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Predictive and Adaptive Management Approach for Omnichannel 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.

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

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.

2. LITERATURE REVIEW

2.1 Retail Supply Chain Management

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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.

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.

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.

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.

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.

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.

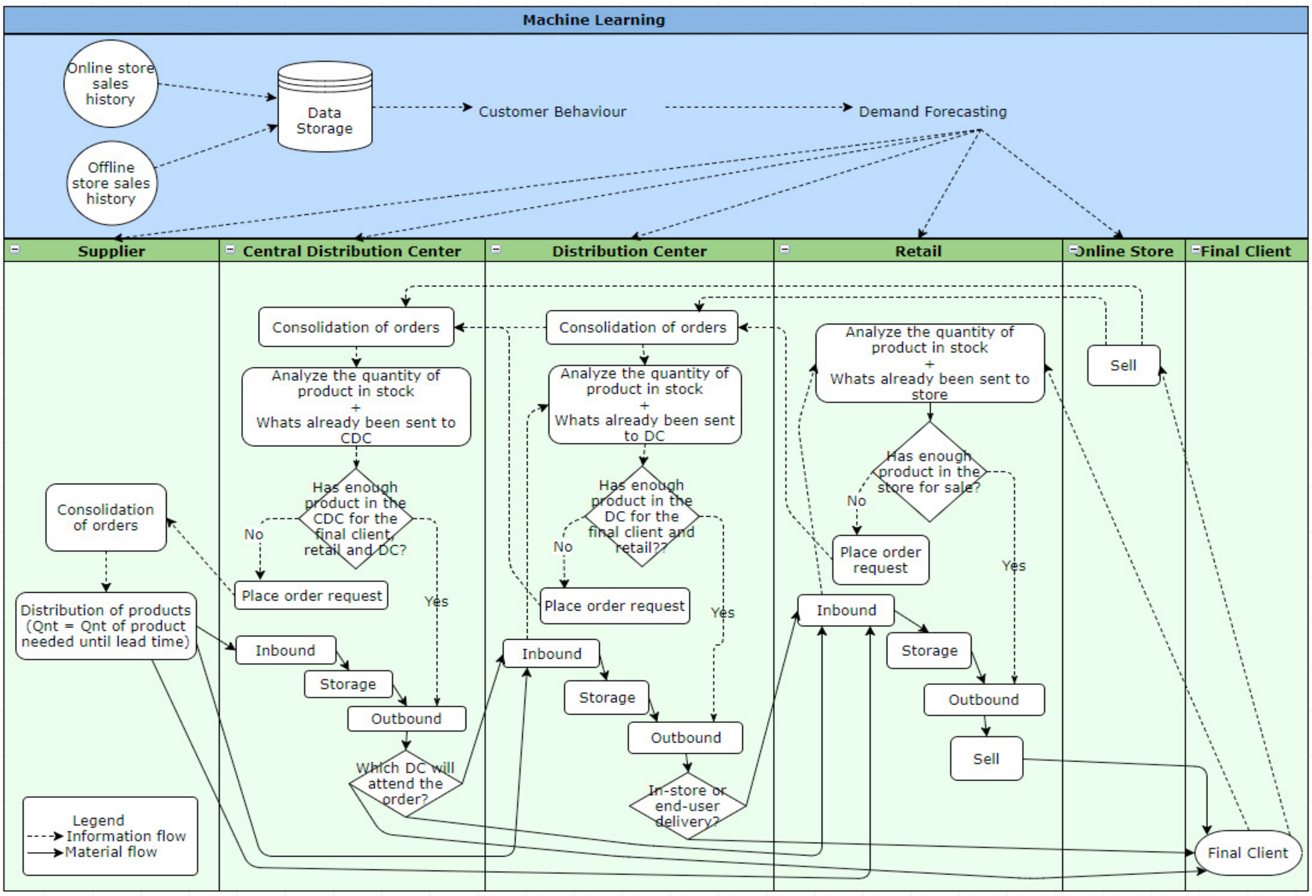

Fig. 1. Proposed conceptual model for omnichannel retailing supply chain management.

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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. After the arrival of the demand forecast information, the supply chain aims to anticipate the distribution process to leave the product in the distribution center closest to the end customer, even before the sale of the product. Therefore, the distribution process represented by the material flow in Fig. 1, adopt the pushed flows from the supplier to the central and regional distribution centers, based on demand forecast information in order to reduce the lead time.

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. 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.

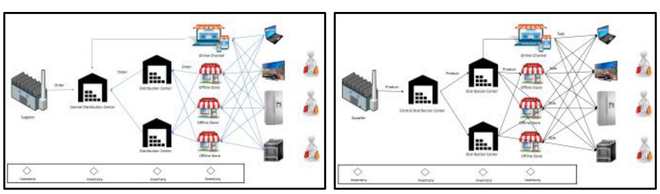

Fig. 2. Simulation first scenario

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.

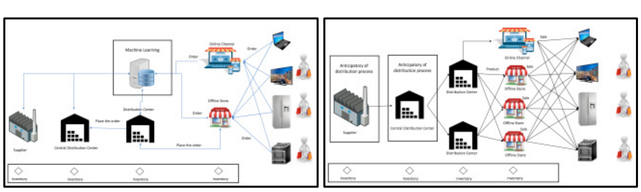

Fig. 3. Simulation second scenario

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.

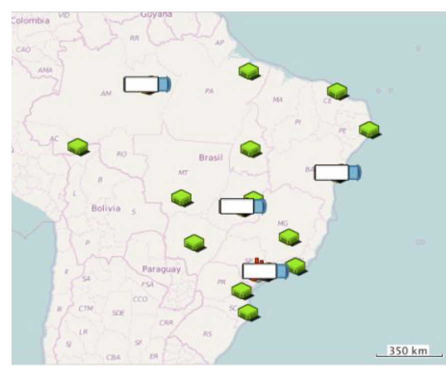

Fig. 4. Omni-channel retail supply chain structure

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.

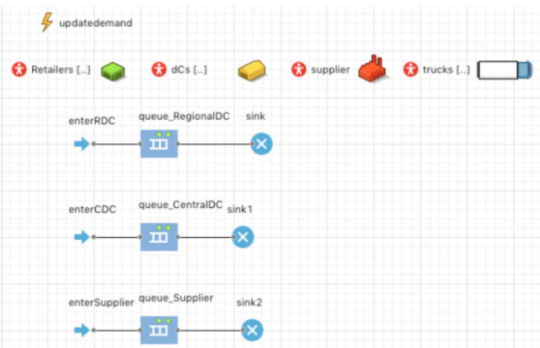

Fig. 5. Simulation flow in Anylogic

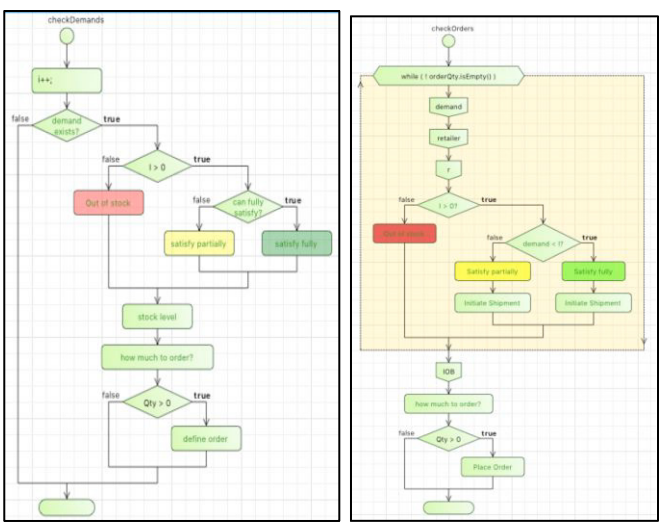

Fig. 6. Logic process of the retailers on the left, and the logic process of the distribution centers of the right

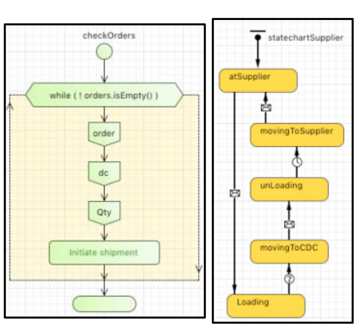

Fig. 7. Logic process of supplier on the left, and the logic process of the trucks on the right

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.

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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