. This ongoing process of integrating digital / virtual technologies into the physical management processes of the various channels influences the interaction of organizations with customers. Customer consumption behavior is influenced by the increase in convenience, however, making the operational management of retail supply chains more complex. For the management of the omni-channel retail supply chain the complexity lies in uncertainty, fluctuations in sales volume and incompatibility between supply and demand. To address this complexity, it is necessary to adopt innovative approaches related to information technologies and intelligent decision methods, highlighted by industry 4.0. However, there is still a lack of research on the connection between the digital and real worlds, especially when it comes to omni-channel retail supply chains, which are based on the integration of multi-channel flows and activities to better serve the consumer. In this context, this research aims to propose a predictive and adaptive approach to operational management combining machine learning to minimize uncertainty, and simulation-based optimization to deal with synchronization between supply and demand, applied to the omni-channel retail supply chain. For this, the machine learning, simulation and optimization methods applied to the supply chain and industry 4.0 were identified in order to support the choice of neural networks method and simulation-based optimization through the genetic algorithm. The neural networks method and the simulation-based optimization were analyzed by applying a test case, aiming to identify the applicability of the method raised in the literature, in the operational management of the omni-channel retail supply chain. The predictive and adaptive approach is then applied to a Brazilian retail company and as a result an operational demand and supply management model is proposed for the omni-channel retail supply chain. The results of the model application showed a reduction in the supply chain costs, in the products fulfillment time and in the quantity of orders resulting from the incompatibility of supply and demand. In this way, the thesis allowed reduce uncertainties arising from demand forecasting, reduce product shortages in the chain, and thereby better manage supply chain distribution.

Keywords: Omni-channel retailing. Supply Chain Management. Industry 4.0. Machine Learning. Simulation-based Optimization.

LISTA DE ABREVIATURAS E SIGLAS

ABS – Agent-Based Simulation

AG – Algoritmo Genético

AI – Artficial Intelligence

ANN – Artificial Neural Networks

APS – Automated Parcel Station

ARIMA – Autoregressive Integrated Moving Average

BOPS – Buy-online-pick-up-in-store

BPF – Best Performance Frontier

C&C – Click-and-collect

C&R – Click-and-Reserve

CAPES – Coordenação de Aperfeiçoamento de Pessoal de Nível Superior

CCI – Cross-channel Integration

CDC – Central Distribution Center

CEO – Chief Executive Officer

CFA – Confirmatory Factor Analysis

CLT – Constructive Level Theory

CSCMP – Conselho de Profissionais de Gerenciamento de Cadeia de Suprimentos

CSV – Comma-separated-values

DC – Distribution Center

EA – Evolutionary Algotithm

EFA – Exploratory Factor Analysis

ENI-P – Enterprise Network Integration

ERP – Enterprise Resource Planning

FMCG - Fast-moving-consumer-goods

GA – Genetic Algorithms

GIS – Geographic Information System

IBM – International Business Machines Corporation

IFAC – International Federation of Automatic Control

IoT – Internet of Things

JCR - Journal Citation Reports

LML – Last-Mile-Logistic

MA – Moving Average

MANOVA – Análise Multivariada da Variância

MLR – Multiple Linear Regression

MSE – Mean Squared Error

NAR – Nonlinear Autoregressive

NARX – Nonlinear Autoregressive with External Input

NN – Neural Network

OCC – Omni-Channel Consumer

OCRSC – Omni-Channel Retail Supply Chain

PCA – Principal Component Analysis

PLS – Regressão Parcial por Mínimos Quadrados

PPGEP – Programa de Pós-Graduação em Engenharia de Produção

PSO – Particle Swarm Optimization

RQ – Research Question

SBO - Simulation-based Optimization

SEM – Structural Equation Modelling

SC – Supply Chain

SCM – Supply Chain Management

SKU – Stock Keeping Unit

SLR – Systematic Literature Review

SS – State Space

STS – Ship-to-store

SVN – Support Vector Machine

UFSC – Universidade Federal de Santa Catarina

SUMÁRIO

1 INTRODUÇÃO

1.1 PROBLEMA DE PESQUISA

Os varejistas são dinâmicos por natureza e nas duas últimas décadas enfrentaram transformações disruptivas como mudanças de cenários, disponibilidade de novas tecnologias e o canal on-line, fazendo com que suas estratégias evoluíssem (KUMAR; ANAND; SONG, 2017; RIGBY, 2011; VERHOEF; KANNAN; INMAN, 2015). Segundo Galipoglu et al. (2018), os varejistas estão evoluindo rapidamente de canal único para multichannel, depois para cross-channel e agora para omni-channel.

Para Verhoef, Kannan e Inman (2015), o omni-channel é conceituado como "gerenciamento sinérgico dos inúmeros canais disponíveis e pontos de contato do cliente, de modo que a experiência do cliente nos canais e o desempenho nos canais sejam otimizados".

Saghiri et al. (2017) afirmam que o varejista omni-channel tem como objetivo coordenar processos e tecnologias em todos os canais, a fim de oferecer um serviço mais integrado, consistente e confiável aos clientes. Conforme Von Briel (2018), os varejistas terão que se adaptar ao omni-channel se quiserem competir no mercado, sendo que sua competitividade será baseada mais em sua habilidade de proporcionar ao cliente uma experiência holística do que ofertar e vender os produtos corretos.

Além disso Mirsch, Lehrer e Jung (2016) sustentam que os principais fatores para as empresas adaptarem a estratégia omni-channel como uma abordagem contemporânea com vários canais são o desenvolvimento tecnológico, a infraestrutura e a mudança nas necessidades dos clientes. Von Briel (2018) ainda afirma que a integração dos canais irá facilitar a gestão de inventário em tempo real, acelerar a distribuição e integrar a gestão da marca por meio dos canais.

No entanto, para os varejistas proporcionarem um processo integrado de decisão de compra por meio de múltiplos canais ainda é um desafio por terem restrições devido a dificuldade na integração dos canais e na estrutura organizacional descentralizada (BECK; RYGL, 2015). Pois, com a crescente variedade de formatos de canais e a progressão de um mercado único para multicanal e depois para o omni-channel, os varejistas tornaram o processo de compra mais conveniente para os compradores e mais difíceis de gerenciar para fornecedores a montante e revendedores a jusante (AILAWADI; FARRIS, 2017).

Byrne e Heavey (2006) e Tokar et al. (2014) sustentam que fatores como promoção, redução de preços e publicidade por varejistas podem causar incertezas nas demandas, e incertezas, distorções e flutuações são os maiores desafios para o planejamento colaborativo de previsão e reabastecimento da cadeia de suprimentos (CARBONNEAU; LAFRAMBOISE; VAHIDOV, 2008).

Wong et al. (2012) e Okada, Namatame e Sato (2016) argumentam que, devido à complexidade, incerteza e outros fatores envolvidos, a maioria das cadeias de suprimentos reais é conhecida por ter muitos problemas de incompatibilidade oferta-demanda, o que causa excesso ou falta de estoque, bem como atrasos de entrega, com consequentes danos ao nível de serviço oferecido. Fato comprovado por Gao et al. (2017) ao analisar o impacto do efeito de onda causado por interrupções nos processos de oferta, produção e distribuição na cadeia de suprimentos varejista, e destacar que os descontos de preços no mercado de varejo online geralmente amplificam o efeito chicote na cadeia de suprimentos de varejo online.

O efeito chicote foi inicialmente destacado por Forrester (1958) ao analisar que as flutuações na venda dos varejistas, provenientes do comportamento dos consumidores, afetam diretamente nas taxas de pedidos, na produção da fábrica, no estoque do armazém da fábrica e nos pedidos não preenchidos. Forrester (1958) ainda destaca que a visibilidade e confiabilidade das informações de vendas no varejo, proporcionará uma maior estabilidade da produção da fábrica.

Dessa forma, Tokar et al. (2014) afirmam que incertezas relacionadas a demanda poderiam ser reduzidas se agentes da cadeia de suprimentos compartilhassem informação com os agentes a jusante e a montante da cadeia de suprimentos. Kembro e Norrman (2019) destacam que, frente à tendência de estruturas de distribuição mais complexas e descentralizadas, o compartilhamento e coordenação da informação, entre e dentro dos nós de distribuição, é necessária por tornar possível a decisão de como e de onde os pedidos devem ser atendidos, possibilitar o manuseio de material mais eficaz e eficiente em cada nó, melhorar os níveis de serviço e diminuir os custos totais.

No entanto, além do compartilhamento da informação, ainda existem alguns desafios para implementar o canal online da maneira mais eficiente, tal como garantir a conformidade das entregas de produtos tanto nas lojas físicas como diretamente ao consumidor e redesenhar seus processos para criar uma experiência de compra perfeita (HÜBNER; WOLLENBURG; HOLZAPFEL, 2015).

Por uma perspectiva operacional, Yang e Zhang (2019) sustentam que a coordenação do fluxo de materiais e do fluxo de informações em toda uma cadeia de suprimentos cria situações em que todos os participantes dessa cadeia de suprimentos saem ganhando.

Chopra (2016) afirma que uma cadeia de suprimentos omni-channel bem estruturada apresenta as forças dos canais online e offline de forma complementares, fazendo com que a cadeia de suprimentos seja economicamente viável e responsiva ao cliente. Para que os varejistas alinhem e integrem esses canais e forneçam uma experiência perfeita ao cliente, o desafio é entender como múltiplos canais podem ser integrados, gerenciados e operados de maneira sinérgica (MARCHET et al., 2017; MIRSCH; LEHRER; JUNG, 2016).

Butner (2010) argumenta que as cadeias de suprimentos precisam se tornar "inteligentes", e de acordo com Schuster, Allen e Brock (2007) adotar uma infraestrutura inteligente para incorporar conjuntamente os dados, informações, produtos, objetos e processos de negócios. Neste mesmo sentido, Pantano, Priporas e Dennis (2018) destacam que o uso “inteligente” de tecnologias pode ser estendido aos processos varejistas para torná-los inteligentes, sendo que estas tecnologias inteligentes podem afetar os métodos de coletas de dados dos consumidores, a gestão da informação e a transferência de conhecimento entre empresas ao criar uma parceria entre clientes e varejistas.

Dessa forma, o Retail 4.0 ou o Smart Retailing representam os varejistas que fornecem interações dos consumidores com tecnologias inovadoras e com canais on-line e off-line, sem distinção, a fim de melhorar a experiência de compra dos consumidores de acordo com Vazquez, Dennis e Zhang (2017) e Lee (2017). Portanto, os benefícios do varejista smart são a melhor visibilidade dos produtos, o compartilhamento de informações e a cooperação smart entre todos os atores da cadeia de suprimentos segundo Pantano, Priporas e Dennis (2018).

Contudo, Liao et al. (2017) afirmam que ainda há um esforço de pesquisa ausente ou insuficiente na integração digital de ponta a ponta, que foi conceituada como integração em todo o processo de engenharia para que os mundos digital e real sejam integrados em toda a cadeia de valor de um produto e em diferentes empresas, além de incorporar os requisitos do cliente. Pantano, Priporas e Dennis (2018) também relatam a ausência de pesquisa relacionada sobre como pode ser realizada a integração das tecnologias smart no ambiente organizacional para que os varejistas alcancem rentabilidade no negócio.

Wollenburg, Holzapfel e Hübner (2019) ainda afirma que para os varejistas omni-channel, o gerenciamento de clientes com opções de atendimento são um novo tópico na prática e constituem uma nova área de pesquisa.

Portanto, para minimizar os fatores de incerteza relacionadas a demanda e possibilitar um melhor entendimento do consumidor no cenário dos varejistas smart, Gao et al. (2017) argumentam que escolher a melhor técnica de previsão para minimizar o efeito de chicote na cadeia de suprimentos de varejo online é de grande importância e deve ser uma prioridade para pesquisas futuras nesta área, e de forma complementar Lee (2017) e Pantano, Priporas e Dennis (2018) destacam que os varejistas são incentivados a dedicar investimentos na análise de big data dos consumidores como forma de aperfeiçoar a previsão, e Saghiri et al. (2017) sugerem a aplicação de um estudo analítico. Para maximizar a integração e visibilidade, e explorar as implicações operacionais / táticas de omni-channel da cadeia de suprimentos varejista, Ivanov (2017) enfatiza que o campo da modelagem de simulação ainda é um campo inexplorado e de grande benefício para analisar os detalhes e características dos elementos da cadeia de suprimentos.

Esta tese abordará a seguinte oportunidade de pesquisa: como sincronizar demanda e suprimento em uma cadeia de suprimentos varejista omni-channel?

1.2 JUSTIFICATIVA DO TEMA

A fim de coordenar todas as etapas, tipos, agentes de canais e diferentes funções das empresas tradicionais, o Supply Chain Management (SCM) tem como objetivo criar uma rede de valor, sincronizar demanda-suprimento, medir o desempenho global e construir uma infraestrutura competitiva (GAUR; GOEL; JAIN, 2015).

De acordo com o Conselho de Profissionais de Gerenciamento de Cadeia de Suprimentos (CSCMP, 2020), o SCM pretende integrar o gerenciamento de suprimento e demanda dentro e entre empresas, com a responsabilidade de vincular as principais funções empresariais e processos comerciais a um modelo de negócio coeso e de alto desempenho.

A sincronização da demanda com o suprimento também é destacada por Lee (2017) quando afirma que é necessário ter dois focos na gestão dos omni-channel, primeiro a identificação precisa da demanda e, em segundo, o posicionamento do produto no canal correto que irá suprir o cliente. Neste sentido, Shen e Chan (2017) afirmam que as informações sobre a demanda e o suprimento são igualmente importantes para o gerenciamento da cadeia de suprimentos.

Para garantir a sincronização e integração de toda a cadeia de suprimentos, Sarhani e El Afia (2015) afirmam que a identificação da demanda futura de um determinado produto é a base para otimizar a cadeia de suprimentos e os sistemas de reposição. E para Chen, Hsu e Blue (2007) a incerteza relacionada a demanda é a causa crucial do planejamento operacional ineficiente.

Aprender a identificar a demanda permite reduzir os custos de toda a cadeia de suprimentos de acordo com Yan-Qiu e Hao (2016), além de possibilitar a otimização das operações através do desenvolvimento de estratégias de aquisição e redução de custos de armazenamento ao otimizar o inventário (SARHANI; EL AFIA, 2015). Dessa forma, Boone et al. (2019) argumentam que as previsões orientam as decisões da cadeia de suprimentos, tornando extremamente importante devido ao aumento das expectativas dos clientes, a redução dos prazos de entrega e a necessidade de gerenciar recursos escassos.

Ishfaq e Raja (2018) destacam que os varejistas estão buscando alinhar seus processos tradicionais de distribuição baseados nas lojas físicas com os requisitos do canal on-line por meio da coordenação das atividades de gerenciamento de demanda e atendimento de pedidos.

A fim de minimizar a incerteza em relação à demanda e propor uma melhor integração da cadeia de ponta a ponta, Liao et al. (2017) afirmam que alguns esforços de pesquisa podem ser encontrados em relação à Data Science, como análise de dados em tempo real, integração de dados e Big Data Analytics, mas que poucas organizações estão investindo em tecnologias smart para gerir os big data conforme Pantano, Priporas e Dennis (2018). Shen e Chan (2017), Islek e Oguducu (2015) e Sarhani e El Afia (2015) identificaram que o uso de técnicas avançadas de aprendizagem de máquinas para inicialmente treinar a grande quantidade de dados e prever a demanda, fornece informações mais precisas na cadeia de suprimentos.

No contexto da previsão da demanda e do melhor gerenciamento do suprimento para a cadeia de suprimentos, os pesquisadores se diversificaram na escolha das abordagens para prever a quantidade e analisar o comportamento das vendas dos produtos e estruturar e otimizar os processos de distribuição.

Para melhorar o entendimento do perfil de consumidores, Yurova et al. (2017) aplicaram regressão parcial por mínimos quadrados (em inglês, Partial Least Squares - PLS) para desenvolver e avaliar um modelo de comportamento adaptáveis ao vender para consumidores omni-channel em todo o mundo. Balakrishnan et al. (2018) utlizaram algoritmos de clusterização para entender o padrão de consumo dos clientes para poder recomendar produtos aos mesmos. E Blom, Lange e Hess Jr (2017) buscaram demonstrar que o uso de dados digitais de consumidores em promoções pode ter uma reação positiva dos clientes e relevante performance no indicador do omni-channel pela aplicação da análise multivariada da variância (em inglês, Multivariate Analysis of Variance - MANOVA).

Para a análise do compartilhamento de informações de fornecimento, Shen e Chan (2017) salientam que ainda há uma lacuna na previsão de informações de suprimento para o gerenciamento da cadeia de suprimentos, mas que isso pode ser alterado pela aplicação de grandes tecnologias de dados. E na era dos grandes dados, a análise através da simulação é uma das abordagens mais significativas para prever a demanda e o fornecimento do mercado.

Visando a melhor maneira de estruturar a cadeia de suprimentos e consequentemente, a sincronização do fornecimento com a demanda, Modak (2017) desenvolveu um modelo matemático para abordar uma cadeia de suprimentos de canais duplos, sensíveis a preço, tempo de entrega e incerteza na demanda. Gallino, Moreno e Stamatopoulos (2017) aplicaram a regressão de curva de pareto para estudar os efeitos da introdução de funcionalidades do cross-channel na dispersão global de vendas dos varejistas e as implicações disto na gestão de estoque. Okada, Namatame e Sato (2016) descrevem uma ferramenta de simulação baseada em agentes para projetar redes de cadeia de suprimentos inteligentes, bem como redes logísticas.

Portanto, podemos identificar que tanto a demanda quanto os suprimentos impactam de forma significativa no desempenho um do outro em uma cadeia de suprimentos, principalmente ao lidar com uma cadeia de suprimentos varejista omni-channel que está em contato direto com o consumidor, e tem que atender suas necessidades por meio de uma gestão integrada de canais.

Com isso, é relevante que tanto a gestão e a operação da demanda e do suprimento na cadeia de suprimentos varejista omni-channel tenham que ser abordada em conjunto para minimizar as incertezas e a incompatibilidade de demanda com o suprimento. Segundo Kumar, Shankar e Alijohani (2019), as organizações precisam de um método que possa prever e obter uma imagem precisa das demandas do mercado para gerenciar com eficiência todos os aspectos importantes da cadeia de suprimentos, como produção, estoque, distribuição e pedidos.

Propondo essa gestão de forma integrada de demanda e suprimentos, Lee (2017) propôs um modelo de otimização baseado em algoritmo genético (AG) para suportar o envio antecipado dos produtos para os hubs, considerando apenas a relação entre o fornecedor e os centros de distribuição, além de assumir que todos os itens planejados seriam entregues de uma única vez, sem considerar restrições relativas à quantidade de produtos transportados. Pan et al. (2017) aplicaram a análise de série temporal e o problema de roteamento de veículos para propor uma abordagem inovadora ao usar dados relacionados ao cliente para otimizar a entrega em domicílio de uma mercearia, fazendo assim apenas a análise para a logística da última milha e não analisando a cadeia de suprimentos como um todo.

Assim, este trabalho identifica como uma oportunidade de pesquisa, no campo da cadeia de suprimentos varejista, a proposição de uma estrutura integrada e visível entre os canais e entre os elos da cadeia de suprimentos de ponta a ponta. Portanto, objetiva a aplicação conjunta de abordagens que incorpore a análise da previsão da demanda e que trate da estruturação da cadeia de suprimento de varejista, a fim de sincronizar a demanda e a oferta, e melhorar o gerenciamento operacional da cadeia de suprimentos.

Desta maneira, essa abordagem conjunta é considerada preditiva, por incorporar a previsão de demanda compartilhada com todos os elos da cadeia de suprimentos, e adaptativa, visto que, diante da determinação dos pontos de demanda, a cadeia possa identificar os pontos de estoque e analisar a melhor estrutura de distribuição dos produtos, adaptando assim a estrutura da distribuição frente a necessidade do cliente.

Devido à dificuldade de minimização das incertezas e a sincronização de uma cadeia de suprimentos, inserida no contexto do multicanal para um omni-channel, este trabalho estudará a aplicação de abordagens para a gestão operacional de demanda e de suprimentos de forma conjunta na cadeia de suprimentos varejista omni-channel.

1.3 OBJETIVOS

Considerando o problema de pesquisa apresentado, os objetivos geral e específicos desse estudo são apresentados a seguir.

1.3.1 Objetivo Geral

Esta pesquisa tem como objetivo propor uma abordagem preditiva e adaptativa de gestão operacional aplicada à cadeia de suprimentos do varejo omni-channel.

1.3.2 Objetivos Específicos

- Desenvolver uma abordagem de gerenciamento preditivo e adaptativo para cadeias de suprimento de varejo omni-channel;

- Aplicar a abordagem preditiva para realizar previsão de demanda e a abordagem adaptativa para sincronizar a demanda com o suprimento em uma cadeia de suprimentos varejista omni-channel.
- Analisar o desempenho da abordagem proposta em um caso de uso baseado em um cenário real de uma cadeia de suprimentos varejista omni-channel comparando com exemplos da literatura.

1.4 RELEVÂNCIA DO TRABALHO

A relevância da tese para o desenvolvimento científico e tecnológica consiste no desenvolvimento de um método para a gestão preditiva e adaptativa da cadeia de suprimentos varejistas, o qual integra previsão de demanda com a otimização baseada em simulação em um único sistema. Permitindo assim, a aplicação e análise conjunta das técnicas de previsão, otimização e simulação. Com isso, o resultado do estudo pode servir de suporte para novas pesquisas e teses a respeito da cadeia de suprimentos varejista e futuras aplicações do método em demais cadeias de suprimentos. Além de possibilitar um processo de tomada de decisões mais eficaz e assertivo no gerenciamento das cadeias de suprimentos varejistas brasileiras.

1.5 DELIMITAÇÕES

Para que se possa alcançar os objetivos propostos torna-se necessário a delimitação do problema ao presente trabalho.

No desenvolvimento da pesquisa bibliográfica e das análises bibliométricas foram adotadas as quatro bases de dados: Web of Science, Scopus, Emerald e EBSCO host. E para a seleção dos artigos a serem analisados um conjunto de critérios de exclusão foram adotados como informado no capítulo 3.

Devido a restrições e divergências em relação as questões legais e ambientais em cada país, este artigo não avaliará questões de logística fiscal e reversa para desenvolver um modelo que possa representar qualquer cadeia de suprimentos.

Esta tese também não avaliou as opções de buy-online-pick-up-in-store (BOPS), pois a empresa adotada nesta tese, iniciou recentemente esta possibilidade de fulfillment e não tinha dados suficientes para serem analisados. E por causa do sigilo dos dados dos clientes as vendas online foram analisadas em conjunto por estado e não de forma individual, pois foi a forma como a empresa permitiu a coleta dos dados.

1.6 ESTRUTURA

Este trabalho foi desenvolvido por meio da composição de cinco artigos. Dessa forma, este capítulo compreende a parte introdutória, no qual apresenta a introdução para caracterizar o problema e a justificativa da necessidade do desenvolvimento deste trabalho. Também foram apresentados os objetivos gerais e específicos pretendidos. Além disso, foram apresentadas a relevância e as limitações da execução deste estudo.

O capítulo 2 apresenta a metodologia adotada para o desenvolvimento deste estudo, na qual foi pautada na resolução 002/PPGEP/2015, de 24/04/2015, da Universidade Federal de Santa Catarina (UFSC) que dispõe sobre a elaboração de dissertação de tese de doutorado na forma de coletânea de artigos no Programa de Pós-Graduação em Engenharia de Produção (PPGEP/UFSC). Desta forma, seguindo a resolução este estudo é composto por cinco artigos relacionados e estruturados de forma a atingir o objetivo deste estudo. O enquadramento metodológico de cada um dos artigos, que classifica cada um dos artigos quanto à metodologia adotada, e o procedimento metodológico, que visa apresentar a relação e posicionar cada um deles no contexto da pesquisa, são apresentados no capítulo 2. Quanto a aspectos específicos acerca da formatação, alguns padrões foram adotados:

- Os capítulos 1, 2, 8 e 9 foram escritos na língua portuguesa e os capítulos 3,4,5,6 e 7 foram escritos na língua inglesa por se tratar de artigos que foram ou serão submetidos em jornais de comunicação internacional;
- As referências, citações e nomes das figuras e tabelas dos capítulos que adotaram a língua portuguesa estão no formato ABNT e as referências estão inseridas compiladas após o capítulo 9 em uma única referência;
- As referências dos capítulos de língua inglesa estão inseridas após seus respectivos capítulos, seguindo os padrões específicos das revistas as quais foram publicados, ou foram/serão submetidos. Da mesma forma, as citações, figuras e tabelas estão no padrão das revistas.

O capítulo 3 apresenta o primeiro artigo da coletânea, que consiste no desenvolvimento de uma revisão de literatura para identificar lacunas e oportunidades de pesquisa e consequentemente abordagens da logística e cadeia de suprimentos estão sendo apresentados na literatura ao varejista omni-channel.

O capítulo 4 apresenta o segundo artigo, no qual propõe um modelo conceitual para abordagem de gerenciamento preditivo e adaptativo para cadeias de suprimento de varejo omni-channel combinando aprendizado de máquina e otimização baseada em simulação.

O capítulo 5 que apresenta o terceiro artigo, desenvolve o modelo computacional do modelo conceitual desenvolvido no capítulo 4, para a abordagem preditiva baseada em aprendizado de máquina, com o objetivo de realizar a previsão de demanda para a cadeia de suprimentos varejista omni-channel.

O capítulo 6 tem o objetivo de desenvolver o modelo computacional da abordagem adaptativa em otimização baseada em simulação, para sincronizar a demanda com o suprimento em uma cadeia de suprimentos varejista omni-channel. Este é o quarto artigo do compêndio.

O capítulo 7 é o último artigo do compêndio, e analisará o desempenho da abordagem preditiva e adaptativa proposta em um caso de teste baseado em um cenário real de uma cadeia de suprimentos varejista omni-channel.

O capítulo 8 irá apresentar os resultados obtidos e o capítulo 9 a conclusão da tese.

2 MÉTODOS DE PESQUISA

Este capítulo é composto pelo enquadramento metodológico, o qual visa a classificação de cada um dos artigos quanto aos métodos adotados, bem como o objetivo e a questão da pesquisa, e também o procedimento metodológico, apresentando todas as etapas adotadas para o desenvolvimento desta pesquisa.

2.1 ENQUADRAMENTO METODOLÓGICO

Esta tese é composta por 3 fases principais, sendo que a fase 2 foi dividida em três etapas, 2.1, 2.2 e 2.3 respectivamente, para melhor estruturar o modelo conceitual e desenvolver as abordagens. As fases e etapas adotaram um quadro metodológico, apresentado no Quadro 1, que é conceitualizado por Miguel (2012):

Quadro 1 – Enquadramento metodológico.

Fases	Objetivo Específico da Tese	Objetivo da Fase	Questão de Pesquisa	Método de pesquisa
1. Abordagens para o gerenciamento do processo operacional na cadeia de suprimentos varejistas omni-channel (Artigo 1)		Realizar uma revisão bibliográfica e sistemática para identificar abordagens da logística e da cadeia de suprimentos aplicado aos varejistas omni-channel.	Quais abordagens da logística e da cadeia de suprimentos para o varejista omni-channel estão sendo relatadas na literatura para permitir o gerenciamento da operação integrada do canal?	1. Teórico 2. Qualitativo 3. Revisão sistemática da literatura
2.1. Abordagem de gestão preditiva e adaptativa para cadeias de suprimento varejista omni-channel (Artigo 2)	Desenvolver uma abordagem de gerenciamento preditivo e adaptativo para cadeias de suprimento de varejo omni-channel;	Propor um modelo conceitual para abordagem de gerenciamento preditivo e adaptativo para cadeias de suprimento de varejo omni-channel combinando aprendizado de máquina e otimização baseada em simulação.	Qual modelo de gerenciamento preditivo e adaptativo seria adequado para integrar e operacionalizar a cadeia de suprimentos varejista omni-channel?	1. Teórico 2. Qualitativo 3. Modelo conceitual

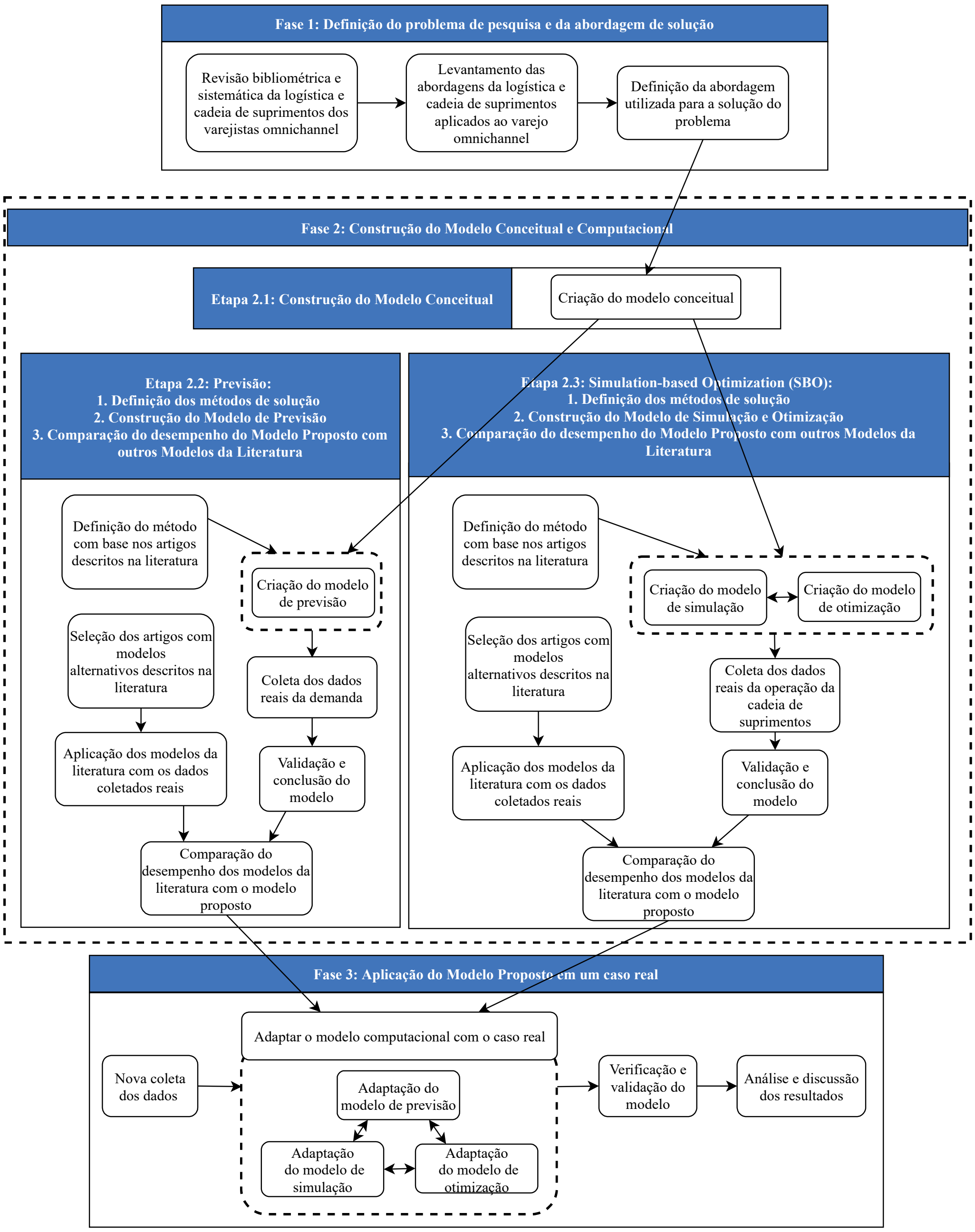
2.2. Aplicação da abordagem preditiva para a cadeia de suprimentos varejista omni-channel por meio da aprendizagem de máquinas (Artigo 3)	Aplicar a abordagem preditiva para realizar previsão de demanda e a abordagem adaptativa para sincronizar a demanda com o suprimento em uma cadeia de suprimentos varejista omni-channel.	1. Desenvolver o modelo computacional da abordagem preditiva baseada em aprendizado de máquina para realizar previsão de demanda; 2. Comparar o desempenho da abordagem desenvolvida com modelos alternativos descritos na literatura científica e / ou técnica.	Qual a abordagem mais apropriada para gestão operacional preditiva da cadeia de suprimentos varejista omni-channel?	1. Modelagem e Simulação 2. Qualitativo e quantitativo 3. Modelo conceitual com parte dos dados reais
2.3. Aplicação da abordagem adaptativa para a cadeia de suprimentos varejista omni-channel por meio da otimização baseada em simulação (Artigo 4)	Aplicar a abordagem preditiva para realizar previsão de demanda e a abordagem adaptativa para sincronizar a demanda com o suprimento em uma cadeia de suprimentos varejista omni-channel.	1. Desenvolver o modelo computacional da abordagem adaptativa em otimização baseada em simulação para sincronizar a demanda com o suprimento; 2. Comparar o desempenho da abordagem desenvolvida com modelos alternativos descritos na literatura científica e / ou técnica.	Qual a abordagem mais apropriada para gestão operacional adaptativa da cadeia de suprimentos varejista omni-channel?	1. Modelagem e Simulação 2. Qualitativo e quantitativo 3. Modelo conceitual com parte dos dados reais
3. Abordagem de gerenciamento de operações preditiva e adaptativa aplicada à cadeia de suprimentos varejista omni-channel (Artigo 5)	Analisar o desempenho da abordagem proposta em um caso de uso baseado em um cenário real de uma cadeia de suprimentos varejista omni-channel comparando com exemplos da literatura.	Aplicar e analisar o desempenho da abordagem proposta em um caso de teste baseado em um cenário real de uma cadeia de suprimentos varejista omni-channel	Quais as vantagens e desvantagens da aplicação do modelo proposto de gerenciamento de operações de forma preditiva e adaptativa de uma cadeia de suprimentos varejista omni-channel em um cenário real?	1. Modelagem e Simulação 2. Qualitativo e quantitativo 3. Modelo conceitual com parte dos dados reais

Fonte: Elaborado pela autora (2020)

2.2 PROCEDIMENTO METODOLÓGICO

Para satisfazer todos os objetivos deste estudo, foi adotado o procedimento metodológico representado na Figura 1, composto por cinco fases que servirão de base para o desenvolvimento dos cinco artigos. Em seguida, consta uma explicação de cada uma das fases de forma detalhada.

Figura 1 – Procedimento metodológico.



Fonte: Elaborado pela autora (2020)

2.2.1 Definição do problema de pesquisa e da abordagem para solução do problema

O primeiro passo consiste na análise da literatura sobre a aplicações da logística e da cadeia de suprimentos ao varejista omni-channel, que estão sendo relatadas na literatura, a fim de identificar tendências, aplicações práticas e principais jornais. Para isso, a pesquisa foi realizada nas bases de Scopus e ISI Web of Science. Para a análise de todo o material pesquisado, o software de análise de dados EndNote e Microsoft Excel foram adotados.

No segundo passo, a partir dos artigos levantados no primeiro passo pela revisão da literatura, foram identificadas as abordagens da logística e cadeia de suprimentos que estão sendo aplicadas ao varejo omni-channel que possibilitam o gerenciamento integrado dos canais. O objetivo deste estágio é identificar as principais abordagens adotadas, destacando a aplicação prática de cada um deles para auxiliar no processo de tomada de decisão e desenvolvimento de um novo modelo matemático e de simulação para a cadeia de suprimentos.

2.2.2 Construção do modelo conceitual e computacional

A segunda fase compreende o desenvolvimento de um modelo conceitual e computacional para abordagem de gerenciamento preditivo e adaptativo para a cadeia de suprimentos varejista omni-channel. Esta fase é composta por três etapas, sendo elas, a etapa 2.1, que é a construção do modelo conceitual, a etapa 2.2, que compreende o desenvolvimento do modelo computacional para a previsão, e a etapa 2.3, no qual foi desenvolvido o modelo computacional da otimização baseada em simulação.

Na etapa 2.1, foi proposto um modelo conceitual para abordagem de gerenciamento preditivo e adaptativo para cadeias de suprimento de varejo omni-channel combinando aprendizado de máquina e otimização baseada em simulação. Para isso, foram determinadas a estrutura da cadeia de suprimentos e a integração dos fluxos de informação, materiais e financeiros.

A cadeia de suprimentos varejista é composta por clientes, varejistas, representados pelo canal off-line e canal online, centro de distribuição regional, centro de distribuição central e um fornecedor, e embora seja uma cadeia genérica de suprimentos varejista omni-channel, suas entidades e relações procuram representar as cadeias de suprimentos varejista apresentadas na literatura e em cenários reais.

Para que o gerenciamento de cadeia de suprimentos varejista omni-channel ofereça uma abordagem preditiva, propôs-se a análise da demanda por meio de técnicas de big data, como a aprendizagem por máquina, e para exibir uma abordagem adaptativa para a coordenação da demanda e oferta, foi proposta a aplicação da otimização baseada em simulação.

Para tornar possível o gerenciamento preditivo e adaptativo da cadeia de suprimentos de lojas online, esse modelo conceitual pressupõe que a cadeia de suprimentos integrou tecnologias de informação e comunicação para permitir o compartilhamento de informações em tempo real e o processo inteligente de tomada de decisão.

O modelo conceitual também foi projetado para apresentar um cumprimento integrado das ordens, para levar a um nível de serviço mais alto para os clientes, e informações sobre produtos para iniciar as ações corretivas necessárias em casos de desajuste em estoque. Uma vez que a gestão conjunta das duas integrações permite a visibilidade do produto, demanda, inventário, envio / entrega e suprimentos.

O aprendizado da máquina foi proposto para prever a demanda, a fim de fornecer uma melhor identificação do comportamento do cliente, redução das incertezas relacionadas à demanda e, consequentemente, antecipar a execução dos processos de distribuição da cadeia de suprimentos.

Na aplicação do aprendizado da máquina, são propostos dois tipos de análise: agrupamento, para identificação do comportamento do cliente pela aplicação de algoritmos de agrupamento e, em seguida, previsão de demanda, pela aplicação de redes neurais à previsão de demanda de cada produto de cada uma das lojas.

A otimização baseada em simulação foi proposta para analisar o comportamento da cadeia de suprimentos varejista omni-channel, se adaptar às incertezas das previsões e demandas reais, e reduzir o tempo de execução, ao realizar as atividades de distribuição com o menor tempo de entrega e custo.

Para reduzir o tempo de entrega, esta cadeia de fornecimento propôs a antecipação do processo de distribuição, e porque este processo é baseado em uma previsão de demanda e pode ter incompatibilidade entre demanda real e previsão, neste modelo também foi proposto o processo de verificação para se adaptar a essas distorções e garantir a venda do produto ao cliente.

Na etapa 2.2 do procedimento metodológico, o modelo computacional preditivo para a cadeia de suprimentos varejista omni-channel foi proposto e desenvolvido com base no modelo conceitual apresentado na etapa 2.1.

Para realizar a identificação das abordagens, os artigos que fizerem uma aplicação prática dos métodos propostos foram selecionados das bases de dados Scopus, ISI Web of Science, Emerald e EBSCO host.

Por meio dos artigos levantados na literatura foram identificadas as abordagens e métodos adotados para analisar a demanda da cadeia de suprimentos varejista omni-channel, e reafirmado a adoção das abordagens de agrupamento e redes neurais para melhorar a análise do comportamento do consumidor e redução das incertezas provenientes da demanda.

A fim de analisar se o aprendizado de máquina possibilita uma gestão preditiva para a operação da cadeia de suprimentos varejista e consequentemente redução das incertezas desta cadeia, foi realizado a aplicação do modelo em um caso real.

Posteriormente, foi realizada uma comparação do modelo desenvolvido com modelos já apresentados na literatura e com a abordagem adotada atualmente pela organização, os quais foram utilizados como benchmark, para comparar os resultados obtidos e destacar as vantagens e desvantagens do modelo desenvolvido. Nesta fase foram adotados dados reais de demanda para que se possa ajustar o modelo de previsão para um cenário real e comparar com outras abordagens.

O software adotado nesta etapa é o software de modelagem matemática Matlab.

A terceira etapa consiste no desenvolvimento de uma abordagem para a gestão operacional adaptativa da cadeia de suprimentos varejista omni-channel, e do modelo computacional desta abordagem.

Para identificar abordagens para a gestão operacional adaptativa foram adotados os artigos que fizerem uma aplicação prática nas bases de dados Scopus, ISI Web of Science. As abordagens foram levantadas e foi destacado a adoção da otimização baseada em simulação como uma abordagem eficaz para representação de uma cadeia de suprimentos adaptativa. Além de identificar diante de diversas heurísticas e meta-heurísticas que o algoritmo genético é uma abordagem capaz de realizar a otimização da alocação dos pedidos para cada agente da cadeia de suprimentos.

Nesta etapa foram adotados dados reais e dados provenientes da literatura para a operação da cadeia de suprimentos, a fim de ajustar o modelo de SBO para um cenário real e possibilitar a análise do desempenho do sistema.

Com o intuito de avaliar o desempenho da abordagem adaptativa, foram analisados dois contextos. O primeiro contexto foi por meio da simulação e o segundo com a otimização baseada em simulação. Para isso, foi adotado o software Anylogic.

E para a comparação dos contextos foram gerados gráficos, no software Excel, com o resultado do sistema a fim de comparar o desempenho dos modelos.

2.2.3 Aplicação do Modelo Proposto em um caso real

Na terceira fase, o modelo desenvolvido será aplicado em uma cadeia de suprimentos varejistas, para propor um modelo preditivo e adaptativo para o gerenciamento operacional omni-chanel. O objetivo é propor uma abordagem de gestão para a cadeia de suprimentos varejistas omni-channel, a fim de sincronizar demanda e oferta e reduzir os custos de logística.

Os dados foram coletados no banco de dados da empresa e foram inseridos no modelo computacional. Caso seja necessário serão realizadas alterações no modelo computacional para representar de forma fidedigna a operação e o comportamento do varejista.

Para avaliar o desempenho da abordagem desenvolvida na fase 2, foram analisados três contextos. O primeiro contexto será sem a aplicação do aprendizado de máquina e otimização baseada em simulação para o gerenciamento de operação preditiva e adaptativa, o segundo foi sem a aplicação do aprendizado de máquina e com otimização baseada em simulação, e o terceiro foi com a aplicação da aprendizagem de máquina e da otimização baseada em simulação.

O software adotado neste passo é o software de simulação Anylogic e o software R. Estes softwares foram adotados, porque ao compará-los com outros do mercado, estes apresentaram um pacote de simulação e modelagem matemática, respectivamente, mais completos e que permitem uma interface mais fácil demais softwares. A substituição do software Matlab para o software R ocorreu pelo fato do Matlab apresentar um tempo computacional alto, o que inviabilizaria a aplicação prática da abrodagem. E para a comparação dos contextos e elaboração dos gráficos foi adotado o software Excel.

3 APPROACHES TO MANAGE AND OPERATE THE OMNI-CHANNEL RETAILING SUPPLY CHAIN

Marina Meireles Pereira, Enzo Morosini Frazzon

Abstract: The advance of technology has changed the relation between retailers and customers. This scenario has created an environment where a client does not need to move to store but can purchase online from home. The challenge to retailers is how to synchronize the offline and online channels to better attend the customer's needs. Then, the purpose of this article is to, through a literature review, identify which approaches are being applied to the omni-channel retailer to enable the integrated channel management, mainly approaches applied in real cases. A systematic literature review method is adopted, and to conduct the research the methodology of content-analysis based literature review was applied. The articles were analyzed and categorized initially by the deductive approach and later, for the identification of the approaches, by the inductive basis. The growing need to jointly address demand and supply issues was identified to enable supply chain integration and the small amount of papers applied in real cases. The originality of this paper consists in identifying approaches used to deal with multiples themes and to integrate the omnichannel retailing, a topic that is gaining visibility but with few practical applications.

Keywords: Supply Chain, Omni-channel retailing, Literature review.

3.1 INTRODUCTION

Traditional retailers are undergoing a major transformation brought about by the impact of technological advancement on their organizations. By blurring the barrier between physical and virtual environments, according to Chen, Cheung, and Tan (2018), Brynjolfsson, Hu, and Rahman (2013) and Marchet et al. (2018) the new approach called omni-channel is emerging to manage and operate retailers. The concept of omni-channel for Verhoef, Kannan, and Inman (2015) consists of the "synergetic management of the numerous available channels and customer touchpoints, in such a way that the customer experience across channels and the performance over channels is optimized".

In agreement with Chen, Cheung, and Tan (2018) the adoption of omni-channel enables retailers to have a better understanding of the consumer behavior of each channel by applying technologies that allow the analysis of customers' buying behavior of both virtual and physical channels, and therefore a more personalized service experience. Li et al. (2018) also emphasize that omni-channel would empower retailers in retaining customers by reducing uncertainty, providing attractive offers, and engendering switching costs, and for Marchet et al. (2018) lead to a competitive advantage by sales growth and revenue increase.

To fully comprehend consumer behavior and meet their needs, from all available shopping channels, retailers must go one step further affirm Mirsch, Lehrer, and Jung (2016). To Ishfaq et al. (2016), to provide a seamless consumer experience, retailers need to align their physical and virtual channels through actions such as coordinate the order management, fulfillment, and logistics process, and for Verhoef, Kannan, and Inman (2015) by integrating customer-brand-retail channel interactions.

In order for retailers to align and integrate such channels and provide a seamless customer experience, the challenge is to understand how multiple channels can be integrated, managed and operated (Marchet et al. 2018; Mirsch, Lehrer, and Jung 2016). Daugherty, Bolumole, and Grawe (2019) affirm that to deal with the complexity and time pressures associated with omnichannel and online retailing, logistics can provide the coordination to integrate supply chain activities.

Conforming Galipoglu et al. (2018), the key areas that shape business activities and determine the channel structure for retailers are marketing, logistics and supply chain. Piotrowicz and Cuthbertson (2014) sustain that supply chain investments are the key issue in channel integration, and activities such as product availability, returns, delivery options, reverse flows, and inventory management across channels should be addressed. Chopra (2016) states that a well-structured omni-channel supply chain presents the strengths of online and offline channels in a complementary way, making the supply chain economically viable and customer responsive.

To Murfield et al. (2017), logistics and transportation are directly linked to retailer’s success, being considered as the main pillar of any omni-channel strategy, and for CEOs surveyed are the key to satisfying omni-channel consumer demands. Wollenburg et al. (2018) sustain that innovative logistics networks need to fulfill customer expectations particularly in terms of high-delivery speed, high-product availability and low-delivery costs, while retailers need to manage their own costs and complexity arising from different channels and network options.

Ishfaq and Raja (2018) point out that retailers are looking to align their traditional distribution processes based on physical stores with the requirements of the online channel through the coordination of demand management and order fulfillment activities.

Lee (2017) states that it is necessary to have two focuses on the management of omni-channels, first the precise identification of demand and, second, the positioning of the product in the correct channel that will supply the customer. Sarhani and El Afia (2015) sustain that identifying future demand for a given product is the basis for optimizing the supply chain and replacement systems.

Learning to identify demand allows to reduce the costs of the entire supply chain according to Yan-qiu and Hao (2016), in addition to enabling the optimization of operations through the development of acquisition strategies and reduction of storage costs by optimizing the inventory (Sarhani and El Afia 2015). Thus, Boone et al. (2019) argue that forecasts guide supply chain decisions, being extremely important due to increased customer expectations, reduced delivery times and the need to manage scarce resources.

From an operational perspective, Yang and Zhang (2019) argue that the coordination of material flow and information flow across a supply chain creates situations in which all participants in that supply chain win. According with Wollenburg, Holzapfel, and Hübner (2019), customer management with fulfillment options is a new topic in practice and constitutes a new research area.

In this context, this research aims to identify approaches of logistics and supply chain applied to omni-channel retailing that enable the operation management of the activities, through the synchronized management of materials and information, to achieve the integration management of channels and satisfy the consumers' need. For that purpose, we seek to answer the following research question (RQ):

RQ: What approaches of logistics and supply chain to the omni-channel retailer are being reported in the literature to enable the channel integrated operation management?

To answer these research question, we perform a bibliographic and systematic review based on content-analysis-based literature review proposed by Seuring and Gold (2012). The main contribution of this article is to identify how, by surveying which innovative approaches and methods, omni-channel retailers are managing and operating their activities in an integrated way. The paper is structured as follows: Section 2 provides a literature review regarding logistic and supply chain of omni-channel retailer. Section 3 presents the adopted methodology. The evaluation of the material in order to identify the approaches of the logistics and the supply chain applied to the omni-channel retail is presented in Section 4. Lastly, a conclusion and future research outlook is presented in Section 5.

3.2 LITERATURE REVIEW

According to Melacini et al. (2018), the omni-channel retailing is first of all a major logistic challenge, being necessary to create new logistics models, because the management and operation of e-commerce differs from the traditional retail in many aspects such picking and delivery process. To Ailawadi and Farris (2017) retailers and suppliers need to construct, manage and reward together many types of channels to match how customers want to search, buy and return.

As logistics and supply chain are considered the main areas to integrate, manage and operate the omni-channel retailer, and the understanding of how to develop those activities the challenge for omni-channel retailers, is important to analyze in the literature approaches of logistic and supply chain that are already being applied to omni-channel retailer.

Some papers have already evaluated logistics and supply chain approaches for the omni-channel retailer.

At the strategic level, Marchet et al. (2018) focused to understand how companies set the logistics variables in their omni-channel management strategy. It was identified, by the application of cluster analysis, four distinct business logistics models: separated model, integrated warehousing model, store-based model, and multiple-configuration model. They found out that channel integration and coexistence of multiple configurations, according to product characteristics and customer requirements, are the main enablers of the omni-channel retailer.

Galipoglu et al. (2018) reveal the intellectual foundation of omni-channel retailing research, and also identified, evaluated and structured the literature of omni-channel retailing from the perspective of logistics and supply chain management. They identified that the foundations regarding omni-channel retailing are originated from the fields of marketing, mainly the marketing channel field. Galipoglu et al. (2018) suggest that there still a lack of research regarding omni-channel retail logistics, mainly those which address logistic and supply chain solutions to omni-channel retailing, considering a promising research topic and proposing the development of researches in the front of theories for solving typical omni-channel retailing related logistics and supply chain problems.

Adopting the focus on channel transition, Beck and Rygl (2015) developed the studied in order to categorizes and conceptualizes retailing by means of its channel interaction and integration, differentiating the Multi-, Cross-, and Omni-Channel; and the transition into an omni-channel of the fashion retailing according to McCormick et al. (2014). Chen, Cheung, and Tan (2018) analyze the opportunities and challenges in the omni-channel business; and Mosquera, Pascual, and Ayensa (2017) understood the customer experience in the omni-channel scenario. And focusing on channel integration Mirsch, Lehrer, and Jung (2016) approached the omni-channel management transformation due to the channel integration.

Focusing on sales, Cummins, Peltier, and Dixon (2016) developed a review to analyze components importance, such as selling process, impact of technology, and the role of various communication tools and platforms, to sales and sales management.

Approaching channel format, Härtfelder and Winkelmann (2016) perform a systematic overview to investigate the influence of mobile internet devices in a local retailer environmental. With the focus on the mobile channel format, which include smartphone and mobile device, they highlighted that most research activities are concentrated in areas such marketing, e-commerce and information systems, and due to the fact that clients path across different channels, retailers need to offer experienced services as well as create effective marketing campaigns.

At an operational level, Melacini et al. (2018) examined the main issues relating to e-fulfilment and distribution experienced by companies shifting towards omni-channel throughout the dimensions: distribution network design, inventory and capacity management, delivery planning and execution dimensions. They also declare that both simulation and analytical models are the methodologies used by many of the examined papers.

Analyzing activities of distribution related to e-commerce, Lim, Jin, and Srai (2018) developed the systematic review in order to examine the interface between e-commerce and Last-Mile-Logistic (LML). When analyzing the LML distribution structure, it was observed that the most adopted structure is the push-centric, followed by pull-centric, and the least used is the hybrid system, but is important to emphasize that the hybrid system is being considered an emerged structure, which align capacity performance excellence, availability-sensitive markets and markets where consumer's priorities physical (over time) convenience. Lim, Jin, and Srai (2018) state that analytical modelling and simulation were the most applied methods followed by statistical methods and survey. Savelsbergh and Van Woensel (2016) approached the challenges and opportunities of city logistics and identified that highly dynamic and volatile decision-making environments with access to massive amounts of near real-time data will be the future research. Yu et al. (2017) also present the state-of-the-art of E-commerce logistics in supply chain management and highlight that technologies like Internet of Things (IoT), Big Data Analytics, and Cloud Computing can assist in the development of e-commerce logistic.

Mou, Robb, and DeHoratius (2018) provided an overview of recent research on retail store operations and analyzed the influence of themes, such as uncertainty, channel integration, market competition, perishability, among others, in store operation. They identified that when analyzing the current research based on store operations decisions, 87% of the papers reviewed cope with one store operations decision. They argue that this may be the result of a trade-off between research relevance and computational complexity but limit the applicability of academic research by the fact that store managers frequently face multiple store operations decisions and research theme simultaneously. Thus, they suggest the need for further research in the interface between multiple decisions and themes.

As can be observed, some literature review initiatives of logistics and supply chain have already started, but in specific areas such as channel format and integration, and e-commerce distribution, last mile and sales. It was found that there is an absence of research that analyzes the approaches of logistic and supply chain, focusing multiple decisions and themes, that are making possible the how to operate the omni-channel retailing.

Therefore, to field the gap of researchers concerning the logistic and supply chain solutions, and improve the understanding of how to integrate and operate the omni-channel retailing, this article aims to raise all the approaches that are being applied to the supply chain omni-channel retailer to improve the information and material flow, by means of a review of the literature.

3.3 METHODOLOGY

A systematic literature review (SLR) was selected as the research method for this study because this method enables to find and aggregate all relevant studies concerning our research question. In order to structure the research and allow the replicability, this study followed the methodology of content-analysis based literature review proposed by Seuring and Gold (2012), which is composed by four steps, presented in Figure 1. These four steps are detail in the following subsections.

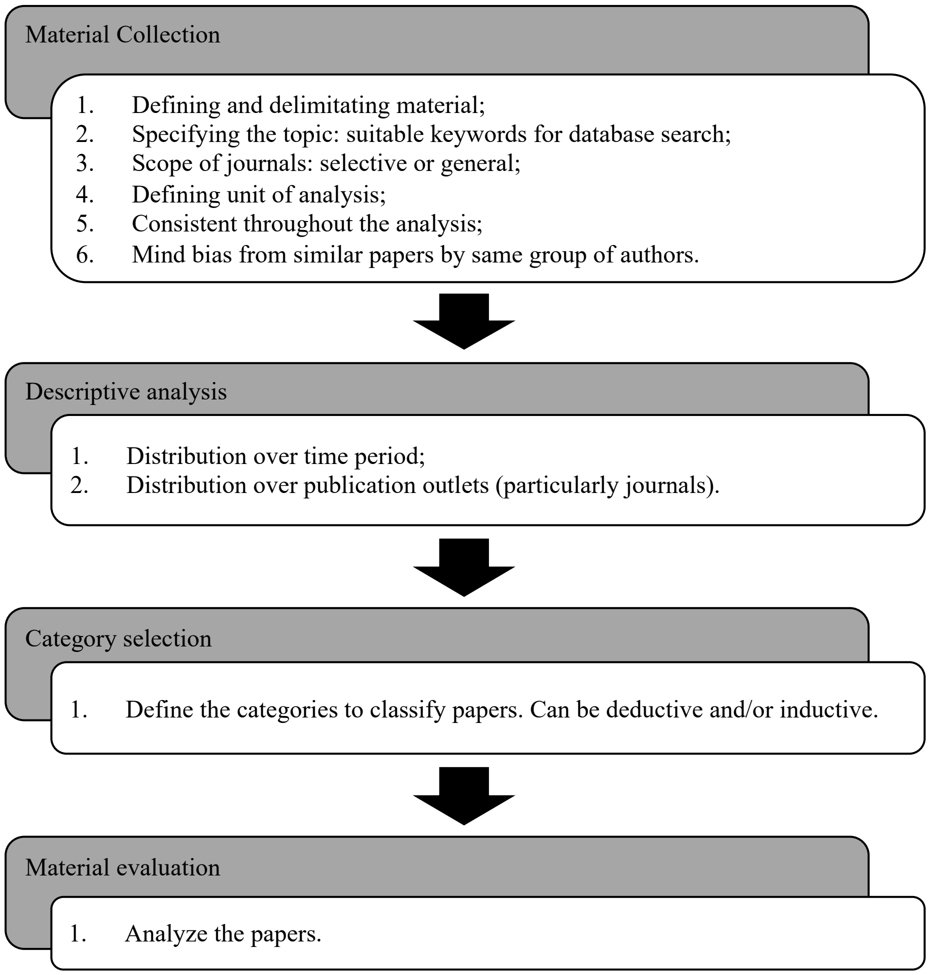


Figure 1 – Methodology adopted from Seuring and Gold (2012)

3.3.1 Material Collection

To develop the material collection, the search was conducted in the Scopus and ISI Web of Science databases without any restriction regarding the period of paper publications. Since the aim of this paper is to identify the approaches of logistic and supply chain applied in omni-channel, it was used a pair of keyword pertaining to both areas ("omni-channel" OR "omni-channel" OR "omni channel"), ("logistic*" OR "supply chain" OR "supply chain management" OR "retail*") and ("demand" OR "forecast*" OR "predict*" OR "supply" OR "distribution" OR "fulfilment" OR "fulfillment") to be found in title, keywords or abstract.

To ensure that the articles were related to the area of this research, the selected articles were related to Industrial/Manufacturing/Production Engineering fields such as engineering, business, computer science, decision science and mathematics. And the unit of analysis adopted were conference/proceedings papers, journals and papers.

The research was carried out in January 2020 and a total of 168 articles were identified as presented in Figure 2. However, it was identified and excluded duplicated articles. Using Endnote software 66 articles were excluded.

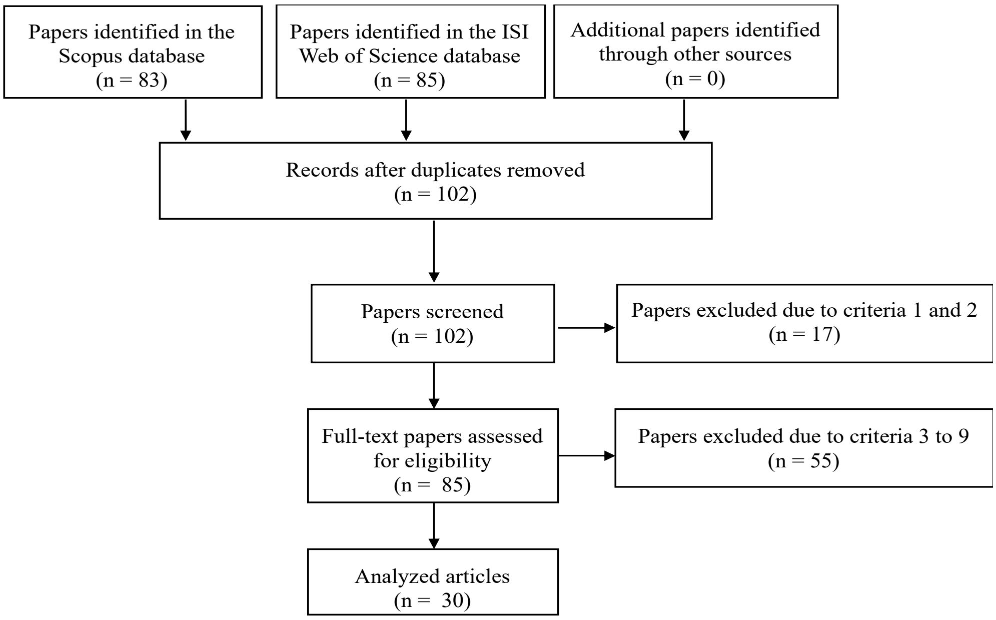


Figure 2 – Phases of the systematic literature review

Subsequently, in order to identify available papers and those which really deal with the topics addressed, a processing step composed by eight exclusion criteria based on Liao et al. (2017) was adopted, as it can be seen in Table 1.

Table 1 – Exclusion criteria and their descriptions

Criteria	Criteria description
1	An article does not have its full text in English
2	A paper without full text to be assessed
3	Articles with no context of logistics, retail, supply chain management and omni-channel
4	Articles focusing only in one channel
5	Omnichannel is only used as an example
6	Omnichannel is only used as a part of its future research direction
7	Omnichannel is only used as a cited expression
8	Only Literature review papers
9	Articles focusing only in one theme

With the reading of the titles and the abstracts, and if necessary, reading the complete article, 72 articles were excluded because they were classified into the exclusion criteria. Thus, after the collection of articles and their exclusions, 30 articles will be analyzed in order to raise the adopted approaches.

3.3.2 Descriptive Analysis

From the selected articles in the material collection stage, were carried out the distribution analysis of the articles over time, in order to understand how is the evolution of the research, and the distribution analysis by the journals. In order to develop this phase, the data set was transferred to the software Excel.

3.3.3 Category Selection

In order to improve the comprehension of the paper's approaches, we adopted a two-step-process. We first classified the papers on a deductive basis based on the classification applied by Uhlmann and Frazzon (2018), which classified the papers in two parameters: by way of approach, being discussion, theoretical and practical solution, and the second by the level of integration, being vertical, horizontal or end-to-end integration.

According to Kagermann, Wahlster and Helbig (2013), the vertical integration consists in the system integration at the different hierarchical levels, the horizontal integration is the system integration in the different stages of the manufacturing and business planning processes within a company, and end-to-end is the integration of engineering across the entire supply chain.

Then, we adopted the inductive basis to determine the analyzed theme and the data analysis methods of each paper.

3.3.4 Material evaluation

After categorizing the papers, the sample of selected articles is analyzed according to these categories and methods, and the results are presented and discussed, with the aim of providing some practical guidance to researchers.

3.4 RESULTS

This topic, presents the discussion on the identification and application of approaches of logistic and supply chain that are being applied to manage, integrate and operate the omni-channel retail.

3.4.1 Descriptive Analysis

The first descriptive analysis is related to the main journals that are publishing on the addressed subject, in order to understand which journals are contributing to the construction and dissemination of knowledge. Table 2 shows the quantity of published papers per journal and 23% of the papers were published in conference proceedings. When analyzing the journals, the authors found that it is also worth noting that 66% are classified in the Incites Journal Citation Reports - JCR (Clarivate Analytics).

Table 2 – Publications by the number of papers in the dataset

Journal	Quantity
International Journal of Production Economics	2
Journal of Business Research	2
Computers in Industry	1
Decision	1
Discrete Dynamics in Nature and Society	1
Ifac Papersonline	1
Information (Switzerland)	1
Interfaces	1
International Journal of Electronic Commerce	1
International Journal of Logistics Management	1
International Journal of Physical Distribution and Logistics Management	1
International Journal of Production Research	1
Journal of Business Logistics	1
Journal of Retailing and Consumer Services	1
Journal of the Operational Research Society	1
Logforum	1
Logistics Research	1
Production Planning and Control	1
Spanish Journal of Marketing - ESIC	1
Supply Chain Forum	1
Total Quality Management and Business Excellence	1

The second descriptive analysis aims to understanding how the evolution of research that deals with logistic, supply chain and omni-channel retail. Figure 3 shows the number of publications over the years. It is possible to identify that the analysis of the multiple themes of logistics and supply chain applied to the omni-channel retailer is recent, with the first publication in 2014. It can still be seen that from 2018 to 2019 the increase was 116%, and this indicates an increase in interest in the study of multiple themes.

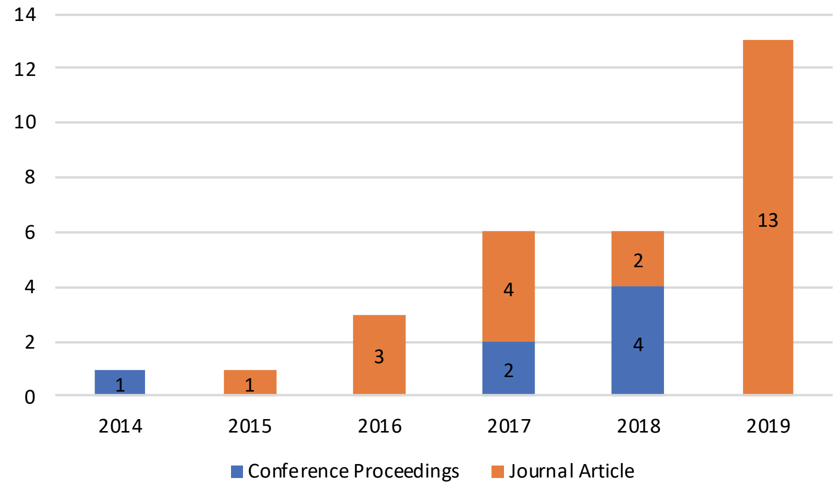


Figure 3 – Publications over the year

3.4.2 Material evaluation

In order to analyze the approaches that were applied to the omni-channel retailer supply chain, the 30 articles were classified based on the category selection and the result is shown in Figure 4.

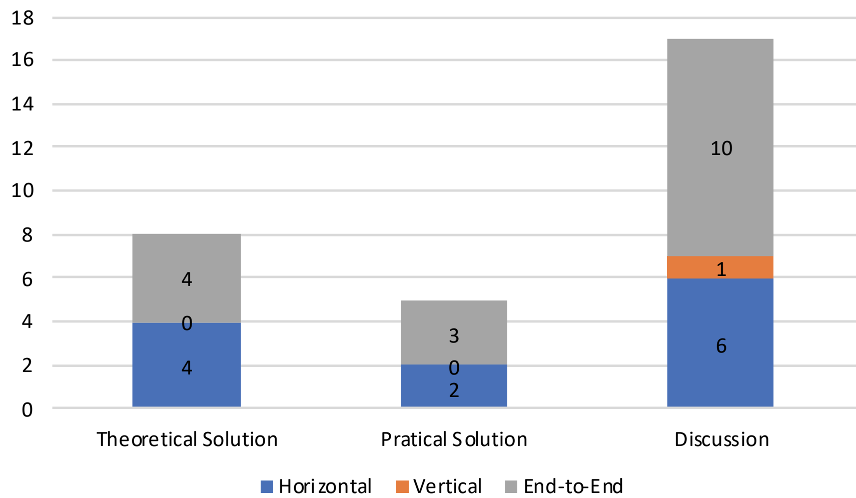


Figure 4 – Category selection of the papers

It can be observed from Figure 4, that most papers are still in the discussion and theory development plan, when analyzing the possible hypotheses and configurations of how the integration, operation and management of the multiple factors of the omni-channel retail supply chain might be.

When analyzing in relation to integration, it is noted that the focus of these researches is on end-to-end integration with 57% of the researches developed in this area, but when analyzing the applicability of these solutions, practical solutions still present themselves as a challenge.

Thus, in order to identify the approaches that are being applied, the five articles that carried out the practical application were analyzed regarding the analyzed theme.

- Realignment of the physical distribution process with Demand

Lee (2017) proposed a genetic algorithm (GA)-based optimization model to support anticipatory shipping. A cluster-based association rule mining is applied to discover the purchase pattern and predict future purchase in terms of If-Then prediction rules, and a modified GA is then used to generate optimal anticipatory shipping plans. They found out that in the optimization problems the industrial practitioners should consider demand, supply simultaneously in such a way that the overall performance of the distribution network in most aspects is being controlled closer to the optimal one.

Andrews et al. (2019) formulate the omni-channel fulfillment problem as an online optimization problem based on the primal–dual schema. The primal–dual approach judiciously uses inventory across nodes to satisfy e-commerce demand in a manner where the risk of cannibalizing an in-store sale is minimized so that lost sales are minimal. And after application they identified that the system has resulted in substantial savings through optimal order-fulfillment decisions that simultaneously increase turn and lower shipping costs.

- Forecast information sharing with Distribution

Yang and Zhang (2019) investigate the benefits of forecast information sharing in a supply chain and addressing the forecast inconsistencies, in fast-moving-consumer-goods (FMCG) demand, through reconciliation and forecast combination. Through statistical analysis they identified that that it is not necessary for retailers to share pricing and promotional strategies explicitly, which protects them from leakage of sensitive competitive information and puts greater weights on the more accurate forecasts.

- Price with Channel Decision

Gao, Chen, and Wang (2018) combine the basic model of queuing theory and retailer's profit function to study the impact of omni-channel service on customers' demand, customers' waiting time, restaurant’s service capacity and profits. And used statistical analysis to conclude that if retailer’s target customer is sensitive to time, online service is the best choice with a right delivery fee and price; if retailer’s target customer is sensitive to price, retailer choose the offline channel will be better.

- Enterprise software with Supply

Li et al. (2015) the developed an architecture of the Enterprise Network Integration Platform (ENI-P) for the data-oriented product lifecycle management and omni-channel marketing management challenges of enterprise networks and an industrial experiment system is deployed to illustrate the usage of developed technologies. They presented all the difficulties of implementing this software by the organization and identified that the ENI-P developed in the case can only solve part of the typical problems and is only suitable for product whole lifecycle management and omni-channel marketing.

With this, it is possible to identify that the most adopted approach was the joint approach of demand and supply, because of the four main themes, two of them, which were the realignment of the distribution and forecasting process, both addressed the issue of demand together with supply. Through these papers presented, it is evident that to enable the realignment of the operational management of the distribution process, the identification of where to locate the product to supply the demand is crucial to reduce the costs of the supply chain and meet customer expectations. But for this to be possible, it is necessary to correctly identify where the demand will come from, the quantity and the time that they will occur. And on the forecasting theme, this analysis is also carried out, but with a focus on the impact of sharing demand information on the product distribution process. Thus, evidencing the need for a joint approach of these themes for the better operationalization of the omni-channel retail supply chain.

In the main theme that addresses enterprise software, there is a need to develop software capable of integrating the entire supply chain, providing the sharing of information and materials together to obtain better management of products by the supply chain. And in relation to the price theme, it is noted that the price and delivery time of the products directly influence the cost of retailers' operations and that this must be taken into account so that retailers can remain competitive in the current omni-channel scenario.

From the analysis of the applied approaches, it can be said that the main approaches are focused on better identifying information at the end of the chain, such as demand and price, on how to transmit it to the other players and finally on how to operationalize the supply chain from this information, that is, uniting information flows with materials and thus integrating the distribution of retail distribution channels.

Thus, it is clear that the result of one theme directly impacts the efficiency of the other theme, indicating the need to develop approaches that deal with multiples themes. However, despite addressing themes together, we see that there is the possibility of adopting more precise approaches for each of the approaches and treating them together in order to obtain a better result for the entire supply chain. It is important for the forecast to adopt methods that improve its efficiency, in the distribution issues, methods capable to improve the determination of the correct place that will supply the demands, and regarding the software theme focus on methods to enhance the interoperability.

And to better understand the purpose of these articles, they were classified according to the type of analysis, whether it is quantitative or qualitative, and as to the methods of data collection and analysis, as can be seen in Table 3.

Table 3 – Data analysis methods of papers

Paper	Year	Title	Unit of Analysis	Type of data analysis	Method of data gathering	Method of data analysis
Q. Li, H. Luo, P. X. Xie, X. Q. Feng and R. Y. Du	2015	Product whole life-cycle and omni-channels data convergence oriented enterprise networks integration in a sensing environment	Journal Article	Qualitative	Enterprise Database	Not informed
C. K. H. Lee	2017	A GA-based optimization model for big data analytics supporting anticipatory shipping in Retail 4.0	Journal Article	Quantitative	Enterprise Database	Association rule mining and Genetic Algorithm

D. Gao, J. Chen and Y. Wang	2018	Study on Omnichannel Service for Time-Sensitive and Price-Sensitive Demand	Conference Proceeding	Quantitative	Enterprise Database	Statistical Analysis
D. Yang and A. N. Zhang	2019	Impact of information sharing and forecast combination on fast-moving-consumer-goods demand forecast accuracy	Journal Article	Quantitative	Internet Database	Statistical Analysis
J. M. Andrews, V. F. Farias, A. I. Khojandi and C. M. Yan	2019	Primal-dual algorithms for order fulfillment at Urban Outfitters, Inc	Journal Article	Quantitative	Enterprise Database	Heuristic

When analyzing Table 3, in most of the articles the analyzes were quantitative, that is, they really sought to show through numbers the impacts of their approaches. In addition, it is worth noting that the approaches were developed seeking to meet real needs when collecting and analyzing data from real companies and through statistical and heuristic methods.

In order to analyze what the future directions of the research are, the recommendations of future research highlighted by the papers that presented theoretical and practical solutions were analyzed. To facilitate the analysis, the papers were classified according to the theme of the main objective, as well as in the identification of the approaches.

- Price

Gao, Chen, and Wang (2018) suggest that researchers focus on the influence of consumers' different time and price preference on the implementation of the full channel or consider the price as a decision variable, and help retailers make more favorable decisions.

Modak (2017) investigate optimal decisions of retailer’s dual channel supply chain under price and delivery time sensitive additive stochastic demand. The model was illustrated through a numerical example and demonstrates firm’s optimal equilibrium solution under both centralized and decentralized scenarios considering a pricing and delivery-time dependent random demand. And demonstrate that both market potential parameters and price elasticity parameters have huge impact on profit. And suggest that the model can be extended considering multiple retailers and also include manufacturers.

- Realignment of the physical distribution process

Lee (2017) highlighted as future research the focus on the development of the model where the transportation units and time becomes dependent on quantity in order to better simulate the realistic operations.

Ma (2017) investigates the effect of a dimension of logistics service quality (delivery time) interacting with shipping charges and purchase importance on customer satisfaction and purchase intentions in an e-commerce context. They used a scenario-based to develop experiments and as results indicate that increased delivery time significantly increased customers' perceived ambiguity and riskiness which reduced customer satisfaction. Suggest developing research on how online retailers set up their shipping strategy to reduce the total cost and better serve customers, and in the field to predict whether customers are less willing to purchase the real product if they perceived higher ambiguity or higher risk.

Bayram and Cesaret (2017) develop a stochastic dynamic framework to investigates dynamic fulfillment decisions that determine from which location to fulfill an online order when it arrives. They point out to increase the number of stores so that more generalizable results can be obtained and the amount of scenarios in the computational study, by evaluating extensive range of parameter values and performing sensitivity analysis, study the strategic inventory allocation decision and assumed that customers can switching channels if one channel is out-of-inventory.

Pereira et al. (2018) proposed a conceptual model for a predictive and adaptive management approach for omnichannel retailing supply chain combining machine learning to minimize uncertainty and simulation-based optimization to handle supply-demand synchronization. And suggest the practical application of this model in test scenarios to verify its efficiency.

Muir, Griffis, and Whipple (2019) develop research which test through experimentation on a Multi-Echelon retail inventory system within a discrete-event simulation, and it comes to a result that highlight the need for firms to align logistical structures for returns processing with the returns policy and the external environment. So, they propose that in future researches could be examine the cost associated with a cross-channel returns policy or decentralized returns processing structure and seek to understand the extent to which cross-channel return policies influence consumer purchase and return behaviors. It was also suggested that will be important to analyze the demand seasonality in inventory management research.

MacCarthy, Zhang, and Muyldermans (2019) examine store picking operations for same day Buy-Online-Pickup-in-Store services and analyze demand surge scenarios with different order arrival rates in an ordering cycle. They suggest that researchers could also consider the case when retailers adjust the picking rate in each wave according to the workload, and the combinatorial optimization of picking and delivery in 'ship from store' fulfilment is also an interesting area for further investigation.

Zhang et al. (2019) focuses on the integrated optimization of supply chain distribution network and demand network and constructs the joint randomization planning model of location and routing seeking to minimize the total cost of the supply chain network under uncertain customer demands. With the results that the paper reach, they propose that the results can be extended to the scale economy of the distribution network, due to increasing the uncertainty factors and solving larger scale examples.

- Big Data Analysis

Cheng and Lu (2018) developed a conceptual model to examine how big data analysis use affect supply chain performance in an omni-channel. The result of the analyses suggest that big data analytics use, are all positive related to efficiency and to adaptability and that the analysis of big data integration among suppliers, communication and mutual complementarity of resources are key factors in improving efficiency. They highlight that studies on the analyzes of other factors that may affect consumer preferences, such as innovative services or logistics management, and studies could explore whether alternative constructs affect big data analytics use, efficiency, adaptability and supply chain performance.

- Enterprise software

Li et al. (2015) affirm that the implementation of the Enterprise Network Integration Platform (ENI-P) could be more complicated and highlight as future research the understanding on how to implement an ENI-P suitable for different scenes needs further research.

3.5 CONCLUSION

This paper studies the approaches of logistics and supply chain that are being applied to the omni-channel retailer to enable the channel integrated operation management. In our research, a literature review was conducted in order to identify the approaches that are being applied, gaps and opportunities for the integration of the online and offline channels.

In this sense, it was identified that in order to develop approaches to integrate channel and consequently the information and material flows, researchers are analyzing multiple themes in the omni-channel retail supply chain.

From the content-analysis it was possible to identify that the approach of multiple themes is a new theme, with significant growth in the year 2019. It can also be identified that most of the articles that address the multiple themes were published in journals that have a classification of impact factor.

From the analysis of the level of approaches, it is noticed that most papers are still in the discussion phase, being necessary to develop more applicable approaches so that they can actually collaborate with retailers and manufacturers to improve the omni-channel retail supply chain.

From the papers that made practical application of solutions, we can identify a greater focus on the study of demand and supply themes together, and from the papers results it was possible to highlight the benefits of the joint approach in providing cost reduction and improvement of operationalization of the chain close to optimum.

In this sense, it can be highlighted that the integration of channels occurs within the scope of the development of techniques to better jointly operationalize and manage the distribution flows of online and offline channels. However, in order for this to be possible, it is necessary to better identify the consumer demand at each point of sale, in order to enable the best location of the products in the chain and consequently facilitate its operation. For this, it is suggested that the development of joint approaches of demand and supplies, that is, approaches that integrate information flows, through the precise identification of demand, and of materials, by the best distribution of products. And this is evident when we analyze the most adopted methods of the papers that made the application of practical solutions, which were the statistical methods, to analyze the demand, and optimization to improve supply.

Analyzing each of these themes, it is noted that it is important to develop more precise methods for each one of them and then join them to obtain better operational results for the chain. Therefore, applying more advanced methods to detect the consumer's need, in relation to the quantity and time of this demand, and to identify who will supply the given demand, based on the new possibilities of distribution of the omni-channel.

Regarding future research, it is noted that the majority of papers are increasingly suggesting the integrated analysis of themes and the supply chain, whether adding more operational factors / parameters or agents to obtain more accurate and real solutions, for that can be applied to practical cases and help omni-channel retail supply chain organizations evolve operationally and financially.

Some limitations of this study can be highlighted in the number of bases adopted for the selection of articles, but it can be said that this article achieved the objective of identifying the logistics and supply chain approaches that are applied to the omni-channel retailer.

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4 PREDICTIVE AND ADAPTIVE MANAGEMENT APPROACH FOR OMNI-CHANNEL RETAILING SUPPLY CHAINS

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Abstract: The convergence of physical and online retailing paves the way for the emergence of a retailing omnichannel. Omnichannel retailing supply chain management is challenged by uncertainty, oscillations in sales volume and supply-demand incompatibility. Dealing with those challenges requires the adoption of strategies focused on complex systems that properly employ new information and communication technologies as well as intelligent decision methods. In this context, this research paper aims to propose a reference model for a predictive and adaptive management approach for omnichannel retailing supply chain combining machine learning to minimize uncertainty and simulation based optimization to handle supply-demand synchronization.

Keywords: Supply Chain Management (SCM); Retail supply chain; Omnichannel; Machine Learning; Simulation-based Optimization.

4.1 INTRODUCTION

The fast development of the global economy, information technology, and the advance of e-business, are making people demand higher levels of logistics service (FRAZZON. 2009; YAN-QIU and HAO, 2016), as well as more agile (GUNASEKARAN and NGAI, 2004) and dynamics supply chains (VAKHARI, 2002). Thus, logistics and supply chain activities management is becoming more complex, uncertain, costly and vulnerable according to Wu et al. (2016). Okada, Namatame and Sato (2016) argue that due to the complexity, uncertainty, and other factors involved, most of the actual supply chains are known to have many supply-demand incompatibility problems, which causes excess or lack of stock, as well as delays of delivery, with consequent damages to the level of service offered.

This scenario is also observed in the retail supply chain, because with the emergence of a strong online channel a major transformation in retail logistics in the last decade has occurred. However, some challenges still remain to implement the online channel in the most efficient way and to create a seamless shopping experience, ensuring the compliance of product deliveries both in physical stores and directly to the consumer, and redesign their processes according to Hübner, Wollenburg and Holzapfel (2015) and fast delivery in accordance with Lee (2017).

In order to face the challenges and ensure the online channel efficiently, it is necessary to minimize the factors of uncertainty and the oscillations in sales volume, since, due to these two factors, companies are having to adopt strategies focused on complex systems that deal with multichannel, and even omnichannels, as is the case with retailers 4.0 (LEE, 2017).

With the same focus on process integration, Butner (2010) argues that supply chains need to become "smart," adopting an intelligent infrastructure to jointly incorporate the data, information, products, objects, and business processes according Schuster, Allen and Brock (2007).

In order to minimize the uncertainty regarding demand Nita (2015) states that the application of big data analysis technologies to predict products demand has increased, such as machine learning techniques. These techniques provide the analysis of the available database and also assist in the information evaluation of the supplies forecast according to Shen and Chan (2017). This fact is also highlighted by Lee (2017) in affirming the growing importance the practice of big data analytics for omnichannel retailers.

And aiming at the best way of structuring the supply chain and consequently the synchronization of the supply with the demand Okada, Namatame and Sato (2016) sustain that the agent-based simulation (ABS) model can be used to analyse different stages of the supply chain, in order to determine what could happen in different scenarios, such as in a supply chain where supply is not sufficient to meet the demand. And analysing different stages of the supply chain can provide information on possible effects or consequences of delays, minimizing distorted information and significant inefficiencies in the supply chain (OKADA *et al.,* 2017).

This research paper aims to propose a conceptual model for predictive and adaptive management approach for omnichannel retailing supply chain combining machine learning and simulation based optimization. For that purpose, a brief literature review embracing retail supply chain, industrie 4.0 and simulation based optimization methods in supply chain. Finally, the conceptual model is described and a simulation model is proposed. Being the implementation of the machine learning part presented with greater detail and explanation in another moment.

4.2 LITERATURE REVIEW

4.2.1 Retail Supply Chain Management

Due to increased competition, traditional retailers strive to differentiate, offering a greater variety of products and higher levels of product availability in stores, while reducing total operating costs. (DUBEY; VEERAMANI, 2017).

Lee (2017) sustain that with the ongoing digitalization processes and with the distinctions between offline and online channels disappearing, multichannel retailing is moving to the omni-channel retail. Saghiri et al. (2017) states that the omni-channel retailer has the purpose of coordinating processes and technologies across all channels in order to provide more integrated, consistent and reliable service to customers. And with the increasing variety of channel formats on the omni-channel, they have made the shopping process more convenient for buyers, and more difficult to manage for upstream suppliers and downstream retailers (AILAWADI; FARRIS, 2017).

Difficulty that are found in the works of Ivanov (2017) and Gao et al. (2017) by highlighting and analysing the impact of the bullwhip effect, caused by fluctuations in demand, and the ripple effect, caused by disruptions in the supply, production and distribution processes, in the supply chain and the retail supply chain respectively. Thus, the omnichannel concept of Ailawadi e Farris (2017) accepts the inevitability of the need to employ multiple channels and is focused on integrating activities within and between channels to match the way consumers buy.

Saghiri et al. (2017) emphasize that integration and visibility are the two main enablers of the omni-channel structure to reduce uncertainties and variations. To implement the omni-channel integration Saghiri et al. (2017) states that integration is necessary from three perspectives: integration of the stages of the channels (pre-purchase, payment, delivery, return), types of channels (online and off-line), and the agents of channels. And in terms of visibility was highlighted the ability of supply chain members to provide, share, and retrieve timely information such as product visibility, demand, order / payment, inventory, shipment / delivery, and supplies.

The framework presented by Saghiri et al. (2017) mainly reflect the operations an information management on the omnichannel, but does not address problems like customer behaviour. So, in order to minimize the factors of uncertainty and better understand customer purchase behaviour Lee (2017) states that retailers are encouraged to devote investments in big data consumer analytics. And to explore omnichannel operational/tactical implications with more detail Saghiri et al. (2017) suggest the application of an analytical study.

4.2.2 Industrie 4.0 In Supply Chain Management

In the literature, several terms are used to describe this new form of communication and integration of processes to fulfill customer requests, being them industry 4.0, industrie 4.0, supply chain 4.0, smart factory, smart manufactory, smart supply chain, intelligent manufactory, industrial internet, integrated industry, e physical internet.

Within the supply chain Wu et al. (2016) states that the smart supply chain enables data collection and real-time communication of all stages of the supply chain, intelligent decision making, and an efficient and appropriate process to better serve customers.

However, Liao et al. (2017) states that there is still an absence, or insufficient, research effort on end-to-end digital integration, which has been conceptualized as integration into the entire engineering process so that the digital and real worlds are integrated into the entire value chain of a product and in different companies, in addition to incorporating the requirements of the customer (Scholz-Reiter et al., 2011). And while some research guidelines are not officially listed as priority areas, some research efforts can be found in relation to Data Science, such as real-time data analysis, data integration, and Big Data Analytics.

The benefits identified in the use of Big Data and Business Analytics in supply chain are in achieving greater visibility of performance, cost trends and fluctuations, inventory monitoring, production optimization, manage demand volatility, supply chain network design and transportation and sourcing optimization (ISASI et al., 2015; HAZEN et al., 2014; OLIVEIRA; MCCORMACK and TRKMAN, 2012).

When analyzing the demand forecast in the Big Data scenario, Shen and Chan (2017), Islek and Oguducu (2015) and Sarhani and El Afia (2014) they have identified that the use of advanced machine learning techniques to initially train the large amount of data, to later predict demand, provides more accurate information in the supply chain.

The best and frequently used method for uncertain demand forecasts, in the literature, is neural network and its variants, because of their inherent ability to perform better on unpredictable and uncertain demand patterns according to Amirkolaii *et al*. (2017). However, build individual forecasts for a large number of unique customer demands is impractical states Murray, Agard and Barajas (2015), being necessary the application of grouping customers into logical segments, like partitional clustering, that represent the total customer population states.

For analysis of supply information sharing Shen and Chan (2017) point out that there is still a gap in forecasting supply information for supply chain management, but that this can be changed by applying big data technologies and that analysis through simulation is one of the most significant approaches to predicting market demand and supply.

4.2.3 Simulation and Optimization

The complexities of most real-world systems are related to their stochastic nature and the wide variety of internal and external interactions of these systems, and that simulation-based techniques can be used to develop or evaluate complex systems. (KÜCK et al., 2016). However, according to Kück et al. (2016) the simulation cannot guarantee the optimization of these systems in relation to one or more performance indicators such as lead-time, cost of production, among others, and that optimization methods are mainly used when a complex system can be modeled by a simplified abstraction.

Frazzon et al. (2015) argue that the ability of existing models to support intelligent and flexible synchronization, and the coordination of the process involved are limited. For example, linear programming models are not able to cope adequately with stochastic behavior. On the other hand, the simulation models have limited capacity to support the identification of exact and optimal solutions.

Govindan, Fattahi and Keyvanshokooh (2017) sustain that modeling approaches is an interesting research idea in order to fill the gap between stochastic programming and robust optimization. Thus, a promising approach that combines the strengths of simulation and optimization is known as simulation-based optimization (SBO), the simulation model being used as the objective function of the optimization and the optimization method used to determine the optimal configuration of simulation parameters according to Kück et al. (2016).

According to Frazzon et al. (2015; 2017) combination of both can also provide relevant capabilities for the management of supply chains. In the context of demand forecasting and simulation-based optimization of processes for the supply chain, researchers diversified in the choice of methods to predict quantity and analyze sales behavior of the products, and to structure and optimize the distribution processes.

In the field of the optimization Lee (2017) proposed an optimization model based on genetic algorithms (GA) to support anticipatory shipping, Yan-qiu and Hao (2016) have developed a multilevel logistics supply network optimization model with constraints on distribution capacity, inventory capacity and improved customer delivery time. And dealing with simulation, Okada, Namatame and Sato (2016) describe an agent-based simulation tool for designing smart supply chain networks as well as logistics networks. Therefore, it was possible to identify the lack of a research that approached the simulation and the optimization together in a smart supply chain, and consequently of the retail supply chain.

4.3 CONCEPTUAL MODEL

In this section, the conceptual model for predictive and adaptive management approach for omnichannel retailing supply chain is proposed (Figure 1). As shown in Fig. 1, the retailer supply chain is composed of customers/clients, retailers, representing the off-line channel, the online store, which represents the online channel, regional distribution center, central distribution center and a supplier.

Even though it is a generic omnichannel retail supply chain, its entities and relations seek to represent the retail supply chains presented in the literature and in real scenarios.

In order for the omnichannel retail supply chain management present a predictive approach it was proposed the analysis of the demand forecast through techniques of big data, such as machine learning, and to exhibit an adaptive approach, the coordination of demand and supply was proposed through the application of simulation based optimization.

To make the predictive and adaptive management of the omnichannel retail supply chain possible, this conceptual model assumed that the supply chain has integrated information and communication technologies in order to allow the real-time information sharing and intelligent decision making process.

And it was designed to present an integrated order fulfillment, in order to lead to a higher service level for customers, and product information, to initiate the necessary corrective actions in cases of mismatch in stock status according with Saghiri et al. (2017). Since the joint management of the two integrations allows the visibility of the product, demand, inventory, shipment/delivery and supply.

In order to develop this model, it is proposed the integration of machine learning and simulation-based optimization. This integration will occur through the communication between machine learning software and simulation software, where while the machine learning software generates a solution, the simulation software evaluates this solution into a virtual model and returns the results to the first software. And this process occurs until a stopping criterion is satisfied or met.

4.3.1 Machine Learning

The machine learning, represented in the conceptual model by the blue color, was proposed to forecast demand in order to provide better identification of customer behaviour, reduction of uncertainties related to demand, and consequently anticipate the execution of the distribution processes of the supply chain.

In the application of the machine learning, two types of analysis are proposed: clustering, for the identification of customer behavior by the application of clustering algorithms, and then demand forecasting, by the application of artificial neural networks to the demand forecast of each product from each of the stores.

In this way, the input data of the clustering model are the information of the sales history of the online and offline stores, collected and stored monthly and analyzed for the formation of the clusters. As output of clustering will be identified the number of clusters formed and which cluster each product belongs.

Subsequently the data found by the clustering will be analyzed as input for the forecast to provide a demand forecasting with greater accuracy and less uncertainties. The output from the artificial neural network will be the demand of each product from each online and offline store.

And the demand forecast information/data, result of the application of the artificial neural networks, is the input data of the simulation-based optimization model for the anticipation of the product distribution process.

4.3.2 Simulation-based Optimization

The simulation based optimization, represented by the green color in the conceptual model, was proposed to analyze the behavior of the omnichannel retail supply chain to adapt to the uncertainties of the forecast and actual demands and reduce lead time, when performing the distribution activities with the lowest lead time and cost.

In order to reduce the lead time, this supply chain proposed the anticipatory of the distribution process, and because this process is based on a forecast of demand and can have incompatibility between real demand and forecasting, in this model we have also proposed the checking process to adapt to these distortions and ensure the sale of the product to the customer.

To represent both the anticipatory and the adaptive process the distribution process presented in this generic model of the omnichannel retail supply chain is composed by the information and material flows.

As can be seen in Fig 1, the information flow of the simulation-based optimization model is the flow responsible for initializing the distribution process, and this can happen in two distinct moments. Considering that this supply chain share the demand forecast information, the first moment is from the arrival of demand forecast information, coming from the machine learning, and the second moment is with the information of the sale of products by the online and offline stores.

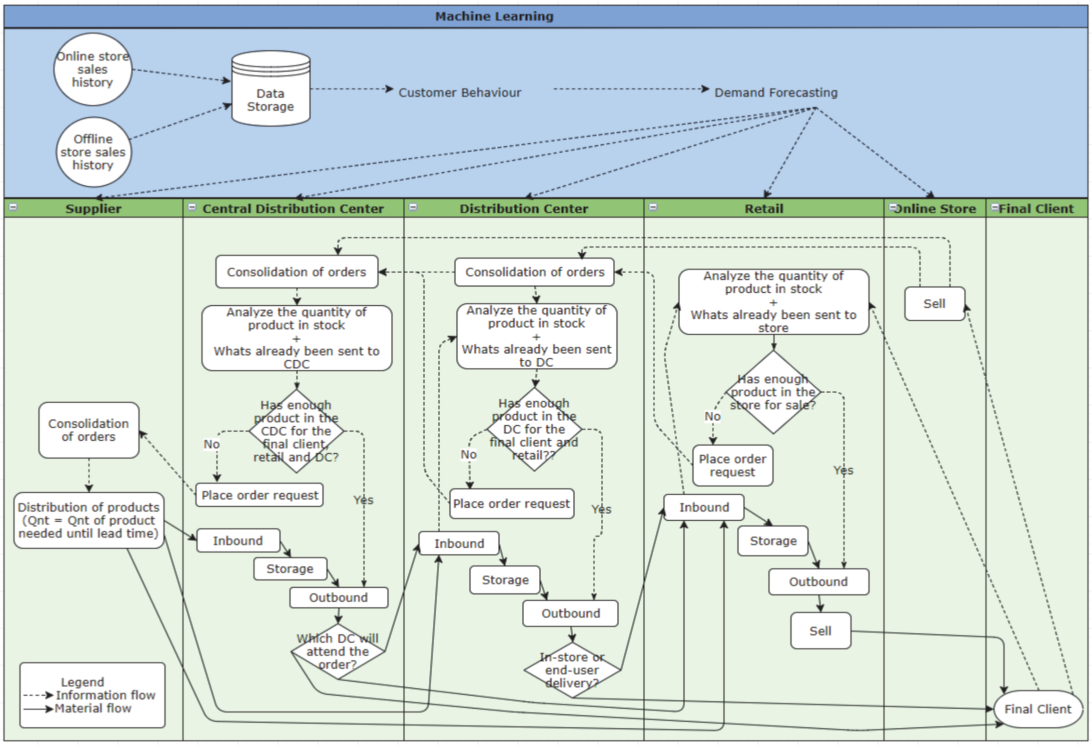

Fig. 1. Proposed conceptual model for omnichannel retailing supply chain management

To represent both the anticipatory and the adaptive process the distribution process presented in this generic model of the omnichannel retail supply chain is composed by the information and material flows.

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From the distribution centers, the distribution process starts according to the sales realized by the online and offline channels. With the product sales, the process of information flow of both online and offline stores starts. In the online stores, the sale information is directed to the distribution center that will respond to the request, and in the off-line stores, the checking process of the availability of the product for sale is started.

The checking process, who is performed by the retailer and regional and central distributors, is carried out with each sale, based on real demand, and on a monthly basis, based on demand forecasting. In this process, firstly is analyzed the necessary amount of product in stock and what's already been sent to each member, that meet the real demand. If the store has the product, it is taken from the inventory and the sale is made, otherwise the member places an order request to the previous member to send the product. With the orders placed and the necessity of product identified, the material flow is started by the regional and central distribution center.

The adoption of pull and push flow types in the same distribution process occurred so that there is a balance between the lead time reduction and the quantity of stocks in the chain. If it were adopted only the pushed flow the product would be left in the off-line stores, which would be the closest link of the customers, the delivery lead time for the customer would be the smallest but there would be a large amount of stock, and if it were adopted only the pulled flow the amount of stock in the chain would be smaller, but the lead time would be higher.

4.4 TEST CASE

In this section, is proposed the application of the simulation part of the conceptual model, using the software Anylogic, and the machine learning and the optimization parts was considered their effect in the supply chain to demonstrate the effectiveness of the machine learning and the anticipatory process of the distribution in the omnichannel retailing supply chain. Thereof, two scenarios will be developed, the first one a generic supply chain, as it has been presented in the literature, and the second with the application of the conceptual model presented in the section 3.

In the first scenario, the omnichannel retail supply chain is represented without the application of machine learning and anticipatory process and is composed by the information and material flows as illustrated in Figure 2.

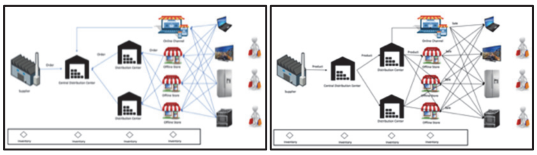

Fig. 2. Simulation first scenario

As shown in Fig 2, in accordance with the sales history the retail place an order to the regional distribution center, which, in turn, place the order to central distribution center, who send the order to the supplier. And after the information flow of the order reach the supplier, the distribution process starts with the material flow.

In order to reduce uncertainties and lead time, and improve service level and synchronization of demand and supply, the second scenario, illustrated in Figure 3, is developed with the application of machine learning and the anticipatory distribution process, presented in the conceptual model, also composed by the information and material flow.

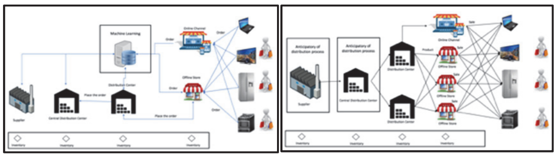

Fig. 3. Simulation second scenario

As described in the section 3, the second scenario firstly propose the application of machine learning, and them the real-time communication between all players of the supply chain to enable the anticipatory distribution process. So, the information flow is represented by demand information and by the orders, to correct the mismatch between demand and supply. And every time the information with demand or order arrives in each player the anticipatory distribution process is initiated at the end of the day. For that, it was considered a five-stage SC that include the customers/clients, 16 retailers in different Brazilian cities, three regional distribution centers in Salvador, São Paulo and Manaus, one central distribution center located in Goiânia, and one supplier in São Paulo. As show in Figure 4.

To represent the effect of machine learning in the simulation model in the second scenario the consumption of some products was influenced by other products that have the same sales behavior and were associated with the same cluster, in order to represent the application of the clustering and improve the forecast. And the optimization of the omnichannel retail supply chain will not be applied in this article, but the parameters that will be included in the optimization process will be analysed in the simulation to evaluate the performance of the model. The following objective function terms, classified by Govindan, Fattahi and Keyvanshokooh (2017), that will be used are the inventory cost, transportation/shipment costs, transportation/shipment time, processing costs in facilities, fixed ordering costs, shortage/backorder costs and routing costs.

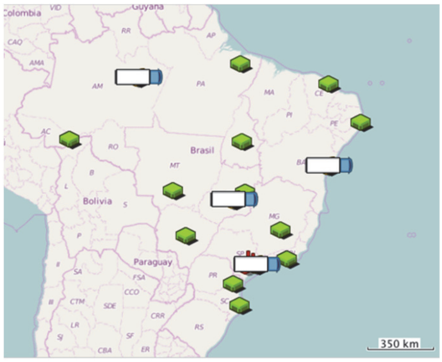

Fig. 4. Omni-channel retail supply chain structure

To represent the effect of machine learning in the simulation model in the second scenario the consumption of some products was influenced by other products that have the same sales behavior and were associated with the same cluster, in order to represent the application of the clustering and improve the forecast. And the optimization of the omnichannel retail supply chain will not be applied in this article, but the parameters that will be included in the optimization process will be analysed in the simulation to evaluate the performance of the model. The following objective function terms, classified by Govindan, Fattahi and Keyvanshokooh (2017), that will be used are the inventory cost, transportation/shipment costs, transportation/shipment time, processing costs in facilities, fixed ordering costs, shortage/backorder costs and routing costs.

So, to represent the conceptual model in the simulation model, the following parameters based on Ivanov (2017) will be included to the simulation: the inventory control policy; transportation costs, computed subject to product weight and shipment distance, and transportation time (real routes are used subject to average truck speeds); fleet size; less-than-truckload shipments are allowed; inbound and outbound processing costs and time; fixed facility and inventory holding costs, and production costs and product price.

To develop the simulation in Anylogic a hybrid simulation will be utilized. To develop the flow between agents, represented in Figure 5, the discrete simulation will be adopt, and based on agent will be adopt to represent the logic of each agent as illustrated in Figure 6.

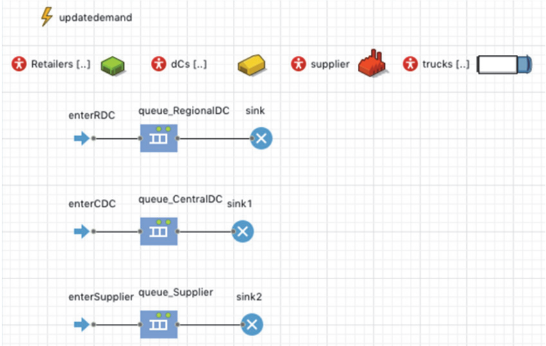

Fig. 5. Simulation flow in Anylogic

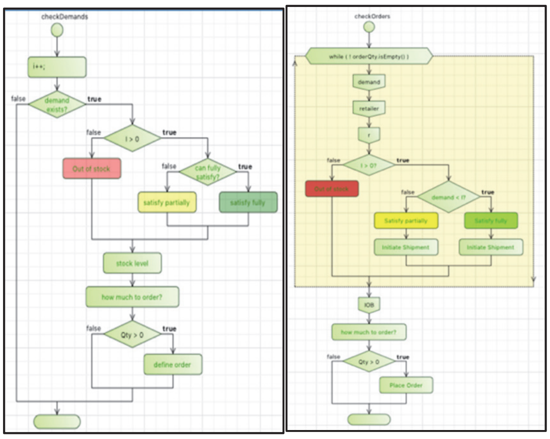

Fig. 6. Logic process of the retailers on the left, and the logic process of the distribution centers of the right

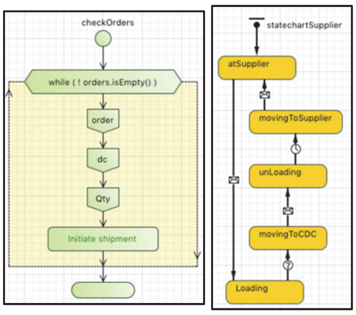

Fig. 7. Logic process of supplier on the left, and the logic process of the trucks on the right

Therefore, with this model is expected to reduce lead time and the total cost of the omnichannel retail supply chain and to improve the efficiency of the supply chain and propose a better synchronization for demand and supply. Thereof, the proposed conceptual model enables managers to perform operations planning with more accurate data, by minimizing the uncertainties of demand forecasting, and allowing for a more responsive and adaptive decision-making of supply chain operations by identifying the scenario with the lower logistics costs and the highest level of customer service.

4.5 CONCLUSIONS

The transformation of the retail supply chain into a omnichannel retail supply chain in the last years are forcing them to become more predictive, accurate, dynamic and smart to deal with uncertainties, oscillations in sales volume and supply-demand incompatibility.

For this reason, is extremely important to adopt intelligent decision methods that address the predictive issue, in which provides a demand forecast with greater accuracy and minimize uncertainties, and tools capable of analyzing scenarios to propose a dynamic and smart chain that reduces the incompatibility between demand and supplies.

Therefore, this paper has presented a conceptual method for a predictive and adaptive omnichannel retail supply chain management by the application of the machine learning and the simulation-based optimization in order to minimize the uncertainties factors and supply-demand incompatibility.

In the machine learning two methods were proposed for the information flow, the clustering method to analyze the behavior of the consumers coming from big data, and the artificial neural networks method to realize the forecast of demand with greater accuracy. And in the simulation-based optimization, which analyze the information, material and financial flow, a supply chain that use the pull and pushed flows, and checking process was adopted to optimize the costs and the lead time.

In this way, the integration and analysis of material, financial and information flows through the application of machine learning and simulation-based optimization methods in the omnichannel retail supply chain management enables them to identify and respond to the needs of consumers in a competitive and dynamic way. As future research, the practical application of this model in test scenarios to verify its efficiency when compared to other models presented in the literature is recommended.

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5 TOWARDS A PREDICTIVE APPROACH FOR OMNI-CHANNEL RETAILING SUPPLY CHAINS

Artigo apresentado no 9th IFAC Conference on Manufacturing Modelling, Management and Control.

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Abstract: The adoption of omni-channel strategy has changed the relation between retailers and customers and brought more complexity to the retailing supply chains. To address the increasing complexity, it is necessary to adopt innovative approaches based on information technologies and intelligent decision methods. The challenges to retailers are improving the accuracy of offline and online channels demand forecasting, better managing offline and online customer's needs, thus reducing the uncertainties of the omni-channel retailing supply chain. In this context, this research paper aims to propose a predictive approach for omni-channel retailing supply chain combining clustering with artificial neural network to handle demand uncertainty.

Keywords: Supply Chain Management; Retail supply chain; Omni-channel; Machine Learning; Clustering; Artificial Neural Network.

5.1 INTRODUCTION

Retailers are dynamic in nature and in the last two decades have faced some disruptive transformations such as changing scenarios, availability of new technologies and with the online channel, specifically states of mobile channels, have made their strategies evolve (Verhoef, Kannan and Inman, 2015; Kumar, Anand and Song, 2017). According to Galipoglu et al., (2018) retailers are rapidly evolving from single channel to multichannel, then to cross-channel and now to omni-channel.

Saghiri et al. (2017) states that the omni-channel retailer aims to coordinate processes and technologies across all channels to provide a more integrated, consistent and reliable service to customers.

The adoption of omni-channel enables retailers to have a better understanding of the consumer behavior of each channel by applying technologies that allow the analysis of customers' buying behavior of both virtual and physical channels, sustain Chen, Cheung and Tan, (2018). Li et al. (2018) also highlight that omni-channel empower retailers in retaining customers by reducing uncertainty, providing attractive offers, and engendering switching costs. In addition, Mirsch, Lehrer and Jung (2016) argue that the key factors for companies adapting the omni-channel strategy, as a contemporary multi-channel approach, are technological development, infrastructure, and the changing on customer needs.

In this sense, Pantano, Priporas and Dennis (2018) point out that the "intelligent" use of technologies can be extended to the retail processes to make them intelligent, and these intelligent technologies can affect the methods of collecting data of the consumers, the information management and the transfer of knowledge between companies, by creating a partnership between customers and retailers. The Retail 4.0 or Smart Retailing represents retailers that provide consumer interactions with innovative technologies and with online and offline channels without distinction to enhance the consumer shopping experience according to Vazquez, Dennis and Zhang (2017) and Lee (2017). Being the smart retailer benefits the best visibility of the products, and sharing information and cooperation smart among all actors in the supply chain according to Pantano, Priporas and Dennis (2018).

However, Byrne and Heavey (2006) argue that factors such as promotion, price reduction and advertising by retailers can lead to uncertainties in demand, and uncertainties, distortions and fluctuations are major challenges for collaborative supply chain forecasting and replenishment planning (Carbonneau, Laframboise and Vahidov, 2008).

Wong et al. (2012) and Okada, Namatame and Sato (2016) argue that because of the complexity, uncertainty, and other factors involved, most of the actual supply chains are known to have many supply-demand incompatibility problems, which causes excess or lack of stock, as well as delivery delays, with consequent damages to the level of service offered. In this way Pereira et al. (2018) suggest the application of the machine learning with the simulation-based optimization in order to reduce uncertainties and supply-demand incompatibility. Thereof, the identification of the future demand for a given product is the basis for optimizing the supply chain and replacement systems sustain Sarhani and El Afia (2015). Learning to identify demand reduces the costs of the entire supply chain according to Yan-qiu and Hao (2016) and enables the optimization of operations through the development of strategies for acquisition and reduction of storage costs by optimizing the inventory (Sarhani and El Afia, 2015).

This fact was confirmed by Gao et al. (2017) by analysing the impact of the wave effect caused by interruptions in the demand, production, and distribution process in the retail supply chain, and to point out that price discounts in the online retail market generally amplify the bullwhip effect in the supply chain of online retail.

Therefore, to minimize the uncertainty factors in the smart retail scenario, Gao et al. (2017) argue that choosing the best forecasting technique to minimize the bullwhip effect in the online retail supply chain is of great importance and should be a priority for future research in this area, and in a complementary way Lee (2017) and Pantano, Priporas and Dennis (2018) point out that retailers are encouraged to invest in the analysis of consumer big data as a way to improve forecasting.

In order to minimize uncertainties of the demands, this research paper aims to propose a predictive model for omni-channel retailing supply chain combining clustering, to understand consumers' consumption pattern through the product sales pattern, with artificial neural network, to improve the accuracy of product forecasting. For that purpose, a brief literature review embracing demand of omni-channel retail and supply chain and demand on smart scenarios. Finally, the predictive model is presented and applied in a Brazilian retailer.

5.2 LITERATURE REVIEW

5.2.1Demand on Omni-Channel Retail Supply Chain Management

In order to minimize uncertainty about demand and better understand the consumer behavior in the omni-channel retailing supply chain scenario, researchers diversified into the choice of methods used to collect and analyze data. To carry out this analysis, the searched keywords were supply chain and logistic with the variations of omni-channel on Scopus, ISI Web of Science, Emerald and EBSCO host, and selected conference / proceedings papers, journals and articles related to Industrial/Manufacturing/Production Engineering such as engineering, business, computer science, decision science and mathematics. The articles were analyzed in relation to the objective, if they were applied, area of application, qualitative or quantitative analysis, data collection method, data analysis method and which software used.

The most adopted method was Partial least squares (PLS). Yurova et al. (2017) developed and evaluated a model to test the hypothesis concerning the adaptive selling behavior for omni-channel consumer (OCC) and Murfield et al. (2017) applied a survey to investigate the impact of logistics service quality on consumer satisfaction and loyalty in an omni-channel retail environment, among other papers.

The second most adopted method was the confirmatory factor analysis (CFA) method. One of its applications was in the work of Vazquez, Dennis and Zhang (2017) which applied CFA to examine the effects of an emerging smart retailer-consumer communications technology and consumer behavior and Li et al. (2018) to identify which mechanisms driving customers' reactions to CCI in omni-channel retailing.

Wang et al. (2018) in order to develop a behavioral study on consumers' adoption of self-collection service via Automated Parcel Station (APS) adopted the exploratory factor analysis (EFA), to analyze the factors that impact on the variance of the data, the Structural Equation Modelling (SEM) to test the measurement of the model and to the test the hypotheses the application of CFA.

The clustering algorithm was applied by Xue and Lin (2017) to explores the behavior characteristics and the customer segmentation based on consumption data stream mining. Balakrishnan et al. (2018) applied clustering for studying buying behaviour of customers and improve product recommendations and Wang (2018) combined the method clustering with Particle swarm optimization (PSO) to help retailers find and utilize complementary tariff products for mobile numbers as the basis for future sales and procurement.

Another method adopted is the Statistical Analysis. Gao and Yang (2016) adopted the statistical analysis to identify which factors influence consumer's buying decision and Chatterjee and Kumar (2017) examines differences in consumer willingness to pay for online purchases of functional and expressive products that differ in the length of product life.

Willems, Brengman and Van de Sanden (2017) present a study on the effectiveness of in-store marketing communication appeals via digital signage and for that adopted construal level theory (CLT). Blom, Lange and Hess Jr (2017) used the multivariate analysis of variance (MANOVA) to test hypotheses that using digital customer data in goal- congruent promotions may lead to positive customer reactions. And Frasquet and Miquel (2017) applied Principal component analysis (PCA) to investigate the effects of multichannel integration on customer loyalty.

That way, it can be verified that the choice of methods is divided into mathematical, statistical and data mining models

and in the great majority these methods seek to evaluate the dependence and correlation relationship between the variables or hypotheses analyzed and even to create such hypotheses, with the consumer response, and from this understanding the consumers' consumption pattern/behavior. Already clustering method has sought from its analyzes to segment customers to identify the individual characteristics of each cluster and thus better understand the profile of consumption of their customers. The only exception was the marketing area that adopted the constructive level theory (CLT) that sought to analyze and align the content of in-store marketing information to direct consumers.

It is noticed that main goal is to understand how the technologies and actions, be they marketing, product recommendation, service quality and consumer relations, are impacting on the consumer's way of doing the shopping or how changing a consumer's purchasing profile across more than one channel is changing their ways of managing and operationalizing activities within companies.

Thus, it is noteworthy that there is still no study that shows how these customer profile / behavior analyses can be translated and inserted into the study of demand forecasting of the omni-channel retailing supply chain in order to obtain a forecast of demand with greater accuracy and lower error percentage, in order to reduce the uncertainties regarding the demand for the entire supply chain.

5.2.2 Demand on Industrie 4.0 And Retail 4.0

Wu et al. (2016) states that the smart supply chain enables data collection and real-time communication of all stages of the supply chain, intelligent decision making, and an efficient and appropriate process to better serve customers. Nevertheless Liao et al. (2017) sustains that some research guidelines are not officially listed as priority areas, some research efforts can be found in relation to Data Science, such as real-time data analysis, data integration, and Big Data Analytics. Thus, in order to identify the best method for smart retailers were analyzed all retailers, whether or not omni-channel, but who already do the application of large data analysis techniques.

When analyzing the demand forecast in the Big Data scenario, Islek and Oguducu (2015), Sarhani and El Afia (2015) and Shen and Chan (2017) have identified that the use of advanced machine learning techniques to initially train the large amount of data, to later predict demand, provides more accurate information in the supply chain. However, build individual forecasts for a large number of unique customer demands is impractical states Murray et al. (2015), being necessary the application of grouping customers into logical segments, like partitional clustering, that represent the total customer population states. Loureiro et al. (2018) also suggest that determine the selection of the variables and parameters first will lead to a better performing model than using only historical data, and then, evaluate the performance of the best model.

Loureiro, Miguéis and Lucas (2018) applied data mining techniques to predicting future product sales for new individual stock keeping units (SKUs) in a fashion retail industry. The authors first applied a greedy feature selection method and then utilized the deep neural network. To test the model the authors compared the result with other data mining techniques such as: Decision trees, Random forest, Support vector regression and Artificial neural networks. In conclusion, they sustain that none of the considered techniques exhibits higher performance in all the metrics explored and therefore no single technique can be considered as the best and the choice of the best technique should represent a balance between the performance of the models, their interpretability and their comprehensibility.

Villegas and Pedregal (2018) applied the method hierarchical time series forecasting based on SS modelling for a Spanish grocery retailer. The dataset analyzed contains daily observations on the sold units of 97 products covering the period 2013: Q1–2014:Q2 and concluded that proposed approach provides significantly better results than existing approaches which analyzes and forecasts each product independently.

In the retail 4.0 scenario two articles were found. Bag, Kumar and Chan (2017) develop an approach to build the prediction model using the brands' social perception score and reviews' polarity computed from social network mining and sentiment analysis from an e-commerce. The attributes of each product were analyzed, and a multiple linear regression and a Non-linear regressions analysis (neural network) were developed. Researchers identified that reviews maximize the influence of attribute choice and can increase the product demand and that the choice of the forecast method depends on the data and the variables to be analyzed in the model. However, we can observe that the purpose of this paper is to identify consumers' online purchasing behavior and to propose a prediction model for the products sold by the online channel and not by omni-channel.

Lee (2017) applied a predictive analytic model for customer behavior and proposed an optimization model for determining the allocation of products to different DCs. The prediction analysis was carried out in two stages that consisted of the analysis of the network level, with the application of the association rule mining to discover the relationship between purchased items from customers, and then the application of the cluster level, which the demand point (stores) were divided into different clusters. And afterward the optimization problems were developed. Although the study did not address the forecast as a way to improve demand forecasting performance, but rather to form demand clusters to optimize the distribution process.

What it can observe is that as well as in the omni-channel study, the works developed for the smart scenarios are seeking to evaluate the factors that are impacting the demand. Thus, it is observed that demand is being generated for each of the products in an individualized way, but that external inputs are used to improve forecast accuracy, such as the historical series of other products, the individual characteristics of each product and even reviews on the internet. Therefore, the authors are adopting methods that first analyze which variables present a correlation with each of the products and then apply some methods to forecast the demand.

We can still highlight from the articles studied that to perform demand forecast two of the three articles that carried out the study focused on demand forecasting applied the neural networks and their variations. According to Amirkolaii et al, (2017) the best and frequently used method for uncertain demand forecasts, in the literature, is neural network and its variants, because of their inherent ability to perform better on unpredictable and uncertain demand patterns.

In line with what was found in the literature, as this article aims to identify and better understand the profile of consumption of their customers by historical sales data, this article will adopt the clustering method, that was applied for that purpose in the omni-channel retailing supply chain scenario, and to provide a more accurate forecast the article adopted the neural network as it is the most applied method in the "4.0" scenario.

5.3 METHODOLOGY

5.3.1 General Description

In order to minimize uncertainty about demand and better understand the consumer behavior in the omni-channel retailing supply chain scenario this article followed the methodology presented in Fig. 1 and is described in the following paragraphs.

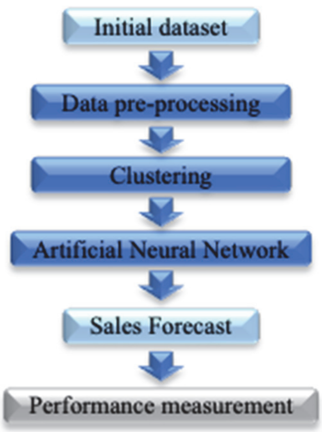

Fig. 1. Methodology adopted

5.3.2 Initial Dataset And Data Pre-Processing

The data was collected from a Brazilian retailer that is migrating its multi-channel operation to omni-channel. The "room" category was chosen because it is the category that most impacts on the company's billing and is composed of 684 products. To forecast future sales based on customers' consumption needs the historical data on the daily sales of the period of January/2016 to October/2018 were collected. Currently the company adopts as a forecast method the moving average (MA) of a period of 6 months.

In order to be able to analyze the correlation of the sale of the products by channels, the products were classified into 4 categories: products that were sold exclusively in the online channel (EOn), exclusiveness in the offline channel (EOff), the products that were sold in both channels but that the sale was effected by the off-line channel (OffOn) and the products that were sold in both channels but that the sale was made through the online channel (OnOff). Thus, separating the 684 products on the 4 categories gave a total of 1,108 historical sales series, being the category EOn with 50 SKUs, EOff with 82, OffOn with 530 SKU's and OnOff with 446 products.

After the data were collected and classified, they were pre-processed to remove the outliers and thus did not negatively impact the analysis. Outliers in the data were identified through statistical methods. And for the analysis Matlab2018 software was initially used to identify and remove the outliers, and later the Excel software to develop demand forecasting through the application of the moving average method as it is performed at the company.

5.3.3 Clustering

The clustering method divide related objects into groups to examine similarities of objects within their corresponding groups and is used to describe a group's characteristics and to simplify comprehension of a whole data set and for that many clustering algorithms have been developed, such as K-means and hierarchical according to Park and Kim (2018).

This paper adopted the K-means method to analyze the historical data sales and group the products based on their product sale pattern. The K-means clustering algorithm aim to find the representative cluster centers in each cluster calculating the square and the minimum of the distance between each data point, and the corresponding cluster center is obtained through repeated iterative operations in an effort to find the most representative cluster center according to Wang (2018). In order to determine the optimal number of clusters, Kantardzic (2011) states that optimum value of the criterion function must be achieved by reducing the total squared error, or until the cluster membership stabilizes.

In this article we used the Matlab clusters evaluation function based on the silhouette, that is, we chose the cluster quantity by the similarity that point is to points in its own cluster, when compared to points in other clusters. Subsequently the products were evaluated by k-means for the amount of cluster defined in the previous step.

5.3.4 Artificial Neural Network and Sales Forecast

Artificial neural networks (ANN) are computational networks that simulate the network of nerve cells (neurons) of a central human nervous system, being cell-by-cell (neuron by neuron) Graupe (2013). Haykin (1998) states that the human brain is a highly powerful, complex, non-linear and parallel computer (information processing system), and because of the neurons it is able to process and organize an immense amount of information in a very short time.

According to Loureiro, Miguéis and Lucas (2018) the neurons are organized in layers where each neuron receives a set of inputs and outputs a nonlinear weighted sum of its inputs to the neurons in the next layer to which it is connected and the most popular neural network algorithm is the backpropagation.

And to Bag, Kumar and Chan (2017) the neural network function is described by (1), where X is the input value, W is the weight, f the activate function and H the output.

$$H_1 = f\left(\sum_{i=1}^{10} W_{1i}X_i\right) \qquad (1)$$

In order to forecast the demand using the artificial neural network, the time series analysis was adopted due to the fact that the data to be analyzed were historical product sales data. Thus, the data were separated into data for training, validation and testing. Finally, the network architecture was determined in relation to the number of hidden neurons, the input delay, which represent how many periods the input take to show its effect on the output, and the feedback delay representing how many periods the output take to show its effect on itself.

5.3.5 Performance Measurement

The forecasting performance of the methods applied were evaluated by the R^2 coefficient of determination to observe the adjustment of the forecast equation and the Mean Squared Error (MSE) to analyze the accuracy measure. To analyze the methods according to R^2 the best method will be the one that achieve the highest value close to 1, and with MSE are those that present the lowest values of MSE. Thus, we compared the performance of the forecast method currently adopted by the company, which is the MA, with the performance of the two aritificial neural networks, the NAR being without external input and the NARX with external inputs provided by the clustering.

5.4 RESULTS

In this section the results obtained are presented and discussed.

5.4.1 K-Means Clustering Algorithm

To determine the optimum number of clusters, the data were initially tested and evaluated by varying the number of clusters from K = 1 to K = 100 and for each one the silhouette value was calculated until the largest value of the silhouette value with the smallest amount of cluster was found. From this it was possible to determine that the optimal number of clusters for the analyzed data are 47 by reaching the maximum value of the silhouette value, which is 1, as shown in Fig. 2.

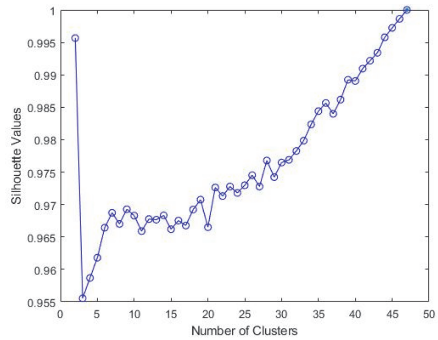

Fig. 2. Optimal number of clusters.

This way the k-means algorithm was applied for the 47 clusters avoiding the local minimum when applied the algorithm replications with different initializations. And we can conclude that the products were well divided in the 47 clusters when evaluating the quality of the clusters by the graph of the silhouette plot as shown in Fig. 3, as all clusters present the silhouette value as 1.

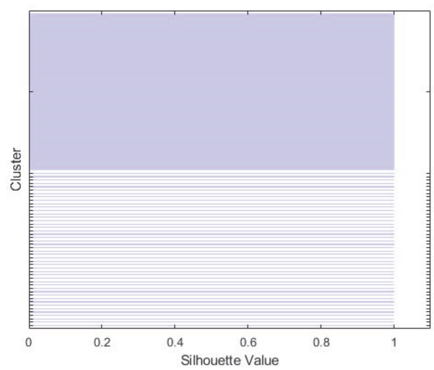

Fig. 3. Silhouette Plot chart with the distribution of families in clusters.

We can observe from the formation of the cluster that cluster 1 was the largest cluster and in it were all the products EOn and EOff, and also products OffOn and OnOff. When analyzing the other clusters, they were formed by only 1 product, that is, their consumption pattern does not resemble any other product, and those products belong to either OffOn or OnOff. And although these products belong to both channels, the products did not show similar sales behavior between the channels, so they cannot be analyzed in a similar way.

5.4.2 Artificial Neural Network

In order to develop the artificial neural network, the ntstool toolbox from Matlab2018 was adopted. And to evaluate if the products within the same cluster positively influence the prediction of the others were selected 4 products that were in cluster 1 to compare the performance of the neural network with and without external inputs. Initially the neural network is applied to the time series without using external inputs the historical series of the product, the nonlinear autoregressive (NAR), and later it is applied the neural network using external inputs, the nonlinear autoregressive with external input (NARX), which in this case are the historical series of the other products, in order to compare the performance of the two.

The products chosen for analysis were the product 1 that is sold in both channels but the sale by the online channel was in cluster 1 and the sale by the offline channel was in cluster 2, product 2 that is also sold in both channels and that both were in cluster 1, product 3 that was sold exclusively in the online channel and product 4 that was sold exclusively in the offline channel.

To analyze the data, these were separated and 70% of the data were used for training, 15% for validation and 15% for the test.

To develop the neural network to forecast each product the number of hidden layers was tested with 1, 5, 10 and 15 layers containing the same number of input and output neurons. In the case of NAR it was a single-layer for the input layer and the standard NARX network is a two-layer feedforward network, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. The Input and Feedback delay values have been tested from 1 to 12 for representing the 1-year period. And to train the algorithm it was chose the algorithm Levenger-Marquardt.

5.4.3 Performance Measurement

The best architecture for each product results is show through the analysis of the R^2 value, of the Testing and All, and MSE in Tab. 1. From Tab. 1 it can be observed that the result of the forecast of demand by the moving average was considerably lower in relation to the adjustment (R^2), although it presented good results in relation to the accuracy, when compared to the NAR and NARX, thus discarding this solution when compared to the others.

The performance of the forecast of demand using external inputs from clustering was superior for products 1 and 4, being respectively the values 0.95 and 0.94. Thus, showing a high adjustment between the actual values used for testing with the predicted values and the R^2 value of the general solution (All), thus compensating for the slightly higher value in the MSE. And that when analyzing products 2 and 3 we can observe that the best performance was without using the external inputs when analyzing the Testing R^2, being 0,99 and 0,95 respectively. However it is worth mentioning that the NAR did not perform much better than NARX in Testing R^2, and in relation to the R^2 of the general solution (All), NARX presented better results for both product 2 and 3 with respective values of 0.9 and 0.94 and very close results for MSE, so it is recommended to use NARX to predict the demand of the products.

In this way, we can highlight that NARX presented a good performance for all the products, thus corroborating that the application of the clustering, for the identification of consumer consumption pattern through the sales history of the products, together with the neural networks, to conduct demand forecasting, is considered a good method for forecasting demand for omni-channel retailing supply chain products.

5.5 CONCLUSIONS

With the increase in the number of sales channels, retailers are having to rethink how to forecast the demand for their products to reduce the uncertainties not only of their processes but also of the omni-channel retailing supply chain.

Table 1. Performance of moving average and artificial neural network

					R^2				MSE
Products	Problem	Hidden Neurons	Input Delay	Feedback Delays	Training	Validation	Testing	All	Validation
Product 1	MA	-	-	-	-	-	0,02	-	64
Product 1	NAR	10	6	-	0,87	0,99	0,8	0,85	171
Product 1	NARX	10	1	6	0,99	0,89	0,95	0,94	200
Product 2	MA	-	-	-	-	-	0,14	-	228
Product 2	NAR	10	1	-	0,76	0,9	0,99	0,75	546
Product 2	NARX	10	2	1	1	0,71	0,94	0,9	532
Product 3	MA	-	-	-	-	-	0,29	-	23
Product 3	NAR	10	1	-	0,63	0,76	0,95	0,62	0,26
Product 3	NARX	10	1	1	0,99	0,57	0,92	0,94	0,28
Product 4	MA	-	-	-	-	-	0,04	-	113
Product 4	NAR	10	1	-	0,81	0,87	0,87	0,82	54
Product 4	NARX	1	1	1	0,89	0,85	0,94	0,87	214

For this reason, it is important for retailers to increasingly understand the behavior of their consumers and to insert this analysis into their operations, thus adopting forecasting methods that combine identification of patterns in forecasting methods.

In this way, this paper has proposed a predictive approach for the omni-channel retailing supply chain base on the application of clustering algorithm and artificial neural network in order to reduce uncertainties related to demand.

And through the application of the method in a Brazilian retailer it was possible to analyze its performance and to conclude that for the omni-channel retailers demand forecasting needs to combine the analysis of patterns and with forecasting methods to improve the accuracy of the forecast and thus enable reducing the uncertainties of the omni-channel retailing supply chain.

As future research, we suggest the insertion of more parameters referring to the products in order to improve the segmentation of the products and consequently the forecast of demand and compare this method with others presented in the literature.

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6 ADAPTIVE OPERATIONS MANAGEMENT APPROACH FOR OMNI-CHANNEL RETAILING SUPPLY CHAINS

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Technology has changed the way retailers manage their operations and their relationships with customers. For omni-channel retailers to provide a seamless customer experience, it is necessary to embrace real-time information, adaptive structures and information sharing. The challenge to omni-channel retailing supply chains is to integrate, and manage information, product and financial flows of multiple channels, connecting the real and virtual worlds. In this context, this paper proposes an adaptive approach to the operational management of omni-channel retailing supply chains. The procedure combines agent-based and discrete event simulation with a heuristic approach based on a genetic algorithm. Computational experiments were conducted to validate the performance of the proposed method, demonstrating that the integration of information and product flows allows for the creation of adaptive omni-channel fulfilment processes, which can support retailing competitiveness.

Keywords: industry 4.0; simulation; optimization; simulation-based optimization; omnichannel retailing supply chains.

6.1 Introduction

Industry 4.0 has brought about significant changes in organizational management as the way people work and the integration of the factory with the entire product lifecycle, as well as in the supply chain activities, due to emerging technologies that are converging to provide digital solutions (Frank, Dalenogare, and Ayala 2019).

The Industry 4.0 can be conceptualized as an integrated system of value creation that comprises 12 design principles, such as smart product, smart factory and interoperability, and

14 technologies trends as cloud computing, big data analytics, internet of things, and simulation and modelling according to Ghobakhloo (2018). Principles and technologies that are also highlighted by Wu et al. (2016) in presenting the basic elements to develop a smart supply chain. These complex adaptive systems that are the smart supply chains, seek to build adaptive structures to the way raw materials and product are delivered, in which products, processes and systems are easily modified in response to changing conditions, involving exchanging real-time information about production orders with suppliers and distribution centers (Wu et al. 2016; Frank, Dalenogare, and Ayala 2019).

Thus, the omni-channel retailers that make the application of some principles and technologies of the Industry 4.0 are known in the literature as Retail 4.0 or Smart Retailing. They represent retailers that provide customer interactions with innovative technologies and with online and offline channels, without distinction, in order to improve the consumer shopping experience (Vazquez, Dennis, and Zhang 2017; Lee 2017).

The adoption of intelligent technologies can affect methods of consumer data collection, information management, and the transfer of knowledge between companies by creating a partnership between customers and retailers, and providing benefits such as the best visibility of the products, and smart cooperation and sharing information among all actors in the supply chain (Pantano, Priporas, and Dennis 2018).

Hübner, Wollenburg, and Holzapfel (2016) state that information exchange, joint operations, logistics and inventories across channel enable conflation of the online and offline fulfillment process. According to Wollenburg, Holzapfel, and Hübner (2019), operations play a key role in omni-channel retailing as it is in direct contact with customers and does not end at the store.

For Melacini et al. (2018) omni-channel retailing is a major logistics challenge because online channel differs from the traditional retail in many aspects, as picking unit and the delivery process, making it necessary to create new logistics models, evaluating the trade-off between the process of integration and separation between the different channels.

With new fulfillment options, omni-channel retailers need a significant effort to integrate the logistics network and product flow (Wollenburg, Holzapfel, et al. 2018), and thereby redefine their fulfillment structures and operations. According to Ishfaq and Raja (2018), the major operational challenge is online orders´ fulfillment while managing their traditional store-based distribution process. Despite the importance of topics such as the evolution of retail distribution networks, the logistics role played by stores in the delivery process and the interplay between different logistics aspects are still under-investigated (Melacini et al. 2018).

Analyzing the logistic role played by the stores Jin, Li, and Cheng (2018) developed a theoretical model in which a physical retailer adopts buy-online-pick-up-in-store (BOPS) and uses a recommended service area to orders´ fulfilment from both online and offline customers in one order cycle. MacCarthy, Zhang, and Muyldermans (2019) examine store picking operations for same day BOPS services and derive Best Performance Frontiers (BPFs) for single wave and multi-wave in-store order picking.

Evaluating the retail distribution networks, Ryu, Cho, and Lee (2019) use stochastic frontier analysis to estimate the technical efficiencies of small-scale enterprises using only one channel or using online and offline channels together. Wollenburg, Hübner, et al. (2018) developed an exploratory study with retailers from different contexts to analyse the internal logistics networks used to serve customers across channels.

The logistics aspects were considered in studies such as Wollenburg, Holzapfel, et al. (2018), which identified, through multiple sources of data, how customers can be guided through channels by means of related options in inventory management, delivery modes, and return modes. Zhang et al. (2019) applied particle swarm optimization (PSO), in order to focuses on the integrated optimization of supply chain distribution network and demand network to minimize the total costs of the supply chain network under uncertain customer demands, however, they did not analyze the participation of suppliers in this supply chain. And Peinkofer et al. (2019) adopt a qualitative research methodology to investigate suppliers in the drop-shipping service through a tactical/operational perspective.

From these papers, there is a need to develop approaches to evaluate new possibilities of distribution networks, including retailers and suppliers as new drop-shipping points, through logistics aspects and supply chain costs.

For this purpose, Pereira et al. (2018) presented a conceptual model for predictive and adaptive management approach for omni-channel retailing supply chain (OCRSC), which includes information, product and financial flows, by the application of machine learning to predict the demand, and simulation-based optimization to synchronize the product flow. However, the authors did not propose the optimization method to the simulation-based optimization and did not apply the proposed model to demonstrate the efficiency of the model and method.

The paper extends the approach presented by Pereira et al. (2018) when proposing and validating an adaptive approach to the operational management of omnichannel retail supply chain, developed by means of simulation-based optimization.

6.2 Literature review

6.2.1 Logistics and supply chain aspects of Omni-channel retailing supply chain

Customers increasingly demand anytime and fulfilment from anywhere, requiring improved inventory management and distribution strategies from retailers (Castillo et al. 2018). Bell, Gallino, and Moreno (2015) sustain that due to the different ability to deliver information and product fulfilment, considered the two most critical channel functions, of the offline and online channels, omni-channel retailer must respond to consumer heterogeneity in preferences for whether information is delivered in-store or online, or whether product is available in-store, or shipped.

Due to the fact that different sales channels create separate demand streams in terms of order size, delivery requirements, and customer expectations, retailers face significant difficulties in shaping their distribution operations in terms of where to stock inventory and its allocation to different demand streams (Ishfaq et al. 2016). Therefore, companies strive to integrate innovative transportation technologies into existing distribution systems (Castillo et al. 2018), and considering allocate inventory in a distribution center (DC) for exclusive use for online orders, pool inventory for use with all demand streams, and use store inventory to fulfill online orders (Ishfaq et al. 2016).

In order to better understand the physical distribution process for retailers' long-term success, executives highlighted the areas of fulfilment, delivery options and leverage the store because they consider as the key operational characteristics of the supply chain (Ishfaq, Defee, and Gibson 2018). The area of fulfilment is the area that analyses the alternatives of fulfilment and inventory, the delivery options are concerned with the value and the time of the delivery, and the leverage the store is the area which analyze the option of "in store pick up". Important areas since online and offline channels have different cost structures depending on how orders are fulfilled, as online channel benefit from inventory pooling and lower inventory costs, and offline channel have to forecast demand for each product and store and usually experience higher demand-supply mismatches and additional inventory costs (Bell, Gallino, and Moreno 2015).

In companies operating in an omni-channel, four main logistics variables related to delivery service must be considered, which are, the delivery mode, velocity, time slot and slot price differentiation (Marchet et al. 2018). However, Murfield et al. (2017) state that timeliness is consistently the most important aspect of logistics service that leads to satisfied and loyal consumers, so retailers need to account for this reality and dedicate substantial resources to meet delivery requirements for time starved consumers in a timely manner.

In an effort to reduce the product delivery time to customers, some retailers are beginning to structure their offline stores to support the storage and distribution operations of online sales products and thereby creating new distribution options. According to Hubner, Holzapfel, and Kuhn (2016) the distribution system of omni-channel retailing consists in three categories that are store delivery, home delivery and store pickup. In store delivery, the products are distributed from supplier or DC to the stores characterizing the offline channel distribution system. For online sales the distribution system is divided in home delivery, composed of "buy online ship from store", where stores can serve as hubs for last-mile deliveries (Ali et al. 2017; Bayram and Cesaret 2017; Wollenburg, Hübner, et al. 2018), buy online ship from DC (Hübner, Wollenburg, and Holzapfel 2016) and buy online ship from supplier (Hubner, Holzapfel, and Kuhn 2016; Peinkofer et al. 2019). And the store pickup is composed of "buy online and pick up in store" (BOPS) (Gao and Su 2017), also known as "click-and-reserve" (C&R) (Hubner, Holzapfel, and Kuhn 2016), where customers buy through the online channel and withdraw in stores and retailers uses in-store inventory to fulfill online customer demand (Akturk, Ketzenberg, and Heim 2018), and "ship-to-store" (STS) (Gallino, Moreno, and Stamatopoulos 2016) or "click-and-collect" (C&C) (Hübner, Wollenburg, and Holzapfel 2016; Marchet et al. 2018), in which customers withdraw the product in stores but retailers use centralized fulfilment, ie after the online purchase the product is distributed from DC to the store to be withdrawn by the customer.

Thus, by providing customers with a variety of shopping and product picking possibilities, Gallino, Moreno, and Stamatopoulos (2016) state that retailers are facing increased inventory level in offline stores by increasing sales dispersion.

Therefore, OCRSC must be able to evaluate the possible distribution scenarios to make the trade-off between service time and costs related to inventory levels, so the best scenario is the lowest total cost for the supply chain. To maximize integration, visibility, and exploit the omni-channel operational / tactical implications of the retail supply chain, Ivanov (2017) emphasizes that simulation modelling is still an unexplored field of great benefit to analyze the details and characteristics of the elements of the supply chain and Saghiri et al. (2017) also suggest the application of an analytical study.

6.2.2 Simulation-based optimization to the omni-channel supply chain

The complexities of most real-world systems are related to their stochastic nature and the wide variety of internal and external interactions of these systems, and that simulation-based techniques can be used to develop or evaluate complex systems (Kück et al. 2016). However, according to Kück et al. (2016), the simulation cannot guarantee the optimization of the systems in relation to one or more performance indicators such as lead-time, cost of production, among others, and that optimization methods are mainly used when a complex system can be modeled by a simplified abstraction.

Govindan, Fattahi, and Keyvanshokooh (2017) sustain that modelling approach is an interesting research idea in order to fill the gap between stochastic programming and robust optimization. Thus, a promising approach that combines the strengths of simulation and optimization is known as simulation-based optimization (SBO), where the simulation model being used as the objective function of the optimization and the optimization method used to determine the optimal configuration of simulation parameters (Kück et al. 2016).

According to Frazzon et al. (2015) and Frazzon et al. (2018), combination of both can also provide relevant capabilities for the supply chain management. In the context of simulation-based optimization of processes for the supply chain, researchers diversified in the choice of methods to structure and optimize the distribution processes.

In order to develop the simulation and optimization model, the papers that applied these methods to the omni-channel retailing supply chain published in the Emerald, EBSCO host, Scopus and ISI Web of Science databases were analyzed in order to obtain the analyzed inputs and parameters in these papers.

From the papers found, it was possible to observe the absence of a work that makes the application of simulation-based optimization in an omni-channel retailing supply chain, and due to this fact, this paper used as basis works that applied the simulation and the optimization separately and an article that approached the optimization-based simulation.

In the survey of the papers that applied the optimization was considered the articles that made the application of optimization methods for operational problems of the retail supply chain. Yan-qiu and Hao (2016) have developed a multilevel logistics supply network optimization model with constraints on distribution capacity, inventory capacity and improved customer delivery time. Zhang et al. (2019) constructed a joint randomization planning model of location and routing to integrated optimization of supply chain distribution network and demand network, and adopted the transportation, operating and carbon treatment costs to minimize the total supply chain. Ishfaq and Raja (2018) develop a modelling framework for the retail distribution system in which online orders can be filled from different fulfilment nodes, and the selection of fulfilment options is based on inventory, transportation, operating, fulfilment costs, and cost of goods. The authors utilized as restriction the storage limits related to every fulfilment node in the network, online demand is fully filled from available inventory, inbound/outbound product flow among others. Lee (2017b) proposed a Genetic

Algorithm (GA)-based optimization model to support anticipatory shipment of products to hubs, considering only the relationship between the supplier and the distribution centers, and for this purpose he adopted the objective function of minimizing transportation cost and traveling time, and maximizing prediction rule confidence. And adopted as restrictions: (i) a capacity of each hub, (ii) the quantity shipped to hub k can reach the service level corresponding to the prediction rule confidence, and (iii) the amount of each product type shipped from each source will not exceed the amount of the product type available in the hub. Bayram and Cesaret (2017) investigates which location to fulfill an online order when it arrives, and for this reason developed an heuristic to analyse three fulfillment policy, which are (i) do not fulfill and thus reject the order, (ii) fulfill the order from the DC, and (iii) fulfill the order from the store and for each of them there was different objective function and considered as restriction the stock level and the handling costs.

Ali et al. (2017) also developed a heuristic in order to address order fulfillment optimization and considers multiple orders simultaneously. For that purpose, proposed the minimization of shipping and load balancing costs and used restrictions to (i) stipulates that units of SKU k sourced is equal to its demand, (ii) setting up the upper and lower limits of the weight intervals for carriers available at nodes, (iii) upper bound for units delivered, (iv) make sure that exactly one weight interval for a carrier is chosen if the carrier itself is chosen, (v) assign of a SKU to node forces carrier selection for the node.

In this way, it can be seen that in order to develop studies that apply optimization in the omni-channel retailing supply chain, it is important to consider in the objective function the costs related to transportation costs and operations costs that support transportation. And in the restrictions, it is important to highlight the maximum and minimum levels of inventory, the supply of demand, storage capacity of distribution centers and stores, and transportation capacity.

Dealing with simulation, Okada, Namatame, and Sato (2016) describe an agent-based simulation tool for designing smart supply chain networks as well as logistics networks. Muir, Griffis, and Whipple (2019) explores the relationship between a retailer's product returns processing structure and Multi-Echelon inventory system performance, and for that, developed and tested research hypotheses through experimentation on a Multi-Echelon retail inventory system within a discrete-event simulation. To develop the simulation the customer demand, inventory, backorder, transportation and fulfilment, and return information's were adopted as parameters.

Some papers can be highlighted for having applied simulation and optimization together, Deshpande et al. (2017) applied the optimization-based simulation to evaluate order fulfillment decisions. The authors used a software developed by IBM, the simulation software is a discrete event simulator, and the optimization software, developed by Ali et al. (2017), uses the mixed integer program. It was point out that the simulation and optimization tools are useful for the planning of fulfilment policies. The simulation represents a two-stage supply chain composed of physical stores and distribution centers and simulated two fulfilment policies. The first policy simulates the distribution of products sold online by the distribution center and the second the distribution, called split mixed orders, is divided between distribution centers and physical stores. In the split mixed orders, the products that are sold online and offline are distributed by the physical stores and the rest are distributed by the distribution centers. The simulation of 5,000 orders was carried out and the optimization-based was used in order to minimize initially only shipping, and subsequently minimize shipping and processing cost. After the application of the simulation, it was identified that the policy of fulfilment split mixed orders was more advantageous, and by the application of the optimization-based approach they identified the potential benefit of multi-objective of the minimization of shipping and processing costs.

In this way, optimization and optimization-based simulation seek to ensure the availability of the products in the various channels and the best way to deliver these products, and that the fulfilment process is extremely important for the coordination between demand and supply and consequently for the management of the omni-channel retailing supply chain.

6.2.3 Evolutionary and Genetic Algorithm Optimization Approach

In this section, it is presented the relevant literature regarding Evolutionary Algorithms (EA), focusing in the main heuristic that was applied in this study, the Genetic Algorithm (GA).

According to Lin, Gen, and Wang (2009), evolutionary algorithm uses a structure but randomized way to utilize genetic information in finding new search directions. Aljarah, Faris, and Mirjalili (2018) and Yang (2014) explain that EAs are population-based, in which a number of possible random solutions are generated, evolved, and updated until a non-unsatisfactory, bounded by a performance frontier, solution is found, or a maximum number of iterations is reached. EA incorporates randomness as the main mechanism to move from a local search to a global search, and therefore, they are more suitable for global optimization. The main evolutionary algorithm used in the literature is the Genetic Algorithm (Jalali and Nieuwenhuyse 2015).

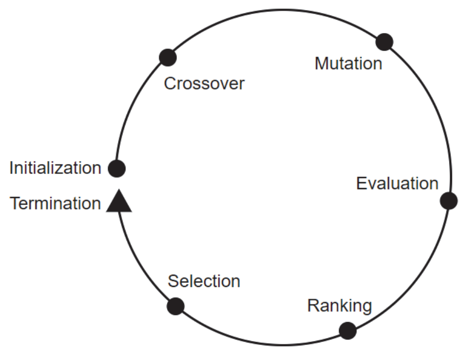

Figure 1. The GA, adapted from (Kramer 2017)

The GA is inspired by the laws of natural evolution, simulating the Darwinian evolution (Mirjalili and Lewis 2016). As presented in Figure 1, the search process starts with a randomly generated population that evolves over generations. This evolution is guaranteed at the crossover and the mutation steps. The strength point of this method is that the best individuals are the ones that keep evolving despite the worst ones that are removed from the population. In the two final steps (called ranking and selection), the worst fitted individuals are separated from the population, being removed while the best ones continue the evolution process. This way, the best individuals are always combined together to form the next generation, what allows the population to be optimized.

The crossover process works as follows. From the population, some individuals (called parents) generate new individuals (son) that join the population. Two sons are generated by receiving parts of the chromosome from both parents that changes part of the genes. The chromosome that composes individual A and B change a specific part that generates individuals C and D, as show in Figure 2 (Bandyopadhyay and Bhattacharya 2014).

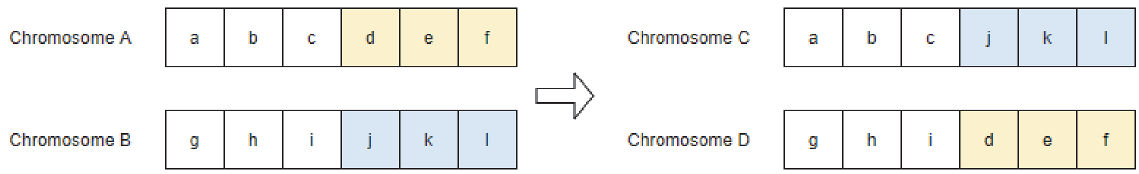

Figure 2. Crossover

After the crossover step, the new individuals can be mutated according to a probabilistic distribution, as represented in Figure 3. The mutation occurs only in the sons changing a specific gene of the chromosome (Wang et al. 2020), which guarantees that the population evolves and not stablished. It is also important to emphasize that not all the sons generated that will be muted and that the chromosomes mutated may not generate a new individual (it will be the same, but mutated).

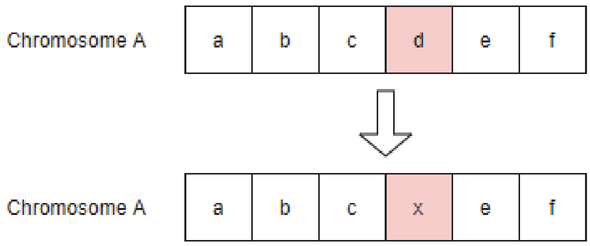

Figure 3. Mutation

6.3 Adaptive operations management approach for omnichannel retailing supply chain

The conceptual model developed by Pereira et al. (2018), presented in Figure 4, is a conceptual model based on the integration by data of the information and product flow to coordinate in real-time the management of the entire omni-channel supply chain. To reduce the uncertainties of the information flow and to provide predictability to the omni-channel retailing supply chain, the model presents the application of a hybrid system composed of the application of machine learning, combining clustering and neural network, to forecast the demand and then share this forecast among all players in the supply chain. And to improve the flow of products, the model proposed the application of the simulation-based optimization to evaluate the possibilities of deliveries of the products sold in the channels to ensure the availability of the product at the time needed and better coordination between demand and supply of the omni-channel retailing supply chain.

The conceptual model allows the visibility and a better management of the product, demand, inventory, shipment/delivery and supply. A complete description about the conceptual model can be found in Pereira et al. (2018).

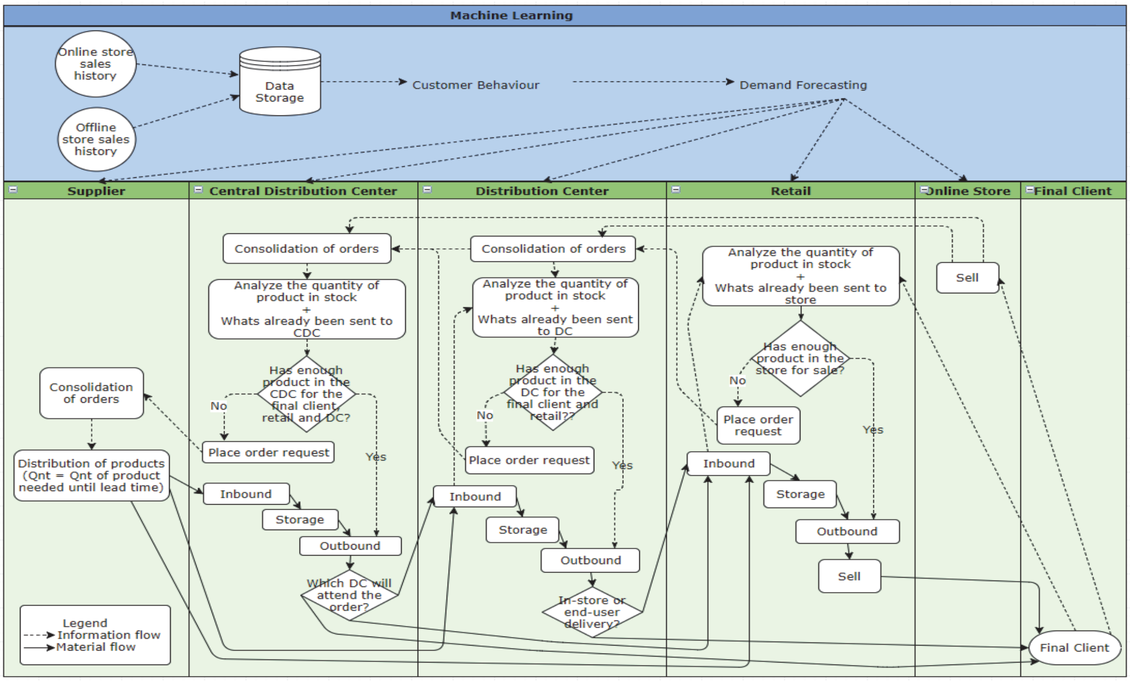

Figure 4. Conceptual model developed by (Pereira et al., 2018)

In order to achieve an adaptive operations management approach for omnichannel retailing supply chains and based on the conceptual model proposed by Pereira et al. (2018), a simulation-based optimization is developed. The simulation model is created according to a real-world retail supply chain incorporating the stochastic processes through probability distribution. Initially an initial solution is generated based on the current distribution structure in which each agent is served by the previous link that presents the shortest distance. Later, the performance of this solution will be evaluated by the simulation model when determining the logistics cost of the supply chain. Based on the results presented by the simulation the genetic algorithm will adjust the parameters of the distribution to optimize the logistic cost and again this solution will be evaluated by the simulation. The processes repeat until convergence criterion is reached. According to Kramer (2017), when the convergence is approximating to the optimum value, the progress of fitness function improvements may decrease significantly. Thus, if no significant progress is observed, the evolutionary process stops. Then, if the best cost in the generation t is at most 0.1 better than the best cost in the generation (t-1), the system reached the best value. Or if the system reached 100 iterations the evolutionary process stops.

6.3.1 ***Simulation-based optimization***

Simulation-based optimization is a promising alternative to solve complex problems intractable for mathematical programming methods for (Chu et al. 2015). This work proposed a simulation-based optimization approach for integrated demand, material inventory and warehouse information's, and production and transport planning operations.

The simulation represents an OCRSC with the following characteristics: sixteen physical stores, four distribution centers, one supplier, and 16 physical and 27 online clients. The simulation of the system was run for one month and the results presented in this paper are the average of 30 replications.

The information and material flow in the simulation-based optimization model are represented in the Figure 4. The information flow is composed of demand, orders and inventory information's, and the material flow is represented by the production and transportation activities. According to Figure 4, there are two sources of demand. The first demand is the demand forecasting, resulting from the application of machine learning, and the second is the real demand, resulted from the triangular distribution of the historical sales time series of each product, represented in Figure 4 by the final clients. The forecasted demand are allocated to the players according to the physical distribution matrix generated by the optimization.

The orders information from the lack of inventory, is caused by the mismatch of supply and real demand, at each of the physical stores, distribution center and suppliers.

Orders are determined based on the backlog, representing pending orders, expected product receipt quantity, and inventory parameters. However, orders for physical retailers will only be generated if the customer agrees to wait for the products. Inventory information is entered into the model from the stock parameter information for each of the SC stock points, and this information comes from the company's ERP.

Material flows begin with the arrival of information flows. After assessing the demand and the orders that each player can fulfil, the distribution orders are established. Based on distribution orders, the transportations activities initially perform the load consolidation of each player, and then begins the physical distribution of materials. Physical distribution used real routes to map distribution routes through the GIS map available in Anylogic software.

The production activity is the manufacture of products that the supplier could not supply due to shortage of stock. After production, the products are released to the transportation activities. Since the objective of this work is to evaluate the demand and supply planning operations of the omni-channel retailing supply chain, production was considered due to impact product availability time, so, its performance will not be evaluated in this article.

In this manner, the objective function and output of the simulation, is the total cost of the supply chain, including the transportation, loading, unloading, inventory and lost sale costs.

6.3.1.1 Mathematical formulation

The model considers the singular properties and characteristics of presented scope to reach the best solution to the problem. This formulation was implemented using Java programming language. The relevant variables are presented in Table 1.

Table 1 – Model variables and parameters

Variable	Definition
$dc_{i,j}$	Delivery cost from node i to node j
uc_j	Unload cost at node j
lc_i	Load cost at node i
sc_i	Stock cost at node i
$x_{i,j}^k$	Quantity of product k to be delivered from node i to node j
d_j^k	Demand of product k at node j
st_i^k	Stock of product k at node i
s_i	Minimum stock at node i
S_i	Maximum stock at node i
$y_{i,j}$	Binary variable that indicates if it is possible to node i to deliver products to node j. $y_{i,j}$ = 1 if node i can supply node j; = 0 otherwise
Parameters	Definition
N	Total quantity of nodes
K	Total quantity of different products

Equations (1) to (8) present the objective function and the mathematical model.

$$Min\ Z = \sum_{i=0}^{N}\sum_{j=1}^{N}\sum_{k=0}^{K} y_{i,j} dc_{i,j} x_{i,j}^k + \sum_{i=0}^{N}\sum_{k=o}^{K} lc_i x_{i,j}^k + \sum_{j=0}^{N}\sum_{k=o}^{K} uc_j x_{i,j}^k + \sum_{i=0}^{N}\sum_{k=0}^{K} sc_i st_i^k + \sum_{j=1}^{N}\left(d_j^k - \sum_{i=0}^{N} x_{i,j}^k\right) \tag{1}$$

Subject to:

$$\sum_{i=0}^{N} x_{i,j}^k \leq d_j^k \tag{2}$$

$$\sum_{j=1}^{N} x_{i,j}^k \leq st_i^k \tag{3}$$

$$s_i \leq \sum_{k=0}^{K} st_i^k \leq S_i \tag{4}$$

$$\sum_{j=0}^{N}\sum_{k=0}^{K} x_{i,j}^k - \sum_{k=0}^{K} st_i^k \geq s_i \tag{5}$$

$$\sum_{i=0}^{N}\sum_{k=0}^{K} x_{i,j}^k + \sum_{k=0}^{K} st_j^k \leq S_j \tag{6}$$

$$d_j^k - \sum_{i=0}^{N} x_{i,j}^k \geq 0 \tag{7}$$

$$x_{i,j}^k, st_i^k, d_j^k \geq 0 \tag{8}$$

The objective function (1) is to minimize the total cost in the supply chain, including the transportation, loading, unloading, stock and lost sale costs. Equation (2) ensures that the total quantity of product k to be delivered to node j is less or equal to the demand of product k in that node. Equation (3) ensures that the total quantity of product k to be delivered from node i is less or equal to the quantity of product k in stock at that node. Equations (4), (5) and (6) ensure that the quantity of product k at any node is between the minimum and maximum quantity allowed. Equation (7) ensures that the lost sale cost will never be negative (i.e., revenue) and, finally, Equation (8) ensures the non-negativity.

6.3.1.2 Genetic algorithm

To determine the delivery/physical distribution configuration to fulfill offline and online orders, it was applied the genetic algorithm. The GA receives the inventory and demands information of all the products at each node. Respecting the level delivery rules, where each player can send products downstream, but cannot send to the same level or upstream, a population of n feasible solutions is created. Then, the crossover of m individuals expands the population to a size equal to $n + \frac{m}{2}$. The $\frac{m}{2}$ individuals generated in the crossover process can be muted.

The mutation depends on a probability defined by $p = \frac{1}{L}$, where L is the quantity of nodes. The final population, after crossover and mutation, is simulated generating a vector of costs. The population is then ranked according to costs. If the cost in the iteration i has a change equal or less to 1% in comparison with the iteration $(i - 1)$, then the optimization reached the optimal solution and it returns the delivery configuration matrix. If the cost has an error greater then 1%, then the $\frac{m}{2}$ worst solutions are removed from the population and the optimization returns to the crossover step.

6.4 Test case

For this study, a Brazilian retailer provided the data. The retailer operates 139 physical stores and the online store and sells a wide assortment of products including home appliances and decor, furniture, housewares, health and beauty, kitchen appliances, tv and cell phone among others.

The furniture category was chosen because it is the category that most impacts on the company's billing and is composed of 684 products. To develop this work, 5 best-selling products in this category were chosen, because even representing 0.7% of the quantity of products, they represent 7% of furniture sales volume.

The retailer operates three regional and one central distribution centers, the central receiving the products from suppliers and distributing the products to regional DCs. To fulfill the online orders, the retailer uses the distribution centers and does not use any means of information or operation integration. Thus, the supplier has no visibility of the retailer's actual sales, only the order based on moving average forecast placed at the beginning of each month. As this paper does not analyze the last mile, online sales for the same state were analyzed together, and also delivered together for pick-up points.

In order to evaluate the operational performance of the adaptive approach for omni-channel retailing supply chain, two contexts were analyzed. The first context is with the application of simulation and the second with the simulation-based optimization. The demand considered for both contexts was the triangular distribution of real demand and the forecast demand determined by moving average, and orders were used to balance supply and demand.

To analyze the fulfillment process in the simulation, the orders were sent to the closest fulfillment option, thus, the retailers send the order to the closest distribution center, the regional distribution centers sent to the central distribution center (CDC), and CDC sent the orders to the supplier.

To assess the fulfillment processes by the simulation-based optimization three scenarios were evaluated to validate the approach with various players and echelon for retail supply chain distribution. The scenarios were assessed through the delivery options presented in the literature for the omni-channel retail supply chain, and the fulfillment were determined by the genetic algorithm in the simulation-based optimization. First, it was analyzed the delivery to final customers only through distribution centers, then adding retailers as delivery points and finally the fully integrated chain with the delivery also being performed by the suppliers.

According to Andrews et al. (2019), a good fulfillment strategy from retailers need to attempt to avoid lost sale, minimize costs, minimize time to customer and respect operational constraints. For this reason, all the analyzed scenarios were evaluated with and without the cost of sale lost in the objective function. In cases without the lost sale cost, this cost was computed to analyze its value in the supply chain but not entered into the objective function, the objective function only minimizes the operational cost from the supply chain.

6.5 Results and discussions

To assess the application of the adaptive approach to the OCRSC and to evaluate the adoption of the genetic algorithm, the operational costs of the supply chain, the fulfillment time for offline and online customers, and the quantity of orders requested by the demand and supply mismatch were analyzed.

The operating costs of the supply chain were assessed using the costs of loading, unloading, transportation, inventory and lost sale, as shown in Figure 5.

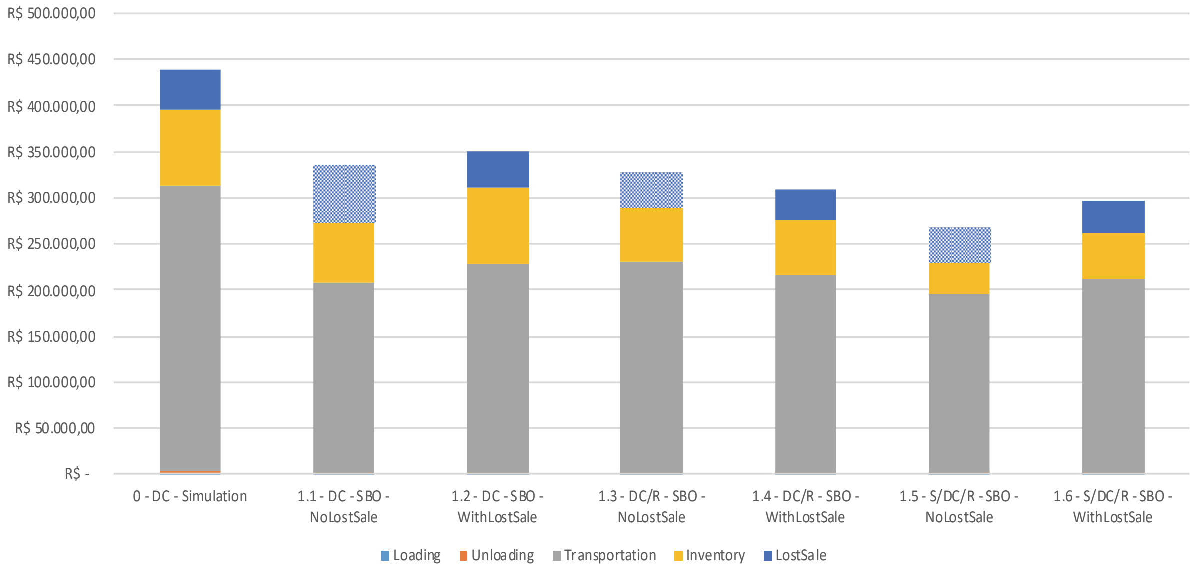

Figure 5. Operational cost of the omni-channel retailing supply chain

With the application of simulation-based optimization, operating costs of scenario 1.2, which had the highest cost of SBO, reduced by 20% when compared with scenario 0 that applied the simulation. In the scenario 1.2 the distribution of online customer orders was performed only by the central distribution center with lost sale in the objective function.

As noted in Figure 5, without the lost sale cost, scenarios 1.1 and 1.5 yield operational costs lower than scenarios 1.2 and 1.6, that include it.

However, due to the need to avoid lost sales for retailers, it is important to note that with the shortage of product at the right time, Verhoef and Sloot (2010) state that retailers face an average direct loss of 21% of the potential sale and the manufacture of 35%.

Another reduction was the number of orders placed due to the mismatch of demand and supplies, shown in Figure 6 and Figure 7. In the simulation, there were a total of 47,652 orders and in scenario 1.2, which had the largest number of orders from the SBO, was 6,358, reducing the number of orders by 87% and consequently unbalancing the supply chain.

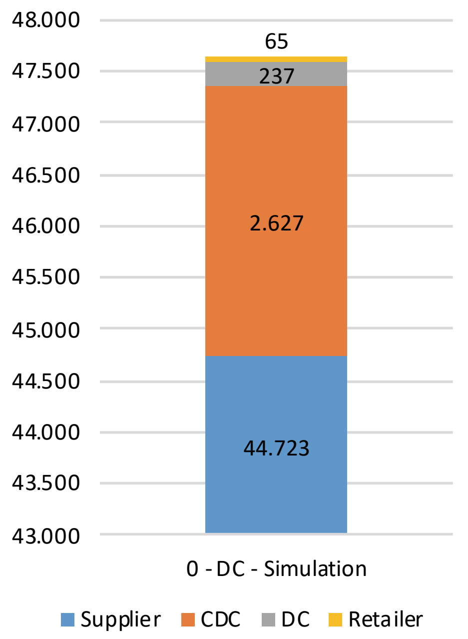

Figure 6. Number of orders per echelon of the simulation

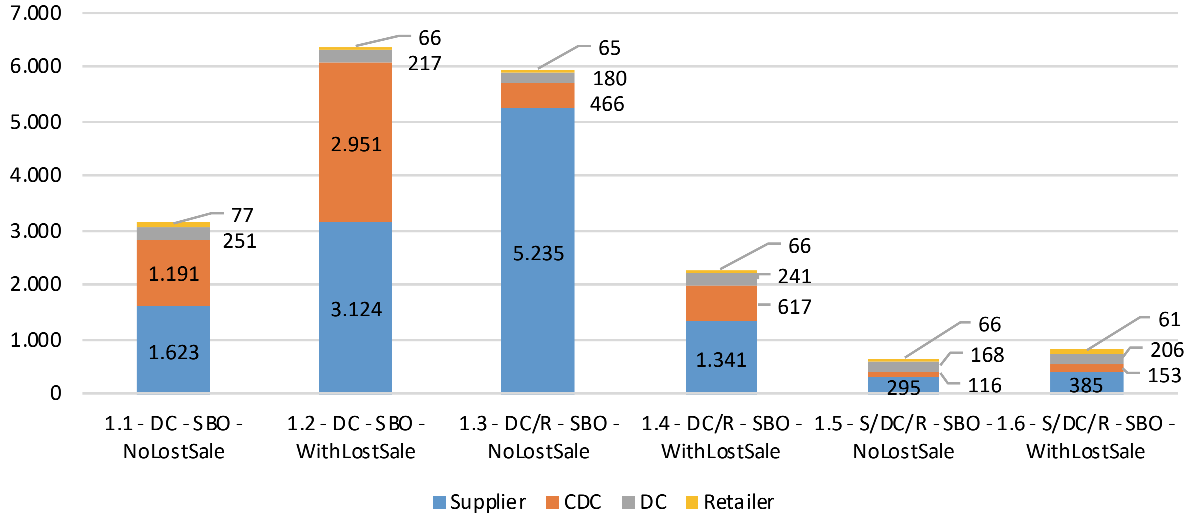

Figure 7. Number of orders per echelon of the simulation-based optimization

With this reduction, we can affirm that the adoption of the genetic algorithm was able to evaluate the location of the products in the supply chain and to make a better allocation of the distribution orders of the products to the players that would distribute them.

Analyzing the fulfillment times for physical customers, in Figure 8, it can be seen that the times of the SBO scenarios remained close to the times of the base scenario (simulation), whose orders are placed for the nearest distribution center.

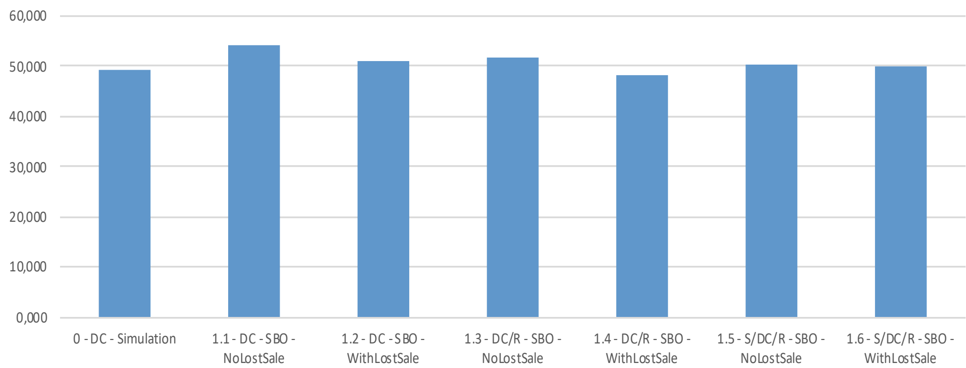

Figure 8. Fulfillment time for physical customers

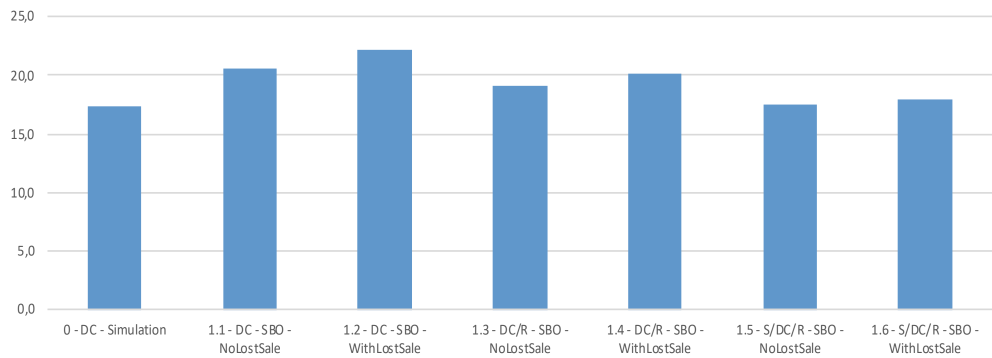

Figure 9. Fulfillment time for online customers

When analyzing the fulfillment time for online customers, in Figure 9, it can be seen that the scenario that came closest to scenario 0 was the scenario in which the supplier also does the distribution. This is justified by the fact that due to the supplier's location being in a state where there are no physical stores, the possibility of delivery of products by this player reduced the delivery time for online customers.

Therefore, we can highlight that the application of simulation-based optimization, through hybrid simulation (agent-based and discrete) with genetic algorithm, is an adaptive approach capable of reducing the operational costs of the omni-channel retailer chain, maintaining fulfillment times and significantly reduce the quantity of orders resulting from the mismatch of demand and supplies.

6.6 Conclusion

With the technological evolution and the emergence of the online channel, retailers had to became smart and adopt technologies and principles presented in industry 4.0 to provide a better service to customers and have a greater visibility of their operations and cooperation with other agents in the supply chain.

Due to these organizational changes, the management and visibility of operations started to play a fundamental role for retailers, with logistics being the main challenge due to new distribution options and differences in operational in the service of online and offline channels.

In order to develop approaches capable of assessing the new possibilities of distribution networks, including retailers and suppliers as new delivery points, this paper extends the approach presented by Pereira et al. (2018) in proposing and validating an adaptive approach to the operational management of omnichannel retail supply chain, developed by means of simulation-based optimization. To deal with adaptive, the genetic algorithm was adopted in order to better allocate the order to the agent who is going to deliver the product.

Through the application of the approach in a Brazilian retailer, it was possible to analyze and compare the performance of simulation-based optimization with simulation. When analyzing the results, it can be concluded that given the logistical complexity that retailers are facing, they need approaches such as simulation-based optimization that are capable of evaluating all distribution alternatives through the location of products in the chain, to reduce operating costs, product delivery time and the number of orders resulting from the mismatch between supply and demand, and remain competitive in the market.

As a future research, we suggest inserting the last-mile analysis and the Buy-Online-and-Pick-up-in-Store option in order to improve the approach performance, because due to legal restrictions the organization did not provide such information to be evaluated in the model.

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7 A DATA-DRIVEN APPROACH FOR OMNI-CHANNEL RETAILING SUPPLY

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Abstract: The integration on selling channels and new fulfillment options triggered by omni-channel are transforming the retailer's operational management. However, there is still a lack of research regarding the connection between digital and real worlds, mainly when it comes to omni-channel retailing supply chains, which is based on the integration of flows and multi-channel activities to better serve the consumer. This paper aims to propose and validate a procedure that combines demand forecast, derived from machine learning techniques, and the operational planning of omni-channel retail supply chain, developed by means of simulation-based optimization. The procedure employs computational programming to perform the predictive approach by analyzing the demand through machine learning, along with the application of simulation-based optimization to adaptively synchronize demand and supply. The findings are substantiated through the application of the procedure in an omni-channel retail supply chain, demonstrating that the predictive and adaptive approach, through the combination of machine learning and simulation-based optimization techniques, provide better performance outcomes.

Keywords: Simulation-based optimization, Machine Learning, Omni-channel Retailing Supply Chains, Data-driven.

7.1 INTRODUCTION

Omni-channel retailing embraces a synergetic integration of selling channels in order to create a unified brand experience for customers (Lee, Chan, Chong, & Thadani, 2019; Ovezmyradov & Kurata, 2019). Omni-channel blurred boundary between channels and are breaking down the within-channel structure and emerging different combinations of information provision, such as showrooming and webrooming, with new possibilities of product delivery (Caro & Sadr, 2019).

Chopra (2016) states that a well-structured omni-channel supply chain presents the strengths of complementary online and offline channels, making the supply chain economically viable and responsive to the customer. According to Li et al., (2018), omni-channel retailing assist retailers in retaining customers by reducing uncertainty related to demand and providing attractive offers, and therefore, it facilitates real-time inventory management, accelerates distribution, and integrates brand management through channels states von Briel (2018).

For retailers aligning and integrating these channels, offering product delivery, and providing seamless customer experience, the challenge is to understand how multiple channels can be integrated, managed, and operated synergistically (Marchet, Melacini, Perotti, Rasini, & Tappia, 2017; Mirsch, Lehrer, & Jung, 2016). This challenge is due to the fact that the integration of different channels and touchpoints increases the complexity and presents more obstacles for the omni-channel retailers (Hosseini, Röglinger, & Schmied, 2017).

Liao, Deschamps, Loures, & Ramos (2017) point to the need in research on the end-to-end digital integration, which has been conceptualized as integration throughout the engineering process, so that the digital and real worlds are integrated across the value chain of a product.

Thus, in order to develop an integrated omni-channel retailing supply chain, it is necessary to seek integration between the real and virtual worlds through technologies, meeting consumer needs, and offering profitability for the entire omni-channel retail supply chain, by better management of information, product and fund flows (Chopra, 2018).

Coordination of the material and information flow across the entire supply chain creates a win-win situation for all players in the supply chain. However, in the win-win scenario, the integration of information across a supply chain has received limited attention (Yang & Zhang, 2019).

According to Caro & Sadr (2019), when information and product delivery are decoupled, matching supply and demand become even more difficult to achieve, as the separation of information and fulfillment brings more opportunities to interact with the customer, but it complicates balancing the supply-demand equation.

However, with the globalization of demand-supply networks and the desire for a more integrated operation plan, demand planning is one of the greatest challenges (Chen, Hsu & Blue, 2007). Distortions in demand forecasting cause the bullwhip effect, which can lead to inefficiencies, excessive inventory, stock-outs and backorders (Kumar, Shankar & Alijohani, 2019). And due to the variety of product delivery possibilities, adequate and efficient distribution system are key in omni-channel retail (Rai, Mommens, Verlinde, & Macharis, 2019).

Lawson, Pil, & Holweg (2018) highlighted that the power of having information flow from customers to the factory is equally important from the companies' different order-to-delivery capabilities to the customer.

Proposing this integrated management of information flow, represented by demand information, and the flow of product, by the supplies, Lee (2017) developed a Genetic Algorithm (GA) optimization model to support the advance shipment of products to the hubs, considering only the relationship between the supplier and the distribution centers, and assumed that all planned items would be delivered at one time, without considering restrictions on the quantity of products transported. Pan, Giannikas, Han, Grover-Silva, & Qiao (2017) applied the time series analysis and vehicle routing problem to propose an innovative approach to using customer-related data to optimize the home delivery of a grocery store, thus only analyzing the logistics of the last mile and not analyzing the supply chain as a whole.

Zhang, Zhu, Li, & Wang (2019) applied the traditional particle swarm optimization (PSO) in order to focus on the integrated optimization of supply chain distribution network and demand network to minimize the total costs of the supply chain network under uncertain customer demands. However, they did not analyze the participation of suppliers in this supply chain and the adopted demand was a normal distribution of demand, not making the adoption of more advanced methods to reduce uncertainties.

Pereira, Oliveira, Santos, & Frazzon (2018) proposed a conceptual model for predictive and adaptive management approach for omni-channel retailing supply-chain which includes the information, product and fund flows by the application of machine learning to predict the demand and de simulation-based optimization to synchronize the product flow.

Thus, this paper seeks to identify what performance improvements the integrated management of information flow and material flow can provide to reduce demand and supply mismatch and consequently improve the performance of omni-channel retail supply chain operations. In order to identify those performance improvements, this paper extends the approach developed by Pereira, Oliveira, Santos, & Frazzon (2018), proposing and validating a predictive and adaptive approach to the operational management of omni-channel retailing supply chain.

7.2 LITERATURE REVIEW AND THEORETICAL BACKGROUND

7.2.1 Demand Forecasting for Omni-channel retailer Supply Chain

Evolving supply chains creates challenges and opportunities for forecasting (Yang & Zhang, 2019). Accurate forecasts drive supply chains as customer expectations increase, lead times become shorter, and the pressure to manage resources increases (Boone, Ganeshan, Jain, & Sanders, 2019).

The uncertainty of demand propagates and gets magnified over the network, and becomes it decreases effectiveness of supply chains (Chen, HSu & Blue, 2007).

Kumar, Shankar, & Alijohani (2019) state the that demand planning synchronizes the flow of goods and services in a supply chain, while Chen, Hsu, & Blue (2007) advocate that impacts the quality of subsequent planning activities. Demand estimation is an essential input to management of inventory and labor (Mou, Robb & DeHoratius, 2018).

Rai, Mommens, Verlinde, & Macharis (2019) suggest that a better understanding of consumer behavior patterns, leads to more accurate demand forecasts, which in turn allows gaining insight in the transport flows related to shopping, and to more effectively plan and execute supply chain operations (Boone, Ganeshan, Jain, & Sanders, 2019).

Due to uncertainty, Mou, Robb, & DeHoratius (2018) affirm that retailers need to discern customer purchase behavior while simultaneously make assortment decisions, balancing the trade-off between collecting information on purchase behavior and maximizing revenue.

Some articles that analyze consumer behavior can be highlighted as the article by Xue & Lin (2017) who applied clustering to explores the behavior characteristics and the customer segmentation based on consumption data stream mining. Yurova, Rippé, Weisfeld-Spolter, Sussan, & Arndt (2017) developed and evaluated a model utilizing partial least squares to test the hypothesis concerning the adaptive selling behavior for omni-channel consumer. Gao & Yang (2016) adopted the statistical analysis to identify which factors influence consumer’s buying decision. Balakrishnan, Cheng, Wong, & Woo (2018) applied clustering for studying buying behavior of customers and improve product recommendations.

Nevertheless, it is possible to identify that these methods seek to evaluate the dependence and correlation relationship between variables or hypotheses. It can be observed that they are not used to obtain the demand forecast with greater accuracy and lower error percentage.

In order to improve the forecast demand accuracy, Tokar, Aloysius, Williams, & Waller (2014) argue that decision makers have more difficulty dealing with uncertainty timing than with uncertain magnitude of demand. According to Tao, Qi, Liu, & Kusiak (2018) artificial intelligence (AI) solutions enable "smart" factories to make timely decisions, leveraging an effectively support of data-driven manufacturing. And due to the fact that AI systems learn by training on large datasets, retailers are considered a fertile ground for the use and growth of AI (Shankar, 2018).

Inserted in the field of artificial intelligence, data science models are developed for enabling appropriate decisions (Shankar, 2018). A class of models of data science, and considered one of demand forecasting category, machine learning models are particularly useful for learning from the data and making predictive decisions (Kumar, Shankar, & Alijohani, 2019). The predictive models predominantly offer forecasts of focal outcomes and insight for retailers for key decisions (Shankar, 2018).

Kumar, Shankar, & Alijohani (2019) affirm that neural network (NN) can provide superior forecasting model by incorporating nonlinear models when efficiently mapping nonlinear relationships between input and output data, and by their inherent ability to perform better on unpredictable and uncertain demand patterns (Amirkolaii, Baboli, Shahzad, & Tonadre, 2017). Shmueli, Bruce, Yahav, Patel, & Lichtendahl Jr. (2018) state that neural networks are used for time series forecasting because they incorporate external information into the forecast, and for Yang & Zhang (2019), forecasts that consider exogenous factors are generally better than those solely relying on univariate modeling.

This can be assessed in the paper by Pereira & Frazzon (2019), which proposed a predictive model for omni-channel retailing supply chain combining clustering, to understand consumers' consumption pattern through the product sales pattern, with neural network (NN), to improve the accuracy of product forecasting. In order to analyze the performance, the authors compared the result of the clustering combined with ANN using external inputs, to moving average and an ANN without exogenous inputs. The authors demonstrated that models that used exogenous inputs presented higher performance than those without exogenous input and validate the method combining clustering and artificial neural network to improve forecasting accuracy.

Kumar, Shankar, & Alijohani (2019) improve the accuracy of demand forecasting using historical sales data in combining with advertising effectiveness, promotions and marketing events. For this purpose, the authors utilized the fuzzy neural network and compared with benchmark forecasting methods on time series data such as Autoregressive Integrated Moving Average (ARIMA), ANN, Support Vector Machine (SVM), Multiple linear regression (MLR) and Random forest. The results of the proposed methodology present better performances compared to the other methods, although slightly better performance compare to artificial neural network. However, when applying the forecasting methods, the authors did not distinguish between channels and Chopra (2018) states that a key question is the share of customer demand met by each channel.

For this reason, it is important for retailers to increasingly understand the behavior of their consumers and to insert this analysis into their operations to improve accuracy. Thus, apply methods that can better analyze consumer behavior and incorporate exogenous inputs on forecasting methods. And due to the fact that this paper aim to propose an integrated management of information and material flows, by reducing demand and supply mismatch of OCRSC, this paper will adapt the application of Pereira & Frazzon (2019) to make possible the integration of demand forecast with supply analyzes.

7.2.2 Physical distribution for Omni-Channel Retail Supply Chain Management

According to Mou, Robb, & DeHoratius (2018), a common principle to retailers is to provide the right product at the right place to the right customer at the right time. Nowadays, customers increasingly require anytime and demand fulfillment from anywhere, thus retailers need to improved inventory management and distribution strategies (Castillo, Bell, Rose & Rodrigues, 2018).

Mou, Robb, & DeHoratius (2018) defend that due to omni-channel, stores have essentially evolved into miniature distribution center for online order fulfillment, providing both click-and-collect and home delivery services. Due to the variety of reception options, adequate and efficient distribution system are key in omni-channel retail (Rai, Mommens, Verlinde & Macharis, 2019).

Ishfaq, Defee, & Gibson (2018) state that areas of fulfillment, delivery options and leverage the store are considered as the key operational characteristics of the supply chain. The area of fulfillment is the area that analyzes the alternatives of fulfillment and inventory, the delivery options are concerned with the value and the time of the delivery, and the leverage the store is the area which analyze the option of “in store pick up”(Ishfaq, Defee, & Gibson, 2018).

In the omni-channel retailing distribution context the distribution consists in three categories that are store delivery, home delivery and store pickup (Hubner, Holzapfel, & Kuhn, 2016). The deliveries can be sourced from retailers’ distribution center, retailer’s supplier by means of drop-shipping and retailers’ store (Rai, Mommens, Verlinde & Macharis, 2019).

By providing customers with a variety of shopping and product picking possibilities, Gallino, Moreno, & Stamatopoulos (2016) state that retailers are facing increased inventory level in offline stores due to increasing sales dispersion.

Inventory has important functions in store operations, which are to provide sufficient stock for retailers to match customer demand, and non-negligible impact on customer demand sustain (Mou, Robb & DeHoratius, 2018).

Assuring the availability of products is critical to retail store operations (Mou, Robb & DeHoratius, 2018). According to Gruen, Corsten, & Bharadwaj (2002), and reaffirmed by Bijvank & Vis (2011) and Mou, Robb, & DeHoratius (2018), due to product out-of-stock only 15% of the customers will wait for the item to be on the shelves again, and Verhoef & Sloot (2010) sustain that this percentage is 23%.

In terms of delivery options, Fisher, Gallino, & Xu (2019) state that many retailers have identified speed as an important service quality metric for omni-channel retail. In this sense, Murfield, Boone, Rutner, & Thomas (2017) affirm that timeliness is the most important aspect of logistics service, so retailers need to account for this reality and dedicate substantial resources to meet delivery requirements for time starved consumers in a timely manner.

Nonetheless, the physical separation between the customer destination and the location where inventory is held, impact the cost and speed of delivering online orders (Ishfaq, Defee, Gibson, & Raja, 2016). Despite the fact that faster delivery increases online store sales, retailers must weigh the benefit against the cost of faster delivery (Fisher, Gallino, & Xu, 2019).

In this regard, retailers operating in the omni-channel must evaluate all the fulfillment options, inventory level and delivery speed to make the trade-off between service time and costs of the omni-channel retailing supply chain.

To deal with those aspects, Ivanov (2017) emphasizes that the field of simulation modelling is still an unexplored field of great benefit to analyze the details and characteristics of the elements of the supply chain. An application can be found in Okada, Namatame, & Sato

(2016), who developed an agent-based simulation tool for designing smart supply chain networks as well as logistics networks.

However, Kück, Ehm, Hildebrandt, Freitag, & Frazzon (2016) state that simulation cannot guarantee the optimization of the systems in relation to one or more performance indicators, such as lead-time and cost of production, and optimization methods are mainly used when a complex system can be modeled by a simplified abstraction.

Yan-qiu & Hao (2016) developed a multilevel logistics supply network optimization model with constraints on distribution and inventory capacity, and improved customer delivery time. Lee (2017) proposed a Genetic Algorithm (GA)-based optimization model to support anticipatory shipment of products to hubs, considering only the relationship between the supplier and the distribution centers. Bayram & Cesaret (2017) investigate which location to fulfill an online order when it arrives, and for this purpose developed a heuristic to analyze three fulfillment policy.

According to Frazzon, Albrecht, Hurtado, De Souza Silva, & Pannek (2015) and Frazzon et al. (2018), the combination of simulation and optimization can also provide relevant capabilities for the management of supply chains. Deshpande, Quanz, Koc, Ramakrishna, & Lai (2017) applied the optimization-based simulation to evaluate order fulfillment decisions.

In this way, it is observed that simulation studies are concerned with the design of the supply chain, and the optimization and optimization-based simulation seek to ensure the availability of the products in the various channels and the best way to deliver these products. It can also be verified that fulfilment process is extremely important for the coordination of demand and supply, and consequently for the management of the omni-channel retailing supply chain.

Thus, a promising approach that combines the strengths of simulation and optimization is known as simulation-based optimization (SBO), where the simulation model is used as objective function of the optimization, and the optimization method is used to determine the optimal configuration of simulation parameters, according to Kück, Ehm, Hildebrandt, Freitag, & Frazzon (2016).

For this reason, this article will adopt simulation-based optimization to assess the best fulfillment, inventory allocation, and service time in an omni-channel retailer, in order to minimize the cost of the omni-channel retailer supply chain. To do so, it will use optimization to determine the best product delivery alternatives, and simulation to evaluate these alternatives and determine the lowest cost of the supply chain.

7.3 RESEARCH METHODS

7.3.1 Data-driven approach for omni-channel retailing supply chain

In order to analyze the performance of the predictive and adaptive approach for OCRSC, proposed by Pereira, Oliveira, Santos, & Frazzon (2018), presented in Fig. 1, it was proposed and developed a data-driven model for the omni-channel retailing supply chain as show in Fig. 2. The data-driven approach was developed to integrate virtual and real world and balance the supply-demand equation of a complex stochastic supply chain. For this reason, the approach developed is an integrated two-step model combining machine learning, to deal with demand accuracy, and simulation-based optimization to adapt the supply to demand.

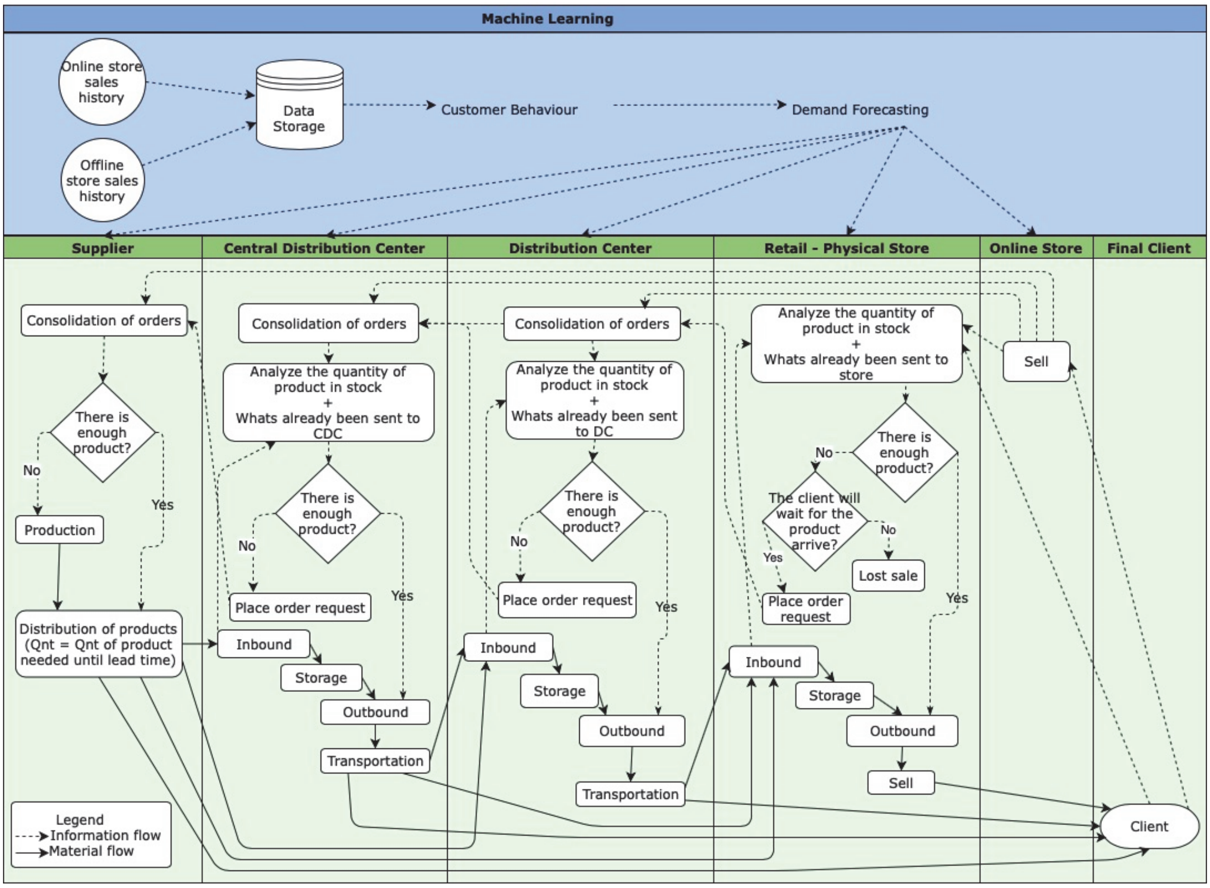

Fig. 1. Conceptual model extended from Pereira, Oliveira, Santos, & Frazzon (2018).

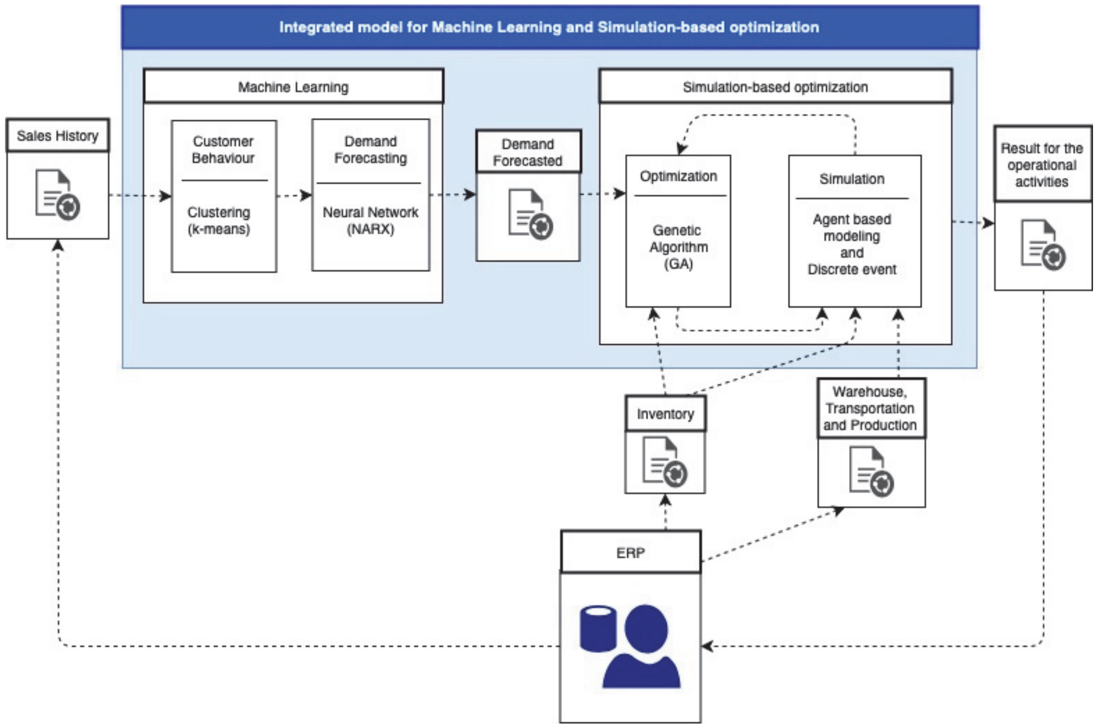

Fig. 2. Method for data-driven simulation-based optimization for omni-channel retailing supply chain.

The first step, which is the machine learning, was developed in R software and comprises the application of clustering and neural network methods to improve the forecast accuracy. As these two methods were developed in the same software, there was no need for an external file to perform the integration between the methods. The input information in the machine learning is the time series dataset based on historical sales of each product, of each channel, and the output are the demand forecasting for each time series. To integrate machine learning with simulation-based optimization, a comma-separated-values (csv) formatted file was used.

The second step, which was developed to improve the flow of materials, is the simulation-based optimization step, and comprises the genetic algorithm and hybrid simulation methods. Both methods work iteratively until the result is achieved, so they have been developed within Anylogic software. Therefore, they did not use external files to integrate either, they used only variables external to the simulation to store the optimization information.

The optimization inputs are forecasted demand and supply chain inventory information, and the output is an initial solution to the distribution planning for the supply chain. The initial values are then applied in the simulation model to test the solution. Working as the objective function, the simulation uses the information of distribution planning, forecasted demand, inventory, warehouse, transportation, and production information to mimic the real scenario. The simulation output is the result of the objective function, which is the logistics cost of the omni-channel retailing supply chain. Then, this objective value is returned to the optimization in order to check the stopping criterion. According to Kramer (2017), when the convergence is approximating to the optimum value, the progress of fitness function improvements may decrease significantly. Thus, if no significant progress is observed, the evolutionary process stops. Then, if the best cost in the generation t is at most 0.1 better than the best cost in the generation (t-1), the system reached the best value. If the criterion is not met the SBO approach is restarted until the stopping criterion is met, or if the system reached 100 iterations the evolutionary process stops.

The outputs of the data-driven approach for omni-channel retailing supply chain are the forecasted demand for each product, in each channel, and the physical distribution planning.

7.3.2 Machine learning model

As shown in Fig. 2, the machine learning method was developed to improve forecasting accuracy, thereby reducing demand uncertainties, and provide more efficient omni-channel retail supply chain operational management. For this reason, in order to better understand the consumption pattern of their customers by historical sales data, this article adopted the clustering method, and to provide a more accurate forecast, the application of neural network method.

Clustering is an unsupervised learning approach to segmentation of data into homogenous sets with the purpose of generating insights (Shmueli, Bruce, Yahav, Patel, & Lichtendahl Jr., 2018).

The k-means and hierarchical algorithms are widely used to cluster data according with Park & Kim (2018) and Shmueli, Bruce, Yahav, Patel, & Lichtendahl Jr. (2018). In this paper, the k-means algorithm is applied to analyze the historical data sales and group the products based on their sales pattern.

In order to be able to analyze the correlation of the sale of the products by channels according to Chopra (2018), the historical time series sales of the products were analyzed by channel and by stores.

In this manner, this work adopted a sequence of three stage to determine the clusters. The first stage was the data preprocessing to detect and remove outliers and then normalize the data.

The second stage was to determine the number of clusters that better represent the data, and for this, the package NbClust was used. The NbClust described on Charrad, Ghazzali, Boiteau, & Niknafs (2014) gather 30 indices to evaluate the number of clusters for each index and proposes to the user the best clustering scheme. And in the third stage, the article adopted the K-Means package to form the quantity of clusters defined in the previous step.

The neural network is a flexible data-driven method and have been highly successful in terms of predictive accuracy sustain (Shmueli, Bruce, Yahav, Patel, & Lichtendahl Jr., 2018). To forecast the demand using neural network, the time series analysis of each point of sale was adopted due to the fact that the data to be analyzed were historical product sales data.

The application of neural networks in this paper occurred in two stages. In the first stage the data was divided into two parts: training and validation. And in the second stage was determined the network architecture with the forecast package of the software R (Hyndman et al., 2019; Hyndman & Khandakar, 2008), which analyzes the best architecture of the neural network and forecast the time series.

7.3.3 Simulation-based optimization

Simulation-base optimization is a promising alternative to solve complicated problems intractable for mathematical programming methods for Chu, You, Wassick, & Agarwal (2015). This work proposed a simulation-based optimization approach for integrated demand, material inventory and warehouse information's, and production and transport planning operations.

To determine the best delivery/physical distribution configuration to fulfill offline and online orders it was applied the genetic algorithm.

The GA receives the inventory and demands information of all the products at each node. Respecting the level delivery rules, where each player can send products downstream, but cannot send to the same level or upstream, a population of n feasible solutions is created. Then, the crossover of m individuals expands the population to a size equal to n+m/2. The m/2 individuals generated in the crossover process can be muted. The mutation depends on a probability defined by p=1/L, where L is the quantity of nodes. The final population, after crossover and mutation, is simulated generating a vector of costs. The population is then ranked according the costs. If the cost in the iteration i has a change equal or less to 1% in comparison with the iteration (i-1), then the optimization reached the optimal solution and it returns the delivery configuration matrix. If the cost has an error greater then 1%, then the m/2 worst solutions are removed from the population and the optimization returns to the crossover step.

The simulation represents an omni-channel retailing supply chain with the following characteristics: sixteen physical stores, four distribution centers, one supplier, and physical and online clients. The simulation of the system was run for one month and the results presented in this paper are the average of 30 replications.

The information and material flow in the simulation-based optimization model are represented in the Fig. 1. The information flow is composed of demand, orders and inventory information's, and the material flow is represented by the production and transportation activities.

According to Fig. 1, there are two sources of demand. The first demand is the demand forecasting, resulting from the application of machine learning, and the second is the real demand, resulted from the triangular distribution of the historical sales time series of each product, represented in Fig. 1 by the final clients. The forecasted demands are allocated to the players according to the physical distribution matrix generated by the optimization.

The orders information is generated from the lack of inventory, caused by the mismatch of supply and real demand, at each of the physical stores, distribution center and suppliers. Orders are determined based on the backlog, expected product receipt quantity, and inventory parameters. However, these orders for physical retailers will only be generated if the customer agrees to wait for the products.

Inventory information is entered into the model from the stock parameter information for each of the chain's stock points, and this information comes from the company's ERP.

Material flows begin with the arrival of information flows. After assessing the demand and the orders that each player can fulfill, the distribution orders are established. Based on distribution orders, the transportations activities initially perform the shipment consolidation of each player, and then begins the physical distribution of materials. Physical distribution used real routes to map distribution routes through the GIS map available in Anylogic software.

The production activity is the manufacture of products that the supplier could not supply due to unavailability of stock. After the products are manufactured, they are released to the transportation activities. Since the objective of this work is to evaluate the demand and supply planning operations of the omni-channel retailing supply chain, production was considered due to impact product availability time, so, its performance will not be evaluated in this article.

In this manner, the objective function and output of the simulation, is the total cost of the supply chain, including the transportation, loading, unloading, inventory and lost sale costs.

7.3.4 General description of the used case

For this study, the data was collected from a Brazilian retailer that is migrating its multi-channel operation to omni-channel. The retailer operates 139 physical stores and the online store in Brazil and sells a wide assortment of products including home appliances and decor, furniture, housewares, health and beauty, kitchen appliances, tv and cell phone among others.

The furniture category was chosen because it is the category that most impacts on the company's billing and is composed of 684 products. To develop this work, 10 best-selling products in this category were chosen, because even representing 1.5% of the quantity of products, they represent 11% of furniture sales volume.

To forecast future sales based on customers' consumption, data were collected from the retailer's enterprise resource planning system the sales historical data over a period of 1026 days from 2016 to 2018 of the 139 physical stores and online store. Currently the company adopts the moving average (MA) of a period of 6 months as a forecast method.

The retailer operates three regional distribution centers and one central distribution center, with the central receiving the products from suppliers and distributing the products to regional DCs. To fulfill the online orders, the retailer uses the distribution centers and does not use any means of information or operation integration. Thus, the supplier has no visibility of the retailer's actual sales, only the order based on moving average forecast placed at the beginning of each month. As this work does not analyze the last mile, online sales for the same state were analyzed together, and also delivered together for pick-up points.

7.3.5 Numerical experiments

To evaluate the operational performance that the end-to-end integrated management of information and material flows can provide to omni-channel retailing supply chain operations, three contexts were analyzed.

The first context is without integration of information and material flows, and therefore without anticipating supply chain operations. In this context, the demand considered was the triangular distribution of real demand and the forecast demand determined by moving average. The real demand data is the same in all contexts. Orders are used to balance supply and demand in the simulation-based optimization.

In order to analyze the material flow for all the three contexts, three scenarios were evaluated to validate the approach with various players for retail supply chain distribution. The scenarios were assessed through the delivery options presented in the literature for the omni-channel retail supply chain, and the distribution were determined by the genetic algorithm in the simulation-based optimization. First, was analyzed the delivery to final customers only through distribution centers, then adding retailers as delivery points and finally the fully integrated chain with the delivery also being performed by the suppliers.

According to Andrews, Farias, Khojandi, & Yan (2019), a good fulfillment strategy from retailers need to attempt to avoid lost sale, minimize costs, minimize time to customer and respect operational constraints. For this reason, all the analyzed scenarios where first evaluated without the lost sale cost in the objective function and then inserting the lost sale cost. In cases without the lost sale cost, this cost was computed to analyze its value in the supply chain but not entered into the objective function, the objective function only minimizes the operational cost from the supply chain.

The second context is the integration and anticipation of operations, by forecasting demand made by the moving average. To determine the anticipation of operations, the forecasted moving average demand was analyzed by the SBO to determine which demand would be anticipated by distribution centers and suppliers.

The third context is the extended approach from Pereira, Oliveira, Santos, & Frazzon (2018) with the demand forecast developed by the neural network, distribution anticipation and the application of SBO to determine the distribution plan. As in scenario 2, the anticipation and distribution programming were determined by the genetic algorithm in the SBO.

7.4 RESULTS AND DISCUSSION

In this section, the scenarios were analyzed from the evaluation of omnichannel retail supply chain operating cost, the numbers of orders due to mismatch between demand and supply and fulfillment time.

First, the operational cost of the supply chain (Brazilian currency) was assessed by the cost of loading, unloading, transportation, inventory and lost sale, as show in Fig. 3.

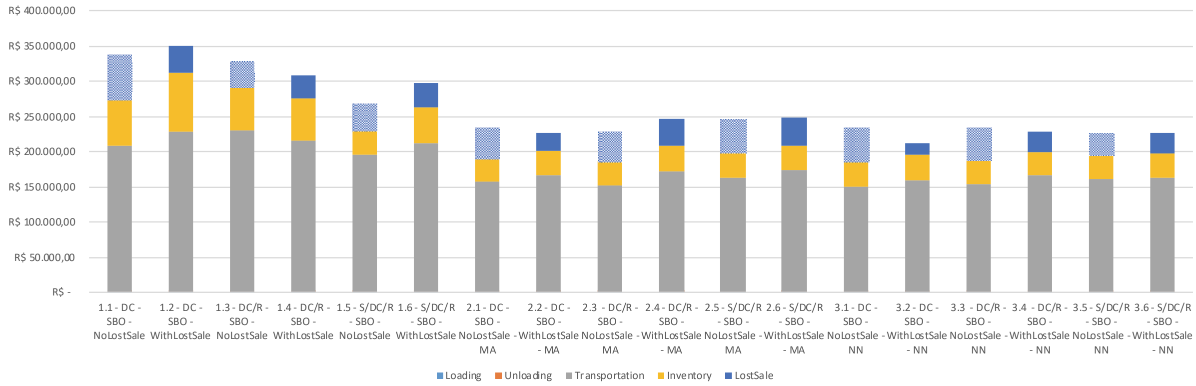

Fig. 3. Operational cost of the omni-channel retailing supply chain.

When analyzing the costs of the supply chain, it is possible to identify that in context 2 and 3, whose information regarding demand is shared with all players and echelons and with the anticipation of product distribution, operating costs are lower than the scenarios presented in context 1.

In scenarios with anticipated distribution and sharing of demand forecast, both in cases with or without lost sale, the scenarios with demand forecast made by neural networks were the scenarios that presented the lowest operating costs and total costs (with the cost of lost sale), with scenario 3.1 being the scenario with the lowest operating cost, $ 185,781, and scenario 3.2 having the lowest total cost of $ 212,057.

With this, it is possible to state that in relation to operating cost and total cost, the scenario with the sharing of demand information, anticipation of distribution and forecasting by neural networks was the best scenario.

When analyzing the number of orders that were placed due to the partial or total absence of the product in stock, it is noted that in the scenarios with anticipated demand, context 2 and 3, Fig. 5 and Fig. 6 respectively, the quantity of orders decreased significantly compared to context 1, shown in Fig. 4.

The largest reduction in orders occurred from scenario 1.2 to scenarios 2.2 and 3.2, with a 97% and 98% reduction in orders respectively. The scenario that obtained a lower reduction in orders was from scenario 1.5 to scenarios 2.5 and 3.5, with a reduction of orders of 66% and 79% respectively. In addition, it can be seen that in context 3, orders were practically restricted to retailers and regional distribution centers.

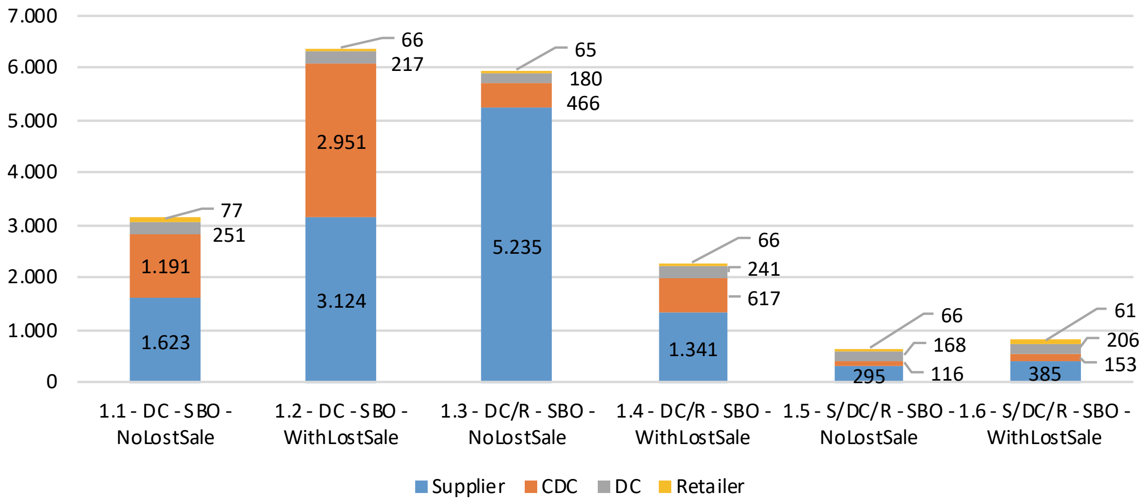

Fig. 4. Number of orders per echelon in the context 1.

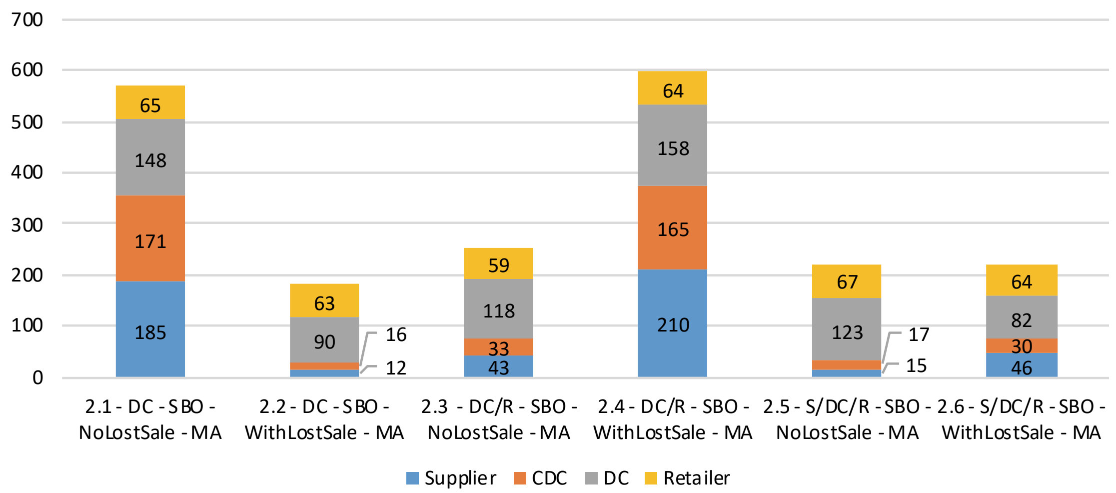

Fig. 5. Number of orders per echelon in the context 2.

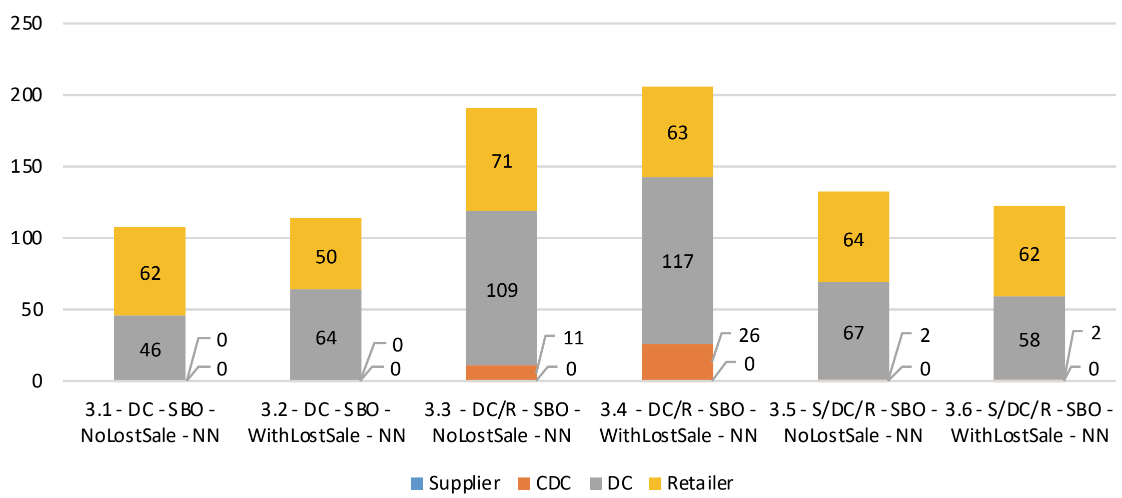

Fig. 6. Number of orders per echelon in the context 3.

Thus, it is evident that in scenarios 2 and 3, there was a better balance between demand and supplies in the chain as a whole. And in the scenario with the application of the neural network, the number of orders was lower when compared to the other scenarios in all delivery possibilities, with or without lost sale.

To analyze the fulfillment time of the supply chain, it was separated into two analyzes. Firstly, the average fulfillment times of physical customers who agreed to wait for the product were analyzed, and then the average fulfillment times for online customers.

Fig. 7 shows the fulfillment time of physical store customers, in hours, for each scenario in each context. From Fig. 7, it can be seen that contexts 2 and 3 did not significantly impact the fulfillment time, that is, the sharing of demand information and the anticipation of distribution did not influence time. This fulfillment time analyzes only the reaction time of the chain and these factors do not influence this aspect, as these are situations in which there was a lack of product at some point and the products had to be replaced.

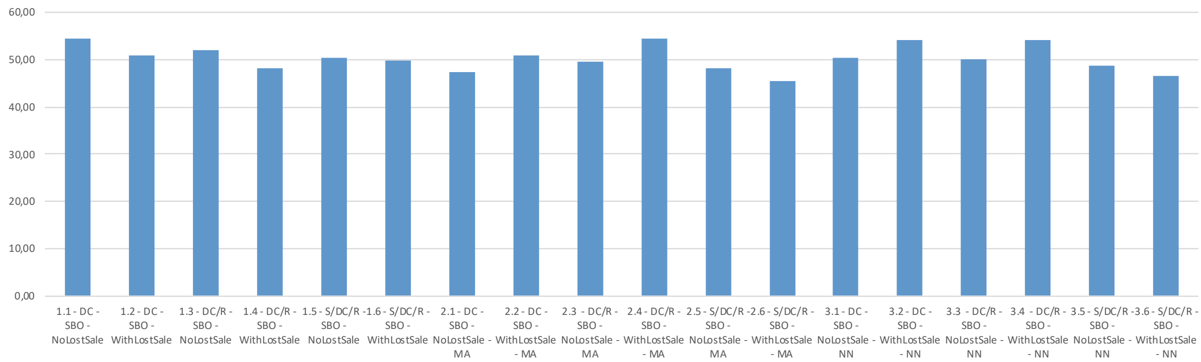

Fig. 7. Fulfillment time for physical customers.

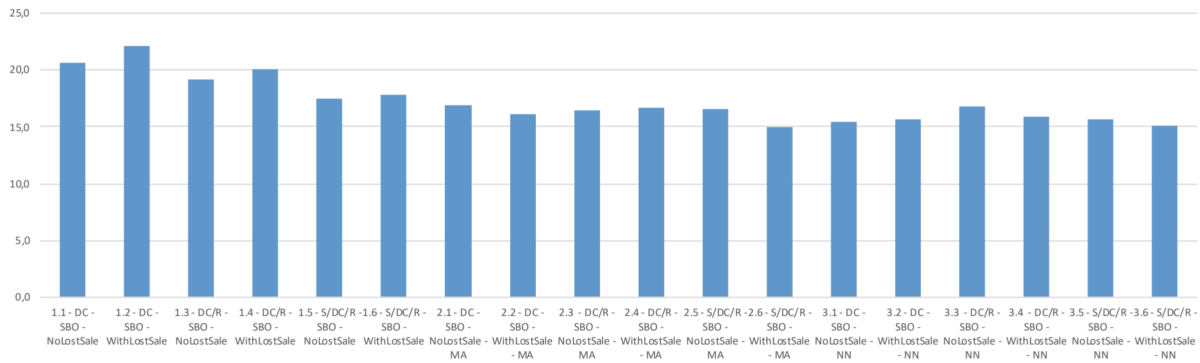

Fig. 8. Fulfillment time for online customers.

Analyzing the fulfillment time for online customers in Fig. 8, it is observed that the increase in the delivery possibilities of the products reduced the fulfillment time, and context 3 presented the shortest times for improving the identification of points and quantity demand for each product.

It is also noted that in contexts 2 and 3, the scenarios in which delivery was made by all players and echelons in the chain and with the lost sale in the objective function, were the ones that presented the shortest fulfillment time, both for customers of physical and online channel. This is justified by the fact that due to the supplier's location being in a state where there are no physical stores, the possibility of delivery of products by this player reduced the delivery time for online customers.

Thus, it can be observed that in all supply chain evaluation metrics, including costs, mismatch between demand and supplies and fulfillment time, the scenario with anticipated distribution of products, forecast demand by neural networks and total integrated supply chain proved to be a more accurate and efficient approach to omni-channel retail supply chain operational management.

7.5 CONCLUSIONS

Due to the complexity that the operational management of omni-channel retail supply chains are facing, caused by the increase in possible distribution points and the growing demand for accurate services from customers, integrated operations management is essential.

Integrated management, through the coordination of information, material and financial flows, is important because it enables a better balance of demand and supply and consequently reduces inefficiencies, costs, excessive inventory, stock-outs, backorders, and thus better serve customers.

In this paper, we extend the approach developed by Pereira, Oliveira, Santos, & Frazzon (2018), by proposing and validating data-driven approach in order to improve predictive and enable an adaptive operational management of omni-channel retailing supply chain. To deal with predictive, a model based on clustering and neural networks was developed in order to reduce uncertainties and improve demand forecasting. And to develop an adaptive supply chain, the simulation-based optimization with genetic algorithm was adopted.

The integrated model presented in this paper was analyzed through application in a Brazilian retailer. The results indicate that the integrated management of materials, information and financial flows, lead to a more efficient supply chain with lower costs and less mismatch between demand and supply.

For this reason, it is possible to state that this model can support the omni-channel retailing supply chain operational management, by providing more accurate demand forecasting and more efficient distribution planning.

As future research, we suggest the application of this approach for other real-world scenarios and products categories in order to validate the performance of the approach with others type of products and with other sales patterns.

Considering the limitation that the operation of buying on the internet and removing the product from the store is recent activities by the company adopted in the study, these data were not included in the forecast and consequently were not analyzed by the SBO. We also suggest as future research, the application of this approach with data that indicates which purchases were made over the internet and collected in stores, to improve distribution logistics and consolidation of shipment, and reduce supply chain costs.

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8 DISCUSSÃO E RESULTADOS ESPERADOS

O objetivo deste trabalho é propor uma abordagem preditiva e adaptativa de gestão operacional aplicada à cadeia de suprimentos do varejo omni-channel.

Para alcançar este objetivo, no capítulo três foi realizada uma revisão sistemática da literatura aplicando a metodologia do content-analysis para identificar as abordagens que estão sendo apresentadas na literatura de logística e cadeia de suprimentos para o gerenciamento integrado de operações dos varejistas omni-channel e principais oportunidades de pesquisa. As métricas e palavras-chaves e os critérios de exclusão foram determinadas com base nos artigos de revisão de literatura a respeito de logística e cadeia de suprimentos aplicados para o omni-channel. Para selecionar os artigos para análise os mesmos foram categorizados em relação a forma de abordagem e em relação ao nível de integração das abordagens propostas. A partir da categorização, foi possível identificar que trinta artigos apresentam abordagens de múltiplos temas da logística e cadeia de suprimentos e estão presentes em 23 artigos, sendo que 66% deles possuem classificação JCR. Ao analisar a evolução da publicação dos artigos, nota-se que no ano de 2019 houve um aumento significativo na quantidade de publicações quando comparado a 2018. Foi possível constatar que 83% dos artigos estão no nível de discussão e desenvolvimentos de teorias, sendo assim identificada a necessidade de desenvolvimento de soluções práticas para que possam ser utilizadas pelos varejistas e demais agentes da cadeia de suprimentos. Dos artigos que apresentaram soluções práticas constatou-se que os temas mais abordados foram a demanda em conjunto com suprimentos por meio da análise estatística da demanda e da otimização para suprimentos. Em relação ao nível de integração é evidente que a maioria dos artigos estão preocupados com a integração de ponta-a-ponta da cadeia de suprimentos, tópico destacado também como pesquisas futuras pelos artigos analisados.

Diante deste fato o quarto capítulo apresenta o modelo conceitual desenvolvido para uma abordagem gerenciamento preditivo e adaptativo para cadeias de suprimento de varejo omni-channel combinando aprendizado de máquina e otimização baseada em simulação. Neste modelo conceitual, foram considerados os fluxos de informação da demanda e dos níveis de estoque, em conjunto com o fluxo dos produtos. Os fluxos foram abordados de forma conjunta para minimizar fatores de incerteza da demanda e consequentemente dos suprimentos, e assim sincronizar os produtos distribuídos com os produtos demandados e prover um gerenciamento operacional integrado. Ainda foi proposta a utilização de um sistema híbrido de distribuição, no qual adota o sistema empurrado dos fornecedores e dos centros de distribuição até a loja física dos varejistas e a partir deste ponto adota o sistema puxado que dispara a distribuição após a compra efetiva dos clientes, a fim de reduzir ao máximo o lead time de entrega sem impactar negativamente nos níveis de estoque da cadeia. O sistema empurrado é iniciado partir da alocação da demanda para cada agente, sendo que a demanda é determinada a partir da aplicação do algoritmo genético com as informações provenientes da previsão de demanda da rede neural.

Com o objetivo de minimizar as incertezas relacionadas a demanda e melhorar o fluxo de informação da cadeia de suprimentos varejista omni-channel, o quinto capítulo apresentou a abordagem preditiva combinando clusterização e redes neurais. Por meio da identificação das abordagens de demanda que estavam sendo estudadas para o omni-channel varejista foi possível identificar que há uma crescente preocupação em relação a identificação do padrão de comportamento do consumo dos clientes, e em como como a mudança do perfil de compras de um consumidor em mais de um canal está mudando a maneiras de gerenciar e operacionalizar atividades nas organizações. Dessa forma, foi possível identificar que o método de cluster busca segmentar clientes para identificar as características individuais de cada cluster e, assim, entender melhor o perfil de consumo dos clientes. No entanto, somente o método de cluster não é capaz de obter a previsão com maior precisão e menor porcentagem de erro para reduzir as incertezas referentes a quantidade e o tempo que iriam acontecer as demandas. Logo, com a análise dos métodos da indústria 4.0 que estavam sendo aplicados para melhoria da previsão de demanda, identificou-se que as redes neurais é o método mais adotado para previsões de demandas incertas. Para análise do desempenho da abordagem adotada os dados, referentes as vendas históricas de um varejista brasileiro, foram coletados e analisados utilizando o software Matlab. A partir da aplicação conjunta da clusterização e redes neurais autoregressiva não-linear com fatores externos (NARX) em um caso real, e comparação com a média móvel e com a rede neural autoregressiva não-linear (NAR), é possível afirmar que a combinação da clusterização com o NARX proporciona resultados com menores desvios e erros. Assim é possível afirmar que a previsão de demanda dos varejistas omni-channel precisa combinar a análise de padrões com métodos de previsão avançados para melhorar a precisão da previsão e, assim, reduzir as incertezas da cadeia de suprimentos de varejo omni-channel.

O sexto capítulo apresentou a proposta de uma abordagem adaptativa para a cadeia de suprimentos que fosse capaz de avaliar as novas possibilidades das redes de distribuição, incluindo varejistas e fornecedores como novos pontos de entrega, através de aspectos logísticos e custos da cadeia de suprimentos. A partir da revisão de literatura foram identificadas as novas possibilidades de distribuição dos produtos no cenário varejista e os aspectos logísticos que estão sendo utilizados para avaliar estas possibilidades de distribuição. Os aspectos logísticos foram levantados de artigos que aplicaram os métodos de simulação, simulação baseada em simulação e otimização devido a ausência de artigos que aplicaram a otimização baseada em simulação, sendo os aspectos os custos operacionais e de transporte. Além disso, foi destacado que a otimização baseada em simulação é um método capaz de fornecer recursos relevantes para o gerenciamento de cadeias de suprimentos por combinar a programação estocástica e otimização robusta. Para realizar a otimização do sistema, foi adotado o algoritmo genético para melhorar determinar quem irá atender cada demanda e a quantidade a ser distribuída. Essa quantidade é determinada com base nas informações de demanda e da disponibilidade de estoque em cada um dos pontos. Os dados operacionais foram coletados da organização adotada neste estudo e na literatura que aborda cadeias de suprimentos e foram inseridos no software Anylogic. Inicialmente foram analisadas a entrega dos produtos para os clientes online e off-line pelos centros de distribuição, posteriormente foi habilitada a distribuição dos produtos comprados pelo canal online pelas lojas físicas, e por fim o cenário em que os fornecedores também podem entregar produtos para os clientes online e off-line. Cada cenário também foi analisado com e sem o valor da perda de venda na função objetivo. Os resultados da aplicação da otimização baseada em simulação foram analisados e comparados com o desempenho da cadeia de suprimentos analisadas por meio da simulação. Foi possível constatar que a adoção da otimização baseada em simulação para a cadeia de suprimentos varejista omni-channel é uma abordagem capaz de propor uma gestão operacional adaptativa para a cadeia de suprimentos por reduzir os custos operacionais da cadeia de varejo omni-channel, mantendo os tempos de atendimento e reduzindo significativamente a quantidade de pedidos resultantes da incompatibilidade de demanda e suprimentos.

Após a análise do desempenho dos métodos e abordagens adotada neste estudo de forma individualizada, o capítulo sete possui como objetivo identificar quais melhorias no desempenho operacional o gerenciamento integrado do fluxo de informações e materiais pode proporcionar para reduzir a incompatibilidade entre a demanda e a oferta e, consequentemente, melhorar o desempenho das operações da cadeia de suprimentos de varejo omni-channel. Alguns dados foram coletados novamente e foram analisados por meio dos softwares R e Anylogic. Para analisar os resultados desta abordagem, estes foram comparados com os contextos em que não há o compartilhamento da informação e com o que há o compartilhamento da informação, porém com o método atual de previsão, que é a média móvel. Os desempenhos dos contextos foram analisados e foram analisados os custos da cadeia de suprimentos, a quantidade de pedidos realizados devido a ausência parcial ou total de estoque no agente e nos tempos de entrega para os clientes online e off-line. Ao analisar o custo da cadeia de suprimentos, é possível destacar que o cenário com total integração da cadeia, com o compartilhamento da informação de demanda, determinada pela clusterização e rede neural autoregressiva com fatores externo, e antecipação da demanda foi o cenário com o menor custo. Este cenário também foi destacado como o melhor cenário ao analisar a quantidade de pedidos por apresentar a menor quantidade de pedidos, ou seja, este cenário possibilitou uma previsão mais assertiva e o algoritmo genético realizou a melhor alocação da demanda para os agentes. E em relação ao tempo de entrega dos produtos este cenário também apresentou os menores tempos de entrega. Dessa forma, foi possível comprovar a eficácia do modelo conceitual proposto por meio de uma previsão mais assertiva, e com custo operacional reduzido. Os resultados foram capazes de demonstrar que o modelo integrado preditivo e adaptativo por meio do gerenciamento integrado de materiais, informações e financeiro, leva a uma cadeia de suprimentos mais eficiente, com custos mais baixos e menos incompatibilidade entre demanda e oferta.

9 CONCLUSÃO

Os varejistas passaram por grandes transformações nos últimos anos, o que fez com que precisassem reestruturar suas estratégias e operações para absorver novos canais de demanda dos clientes e as novas possibilidades de distribuição.

Para se reestruturarem alguns desafios foram apresentados como a dificuldade de integração dos canais, incerteza relacionada a demanda, incompatibilidade de oferta-demanda e garantir a conformidade das entregas. E para lidar com tais desafios (Kembro & Norrman, 2019) e (Tokar et al., 2014) destacaram o compartilhamento da informação para reduzir as incertezas e (Yang & Zhang, 2019) argumenta que a coordenação dos fluxo de materiais e do fluxo de informações de forma integrada estrutura a cadeia de suprimentos de forma com que todos possam sair ganhando.

Neste mesmo sentido, Rafay Ishfaq e Raja (2018) destacam que os varejistas estão buscando a coordenação das atividades de gerenciamento de demanda e atendimento de pedidos para se reestruturarem e Wollenburg et al. (2019) ainda afirma que o gerenciamento de clientes com opções de atendimento são um novo tópico na prática e constituem uma nova área de pesquisa.

O objetivo deste trabalho foi identificar qual abordagem pode ser adotada para o gerenciamento preditivo e adaptativo da cadeia de suprimentos varejista omni-channel, visando a sincronização entre demanda e suprimentos.

A partir da análise da literatura, foi proposta como abordagem preditiva a combinação de clustering, para entender o padrão de consumo dos consumidores por meio do padrão de vendas de produtos, com rede neural com fatores externos, para melhorar a precisão da previsão de produtos. Como abordagem adaptativa para gerenciamento operacional da cadeia de suprimentos omni-channel de varejo, foi proposto otimização baseada em simulação por meio da aplicação do algoritmo genético.

A abordagem integrada foi avaliada em um caso real de um varejista brasileiro e seu desempenho comparado com demais abordagens presentes na literatura e na prática. As métricas adotadas para validação da abordagem foram o custo da cadeia de suprimentos, a quantidade de pedidos provenientes da incompatibilidade de demanda e oferta e o tempo de entrega dos produtos.

A partir dos resultados foi possível analisar que aplicação da abordagem preditiva e adaptativa proposta nesta tese conseguiu melhorar todas as métricas operacionais e financeiras da cadeia de suprimentos varejistas omni-channel, indicando que o gerenciamento integrado de materiais, informações e fluxos financeiros leva a uma cadeia de suprimentos mais eficiente, com menores custos e menor incompatibilidade entre demanda e oferta.

Dessa maneira, esta tese pôde contribuir com a academia e com as organizações ao propor um modelo que suporta o gerenciamento operacional da cadeia de suprimentos de varejo omni-channel, fornecendo uma previsão de demanda mais precisa, um planejamento de distribuição mais eficiente, e consequentemente, um gerenciamento operacional integrado dos canais online e off-line.

Como continuidade a presente tese, recomenda-se:

- A inserção de parâmetros da área de marketing, como promoção e preço, na previsão de demanda;
- O desenvolvimento da previsão da demanda de forma semanal;
- A inserção do Última Milha (Last-Mile) na simulação;
- Inserção da opção de Compra-Online-Retira-Na-Loja (em inglês, Buy-Online-Pick-Up-In-Store - BOPS)
- Inserção da análise de Logística Tributária, e seu respectivo custo no cálculo do custo logístico.

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