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DOES THE THEORY OF CONSTRAINTS IN SUPPLY CHAIN MANAGEMENT REALLY MATTER? An Assessment of the Impacts of the TOC in the Redesign of a Supply Chain

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Dissertation presented to the UNISINOS University in partial fulfillment of the requirements for the Degree of Master of Science in Production and Systems Engineering

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ABSTRACT

In a world with increasing complexity, a challenging scenario and greater competition many companies still feel that their supply chains do not have the competencies required to prosper within such environment. In fact, old supply chain problems are still current challenges for many organizations. Therefore, supply chain management (SCM) and supply chain redesign plays a strategic role for this context, demonstrating distinctive goals and results such as cost reduction, lower inventory levels and bullwhip effect minimization. The supply chain redesign proposals are based on diverse methodologies, such as Just-In-Time, lean manufacturing practices and the Theory of Constraints. Among those methodologies, the Theory of Constraints (TOC) proposes a solution for the supply chain that aims to increase the throughput of sales, while reducing inventories at the same time. Within the SC context, however, TOC research lacks a conceptual model or method for application of its practices, have an absence of studies that evaluate consistently the implementation of its performance measures, and have a deficiency of empirical evidence to support its improvements. Thus, this research aims to fulfill those gaps by utilizing a simulation model of a real empirical case to apply the TOC supply chain replenishment system (TOC SCRS) steps. Using system dynamics to create the base model, other scenarios are created replicating the gradually implementation of the TOC in the system. Inventory levels, throughput and the IDD are measured for each scenario and compared to understand the benefits and their respective significance. Thus, the causal impact analysis is utilized in order to compare the different scenarios with the base model, as well as to compare the scenarios among themselves. The results and the findings are presented and discussed, and the contributions are detailed in both empirical and academic contexts. The conclusion sums up the research and present future venues of studies that can derive from this research.

Index terms: Theory of Constraints, Supply Chain Management, System Dynamics Modeling, Causal Impact, Supply Chain Replenishment System.

RESUMO

Em um mundo com uma complexidade crescente, um cenário desafiador e o aumento da competitividade, muitas empresas sentem que suas cadeias de suprimentos não possuem as competências necessárias para prosperar em tal ambiente. Antigos problemas das cadeias de suprimentos, ainda, são desafios atuais para em diversas organizações. Assim, a gestão da cadeia de suprimentos e o redesenho dessas cadeias possuem um papel estratégico, demonstrando distintos objetivos e resultados, tais como a redução de custos, menores níveis de inventário e a redução do efeito chicote. As propostas de redesenho das cadeias se baseiam em diversas metodologias, como o Just-In-Time, a produção enxuta e a Teoria das Restrições (TOC). Dentre tais metodologias, a TOC propõe uma solução para a cadeia que visa o aumento do ganho ao mesmo tempo que os estoques são reduzidos. Dentro do contexto das cadeias de suprimentos, entretanto, as pesquisas de TOC apresentam lacunas tais como: a falta de um modelo conceitual ou método para aplicação de suas práticas; a falta de estudos que avaliem a implementação das suas métricas de performance; e a deficiência de evidência empírica para suportar seus benefícios. Assim, essa pesquisa objetiva sanar tais lacunas utilizando-se de uma modelo de simulação baseado em um caso empírico real para aplicar a solução de reabastecimento da cadeia de suprimentos da TOC. A modelagem de dinâmica de sistemas é utilizada para a criação do modelo base e os outros cenários que simulam a aplicação gradual de cada um dos passos da teoria. São mensurados os níveis de inventário, o ganho, o inventário-dólar-dia (IDD) e a frequência de reabastecimento são mensurados para cada cenário e comparados para melhor compreensão os benefícios, assim como suas respectivas significâncias. A análise do impacto causal é usada para comparar esses diferentes cenários com o modelo base, assim como comparar os cenários entre si. Os resultados e as descobertas são apresentados e discutidas, e as contribuições são detalhadas empiricamente e academicamente. A conclusão resume a pesquisa e apresenta possíveis pesquisas futuras que podem derivar do presente estudo.

Palavras-chave: Teoria das Restrições, Gestão da Cadeia de Suprimentos, Modelagem de Dinâmica de Sistemas, Impacto Causal, Sistema de Reabastecimento da Cadeia de Suprimentos.

LIST OF CHARTS

LIST OF FIGURES

LIST OF FRAMES

LIST OF TABLES

ACRONYMS LIST

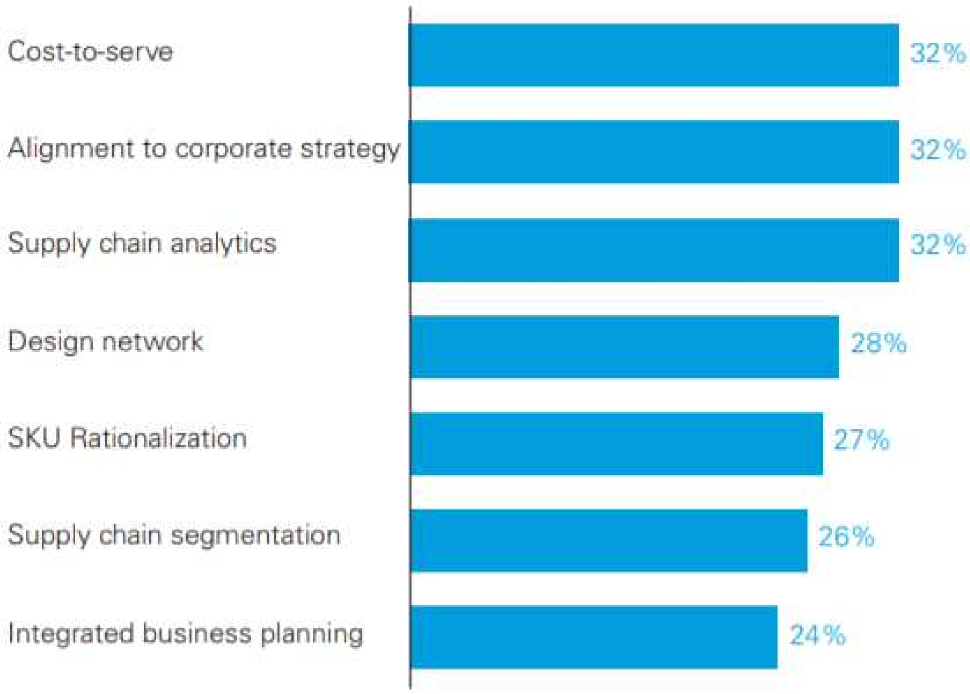
CRT	Current Reality Tree
DBM	Dynamic Buffer Management
DBR	Drum-Buffer-Rope
EC	Evaporating Clouds
ECE	Effect-Cause-Effect
FRT	Future Reality Tree
I	Investment
IDD	Inventory-Dollar-Days
IT	Information Technology
JIT	Just-in-time
MRP	Materials Resource Planning
OE	Operational Expense
PRT	Prerequisite Tree
SC	Supply Chain
SCM	Supply Chain Management
SD	System Dynamics
S.D.	Standard Deviation
SLR	Systematic Literature Review
T	Throughput
TDD	Throughput-Dollar-Days
TOC	Theory of Constraints
TOCRS	Theory of Constraints Replenishment System
TT	Transition Tree

INDEX

1 INTRODUCTION

A supply chain can be defined as a group of entities that manufacture, distribute and/or sell goods within a flow created for an finished product that extends from its raw materials up to the end customer delivery (BLACKSTONE, 2001). Supply chains are integrated systems of ever-increasing complexity levels, therefore, innovative methods for its integrated management are necessary (PONTE et al., 2016). Additionally, the current challenges imposed by a global economy – such as rapid disruptive rates of change and emergence of new innovative competitors – increase the need for effective supply chain management (STEVENS; JOHNSON, 2016). The increased competition, in this context, results in more customization possibilities to end customers, quality improvements and greater demand responsiveness while at the same time aiming for reduced production costs, lead-times and inventory levels, in order ensure profitability (AGAMI; SALEH; RASMY, 2012). A study conducted by the consulting company KPMG in association with Forbes demonstrates the main enablers for supply chain operational improvements such as cost-to-serve, corporate strategy alignment, analytics and SC network design (GATES; MAYOR; GAMPENRIEDER, 2016), as illustrated in Figure 1.

Figure 1 – Key enablers for SC operational improvements



Source: GATES; MAYOR; GAMPENRIEDER (2016)

With increasing complexity, a challenging scenario and greater competition many companies feel that their supply chains do not have the competencies required to prosper within this environment. In fact, old supply chain problems are still current challenges for many companies. As demonstrated by a survey conducted in 17 different countries and 623 supply chain professionals, the top objectives of the supply chains are to ensure deliveries on time and improve product availability or delivery (GEODIS, 2017).

Within this context, supply chain redesign becomes a strategic decision for the supply chain management (SCM) context (PIRARD; IASSINOVSKI; RIANE, 2008), demonstrating distinctive goals and results such as cost reduction (MARTINS et al., 2017), lower inventory levels (BERRY; NAIM, 1996) and bullwhip effect minimization (NAIM; DISNEY; EVANS, 2002). The supply chain redesign proposals are based on diverse methodologies, such as Just-In-Time (HUNT et al., 2009), lean manufacturing practices (BUIL; PIERA; LASERNA, 2011) and the Theory of Constraints (WALKER, 2002). Among those methodologies, the Theory of Constraints (TOC) proposes a solution for the supply chain that aims to increase the throughput of sales, while reducing inventories at the same time. Basically, this is accomplished by aggregating stocks at the SC highest point and utilizing buffers to manage the supply chain replenishment (GUPTA; ANDERSEN, 2018; IKEZIRI et al., 2019). Thus, the TOC practices pose as a interesting and beneficial topic of discussion for supply chain management and consequently is defined as the subject of interest of this present work.

According to Tulasi and Rao (2012), the TOC was derived from the OPT – a system for production synchronization and planning – and has its origins in the ’70s, just as the Just-In-Time (JIT) and the Material Resources Planning (MRP). The TOC is a general approach for managing an organization (GOLDRATT, 1988). Rahman (1998) claims that the TOC is based on two key points: a) every system has at least one constraint; and b) the existence of a constraint represents an improvement opportunity for the system. A constraint, as defined by Goldratt (1988), is anything that limits a system from attaining its goal.

Basically, the TOC is composed of three main areas: logical thinking, performance measurement, and logistics (TULASI; RAO, 2012). The logical thinking aims at solving the problems of a system constraint through the application of the five-step-focusing and the thinking process. According to Goldratt and Cox (2004), TOC's five focusing steps to ensure continuous improvement are:

a) Identify the system's constraint;
b) Explore the constraint;
c) Subordinate the whole system to the constraint;
d) Elevate the constraint;
e) If the constraint is "broken" go back to the first step to avoid inertia stopping the continuous improvement process.

Regarding its performance measures, the Theory of Constraints bases them on the assumption that the goal of the organization is to make money now and in the future (RAHMAN, 1998). Rahman (1998) explains that the TOC's performance measures can be separated in global measures and operational measures. According to the author global measures include Net Profit (NP), Return Over Investment (ROI) and Cash Flow (CF); operational measures are Throughput (T), Inventory (I) and Operational Expenses (OE).

Related to logistics is the Drum-Buffer-Rope (DBR) method, which is a pull-oriented strategy utilized to effectively manage the bottleneck of the system through appropriate synchronization (PONTE et al., 2016; PUCHE et al., 2016). The drum is the constraint or bottleneck, the component with the least capacity that limits the throughput of the whole system (WATSON; POLITO, 2003). The rope acts like a signaling mechanism that ties the constraint to material release (BLACKSTONE, 2001). Lastly, the buffer is a stock of materials that protect the constraint from the rest of the system (BLACKSTONE, 2001)

Being initially applied in production planning, TOC has had its application extended to many other areas such as performance measurement, marketing, sales and supply chain management (BLACKSTONE, 2001). In the supply chain context, the Theory of Constraints challenges the premise that the best way to manage a distribution system is to refill inventory based on sales forecasting (BERNARDI DE SOUZA; PIRES, 2010). The TOC supply chain solution aims to solve common problems as low inventory turnovers, high investment on stocks, lack of finished products that cause missing sales and inventory excess at the same time, stock obsolescence and many others (SCHRAGENHEIM, 2010). According to Scharagenheim (2010), the TOC solution purpose is to answer what, where and when to stock, based upon the frequent replenishment of the consumed inventories through strategically placed buffers.

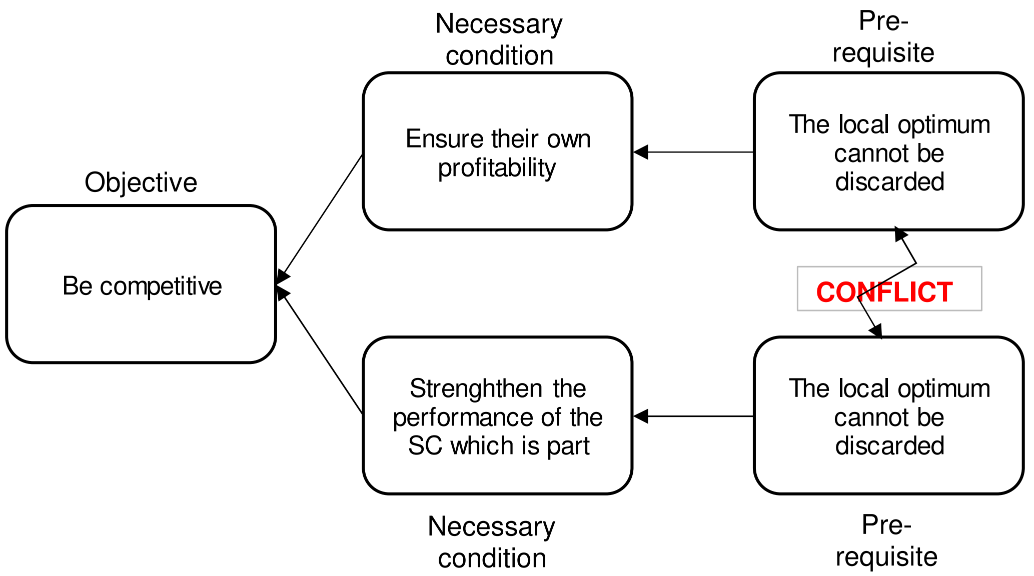
The benefits of implementing TOC's distribution system in the supply chain are demonstrated equally through the theory's performance measures and other more commonly known measures: in a case study Modi, Lowalekar and Bhatta (2018) report up to 40% of product inventory reduction, 75% decrease of lead-time, three times increase in stock turnover e 33% increase in throughput; Watson e Polito (2003) simulate a real case and compare TOC to the current way the organization was managed, presenting increases in profit, return over investment and cash flow; Ponte et al. (2016) apply TOC in the widely known Beer Game and find a 63% increase in net profit, throughput increase, and operational expenses reduction, when compared to the base model.

Given the presented scenario, this work defines its theme as the application of the Theory of Constraints' policies in the context of the supply chains. Going forward with the introduction, the next section presents the research aims and problem definition.

1.1 RESEARCH AIM AND PROBLEM DEFINITION

Bernardi de Souza and Pires (2010) state that TOC questions some basic premises academically widespread in SCM and logistics concepts, citing problems with the current context of the supply chains. Thus, the methodologies for supply chain performance measurement fail when they assume that the maximization of individual performances of each link results in benefits to the whole chain (BERNARDI DE SOUZA; PIRES, 2010). Additionally, they claim that a typical problem in SCM is the performance optimization of isolated processes. Watson e Polito (2003) share the same view, affirming that the attempt to maximize the individual performance of the links of the chain with their own individual metric systems may cause dysfunctional behavior. The TOC approach suggests, then, that the payment to the downstream links of the supply chain should only be realized when an effective sale to the final customer is made, reinforcing the collaboration to eliminate lost sales while keeping inventory levels to as low as possible (SIMATUPANG; WRIGHT; SRIDHARAN, 2004). Figure 2 demonstrates the basic conflict caused by local and global optimum in the supply chain.

Figure 2 – Conflict between local and global optimum in the supply chain.

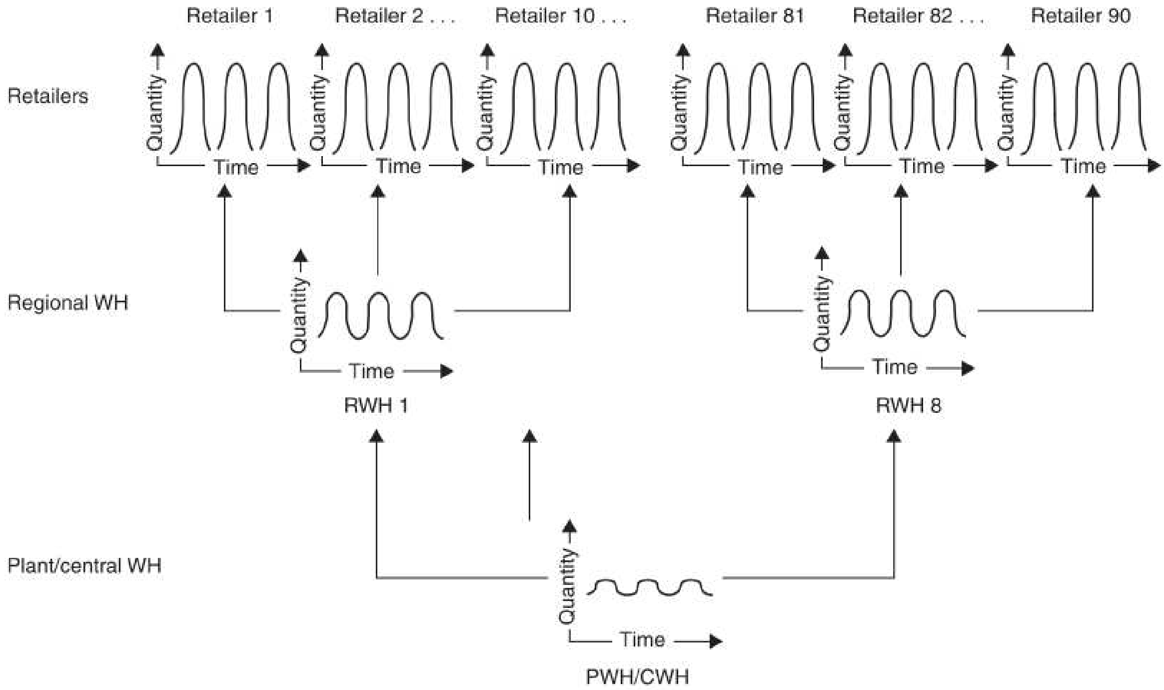


Source: Bernardi de Souza and Pires (2010).

According to Schragenheim (2010) the majority of the supply chains are based on push systems where an entity in a central position (such as manufacturing plant) make the replenishment decisions and supplies goods to regional warehouses or final customers. Such configuration depends heavily on forecasting models to predict what, when and where to stock the necessary goods or productions at specific inventory locations (shops) (SCHRAGENHEIM, 2010). As stated by Bernardi de Souza e Pires (2010), if a sale is realized when the transfer of goods to the next link of the chain occurs, it is created a tendency where each link will try to push inventory to the next upstream entity of the SC. Smith and Ptak (2010) mention that is known that forecasts are always wrong and their inaccuracy tends to increase as the more detailed they are and the longer they look into the future. Scharagenheim (2010) thus presents four fallacies regarding forecasting, being them: i) the fallacy of disaggregation; ii) the fallacy of the mean; iii) the fallacy of the variance; and iv) the fallacy of sudden changes.

The first fallacy suggests that aggregation or disaggregation has no impact on variance. However, it is known that the more disaggregated the data is, the greater is the variation of the elements of this data (SCHRAGENHEIM, 2010). In that sense, while the forecasting of the aggregative elements of the supply chain (manufacturing plants or warehouses, for instance) is more accurate and has less variation, at the disaggregated points the effect is the opposite. Figure 3 demonstrates the mathematical effects of this behavior.

Figure 3 – Mathematical effect of aggregation



Source: Adapted from Scharagenheim (2010).

The second fallacy regards the wrong interpretation of forecasting data. Schragenheim (2010) states that basic statistical knowledge (mean) is not sufficient for a full comprehension of the forecasting models and that the lack of a deeper understanding of those methods may result in huge mistakes. Thus, only a limited number of people can really understand the concept of variance – the third fallacy – and standard deviation to determine without a computer their impacts on sales. The last problem regarding the forecasting methods is related to the sudden changes of demand: the more sudden the change is the worst the forecast will be (SCHRAGENHEIM, 2010). The TOC solution for the distribution explores the fact that forecast accuracy is dependent on the stage (retailers, central warehouses, distribution centers, manufacturing plants, etc.) of the distribution system (YUAN; CHANG; LI, 2003).

Goldratt (2009) provided the initial concepts about the TOC solution for the supply chain. The main points proposed by the author are the following: i) the retailers or shops must keep only the necessary inventory to meet a few days of demand while the rest of the inventory should be kept in a warehouse; ii) the replenishment orders must be based on actual daily sales in order to avoid shortages of products; iii) the stock inventory must be kept at and managed by central warehouses, aggregating demand from shops or retailers, reducing purchase and delivery lead times and the risk of shortages at the retailers; and iv) the increase inventory turn by purchasing smaller lots of the same items and selling quickly in order to avoid investing money in inventory for longer periods. This main concepts and ideas would serve as a base for the TOC distribution solution. Schragenheim (2010), for instance, provides a few more insights at the solution, proposing a six-steps method::

a) Stock aggregation at the highest level in the supply chain: the plant/central warehouse (PWH/CWH);
b) Stock buffer sizes determination for all locations of the chain based on demand, supply, and replenishment lead time;
c) Increase of the replenishment frequency;
d) Manage the flow of inventories through buffers and buffer penetration;
e) Dynamics Buffer Management (DBM) utilization;
f) Set manufacturing priorities in accordance with the urgency in the plant stock buffers.

However, even though those steps of the TOC distribution solution aim to solve many problems related to supply chain management, there are still major gaps to be addressed by its literature. At the early stages of TOC in the supply chain context, Perez (1997) claimed that the theory was limited to manufacturing and lacking extrapolation of its concepts and practices within the SCM theme. Similarly, Blackstone (2001) affirmed that there is no adequate literature addressing the management of the supply chain through the Theory of Constraints. Although there is a growing number of more recent studies discussing the subject, the supply chain and distribution is where the TOC has been least explored (BERNARDI DE SOUZA; PIRES, 2010). Likewise, Kaijun and Wang Yuxia (2010) state that while the usage of TOC's replenishment system has been growing in companies, the model has not been described in the literature.

The empirical application of the TOC's proposed method to validate the improvements is also a concern. According to Watson and Polito (2003), there is a lack of formal research to reveal the improvements in the supply chain with the utilization of TOC's techniques. Yuan, Chang, and Li (2003) say that there is not a rigorous method to apply the theory practices in real-world applications. Costas et al. (2015) state that is uncommon to find real supply chain with TOC practices implemented and therefore more practical examples are needed (FILHO et al., 2016).

Gupta and Snyder (2009) summarize the problems of TOC within SCM claiming that even though being a methodology that effectively competes with other production management techniques, TOC's studies are inconclusive given the lack of: i) realistic examples; ii) deepness in the considered characteristics; iii) rigor in the applied methods; and iv) deep statistical analyses. Sharing the author's view, Tsou (2013) states that the lack of a rational framework and empirical studies when applied to real cases refrains the support of TOC in real-world applications. The TOC, however, has within its literature good examples of: successful applications (KIM; MABIN; DAVIES, 2008; MABIN; BALDERSTONE, 2003), principle dissemination and promotion (GOLDRATT, 1994, 1997, 2009; GOLDRATT; COX, 2004), and directions for its implementation (SCHRAGENHEIM, 2010; SCHRAGENHEIM; DETTMER; PATTERSON, 2009; SMITH; PTAK, 2010). Therefore, it seems that its unacceptance among the academic community (GUPTA; BOYD, 2008; WATSON; BLACKSTONE; GARDINER, 2007) is due to the fact that the link between theory and practice is still absent.

According to Slack, Lewis, and Bates (2004) it is necessary, in operations management, to reconcile research and practice so that is possible to conceptualize practice and operationalize theory. Gupta and Boyd (2008) and Naor, Bernardes, and Coman (2013) affirm that although the TOC is a good theory for the operations management (OM) context it has not yet been accepted by the OM community. Gupta and Boyd (2008) claim that is necessary to empirically test the theory behind the TOC and to analyze the implications and impacts of the theory in the factory and its other functional areas, such as marketing and accounting. According to Naor, Bernardes, and Coman (2013), TOC meets the virtues of a good theory: uniqueness, parsimony, conservation, generalizability, fecundity, internal consistency, empirical riskiness, and abstraction. Also, problems with the theory reflect the scientific process as expected, researchers uncover situations where the theory fails and consequently update, scrutinize, and improve it contributing to the body of knowledge (NAOR; BERNARDES; COMAN, 2013). In that sense, a claim is made for engagement from the scholars to debate the TOC, examine empirically its principles, and uncover the domains where TOC may not hold yet and explain the reasons why it may or may not hold.

Another common problem in supply chain management is related to its measurement systems. Usually, they tend to optimize performance of the individual processes thus, the goals and the measures to control performance are focused in the next downstream node of the SC rather than the customer (WATSON; POLITO, 2003). According to the TOC perspective tough the goal of the whole supply chain is to make money now and in the future (COSTAS et al., 2015). To achieve the goal, TOC proposes its operational (T, I, and OE) and global measures (NP, ROI, and CF) (GOLDRATT; COX, 2004). Within the supply chain context, Goldratt; Schragenheim; and Ptak (2000) would later include the measures of throughput-dollar-days (TDD) and inventory-dollar-days (IDD). Those are collaborative performance measures that guarantee that each node of the SC is doing what is supposed to do to reach the goal of the system (SIMATUPANG; WRIGHT; SRIDHARAN, 2004). However, the literature on the TDD and IDD is sparse and inconclusive (GUPTA; ANDERSEN, 2012). According to Gupta and Andersen (2018) empirical studies and studies that incorporate TOC implementations and performance measures is still a gap in scientific research.

Therefore, from the aforementioned studies, three main gaps can be identified: the lack of a conceptual model or method to apply the TOC's practices in supply chains (TSOU, 2013), lack of studies that evaluate consistently the TOC implementation in supply chains with TOC's performance measures (GUPTA; ANDERSEN, 2018), and, consequently, the absence of empirical evidence to support the improvements brought by the application of theory (GUPTA; BOYD, 2008). More specifically, the TOC supply chain studies: a) do not measure the contribution of the TOC SC steps, in a holistic or step-wise manner; b) do not point the causal effects of TOC's intervention in the supply chain; c) do not assess systematically the impacts of the TOC in an empirical study; and d) do not assess the supply chain either in aggregated terms or at each individual link.

This work uses a real case to address its research problems and fill the gaps within the TOC supply chain literature. The case is the supply chain of a large-sized multinational chemical industry that provides goods for the agricultural sector. The case studies an internal supply chain in the Rio Grande do Sul Brazilian state. The company is multinational organization with headquarters in Europe, but highly active in Brazil. The country's potential is of strategic interest for the organization as, currently, one third of the company's global revenue comes from Brazil. The company possesses four production units located in the Brazilian states of Rio Grande do Sul, Paraná and São Paulo and two central administrative offices. Additionally, the company has also other 24 mixing units that receive manufactured products from the production units. The mixing units are spreadly located among eleven Brazilian states. Many of the raw materials come from Europe from other company's production units and international suppliers. Due to the long lead times of the imported raw materials, the company relies on forecasting to plan production, inventory levels and sales. The accuracy of forecasting, however, is low – around 60%. This inaccuracy leads to high inventory values, low inventory turnover, losses to obsolescence, frequent delay in deliveries and even loss of sales –30 million dollars as estimated by the company. The application of the TOC concepts in the supply chain aim to solve many of those related problems (GOLDRATT, 2009; SMITH; PTAK, 2010) therefore, posing itself as an opportunity to the studied case.

From the clarification of the TOC distribution solution, an overall contextualization of the theory within the supply chain, and the presented problems that arise with the theme, the research question that guides this research is defined as: what are the impacts in supply chain performance when applying TOC practices for supply chain management?

Having defined the research question, the next sections will present the research objectives, followed by its academic justification, which aims to enlighten the relevance of the present work.

1.2 OBJECTIVES

In this section, the general and specific objectives that compose the research are described.

1.2.1 General Objective

The current work aims to evaluate the impacts of the application of the Theory of Constraints practices in an MTO supply chain of a chemical industry.

1.2.2 Specific Objectives

a) Create and validate a system dynamics model of the current case's supply chain with the actual implemented stock and replenishment policies to serve as the base model;
b) Apply the TOC's distribution/replenishment solution steps in the base model, being capable of measuring the impacts of each of the steps in the system as a whole;
c) Utilize TOC's performance measures to measure the supply chain redesign necessary to apply TOC's supply chain policies;
d) Measure the causal impacts of the TOC's supply chain polices at each step application;

1.3 JUSTIFICATION

This section covers the justification of the study considering two different contexts. The first one, presented in the next sub-section provides its academic justification, while the second part elaborates its relevance within the enterprise context. In order to justify the present work in the academic sense, a systematic literature review was conducted to validate the relevance criteria of the research. According to Seuring and Gold (2012), the systematic review allows the reviewer to find relevant information from a growing volume of publications, that might be either similar or contradictory. The decisions that are made from a series of relevant studies are more appropriate than those made from a limited set of studies (MORANDI; CAMARGO, 2015). The relevance, in its turn, can be comprehended as a relation among two entities, being them: i) a document, part of a document (title, abstract, etc.) or information; and ii) a problem, information need, request or *query* – representation of an information as a system's language (MIZARRO, 1997). In the current study, the relevance can be understood as the relation of this research with the problem or gap to be fulfilled.

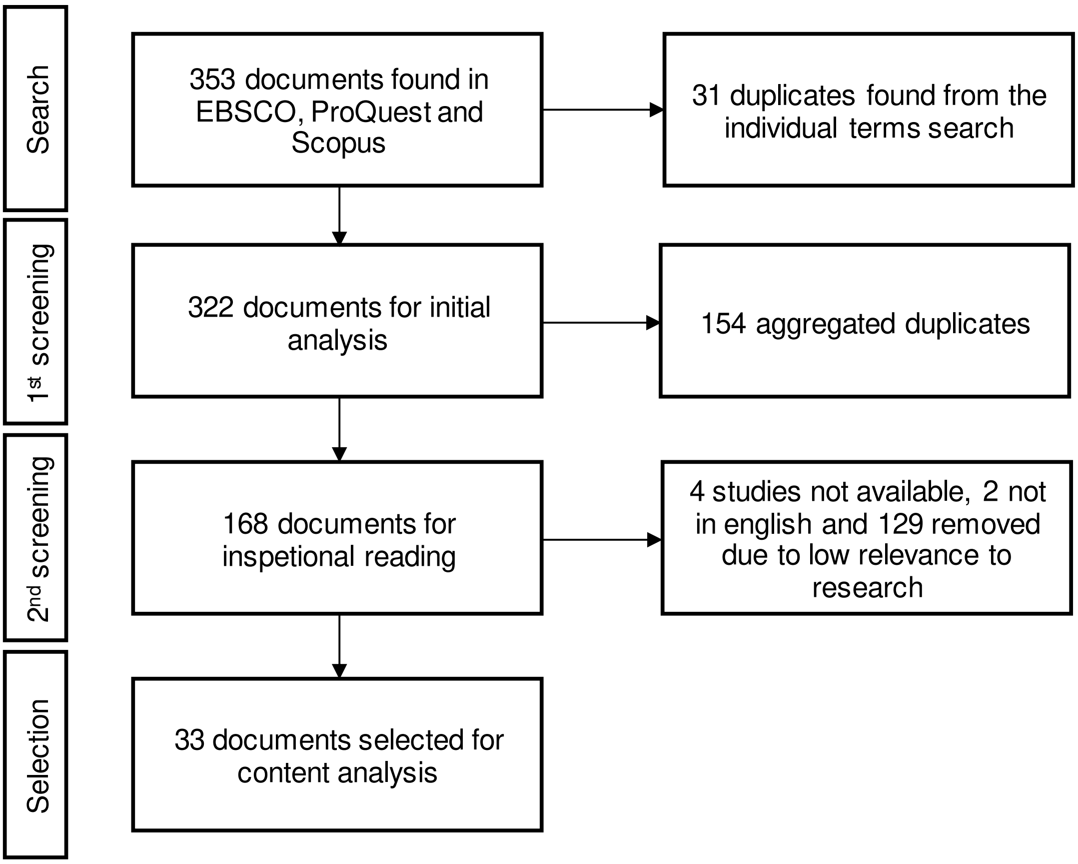
The systematic literature review method was applied as suggested by Morandi e Camargo (2015) and unfolded from the research protocol, presented in Appendix A. The terms search was made in the EBSCO, ProQuest and Scopus databases and its results are presented in Frame 1.

Frame 1 – Search of terms in the databases

Database	**Search Terms**	**Documents Found**	**Without Duplicates**
EBSCO Host	TI ("supply chain" AND "Theory of constraints") OR AB ("supply chain" AND "Theory of constraints") OR SU ("supply chain" AND "Theory of constraints")	49	49
	TI ("theory of constraints" AND Logistics) OR AB ("theory of constraints" AND Logistics) OR SU ("theory of constraints" AND Logistics)	11	11
	TI ("theory of constraints" AND Distribution) OR AB ("theory of constraints" AND Distribution) OR SU ("theory of constraints" AND Distribution)	22	22
	TI ("theory of constraints" AND Replenishment) OR AB ("theory of constraints" AND Replenishment) OR SU ("theory of constraints" AND Replenishment)	5	5
ProQuest	NOFT("Supply Chain" AND "Theory of Constraints")	61	48
	NOFT("Theory of Constraints" AND Logistics)	36	27
	NOFT("Theory of Constraints" AND Distribution)	35	27
	NOFT("Theory of Constraints" AND Replenishment)	7	6
Scopus	TITLE-ABS-KEY ("supply chain" AND "Theory of Constraints")	64	64
	TITLE-ABS-KEY ("Theory of Constraints" AND Logistics)	20	20
	TITLE-ABS-KEY ("Theory of Constraints" AND distribution)	26	26
	TITLE-ABS-KEY ("Theory of Constraints" AND replenishment)	17	17
	Total of documents found	**353**	**322**

In EBSCO host, the terms were searched in the *Academic Search Complete, Business Source Complete* and *Academic Search Premier* databases looking for matches in titles, abstracts or subjects, being represented by the strings TI, AB and SU respectively. In ProQuest the terms were searched at any other part of the text with exception of the text body, this is represented by the search string NOFT. In Scopus, the searches were conducted by the titles, abstracts or keywords, represented by the string TITLE-ABS-KEY. Additionally, in all databases the searches were limited to peer-reviewed academic journals and, in Scopus, an additional limitation to the area of interest was imposed, limiting the searches to the following areas: i) *Business, Management and Accounting;* ii) *Engineering*; iii) *Decision Science*; iv) *Computer Science*; v) *Economics, Econometrics, and Finance*; vi) *Mathematics*; vii) *Chemical Engineering*; viii) *Energy*; ix) *Chemistry*; and x) *Materials Science*. In order to get a full spectrum of the publications, no time restriction was imposed. A total of 353 documents were of which 31 duplicates were removed, resulting in a total of 322 documents. The selection method of the studies is presented in Figure 4.

Figure 4 – Selection method of the studies



Source: created by the author.

After the searches in the databases, the 322 documents found were analyzed and grouped, and more duplicates were found. The screening resulted in 168 studies for evaluation of the titles and abstracts. Four studies presented availability limitations, one study was in Chinese and another one in Spanish, those were removed along with 129 other ones which were excluded due to the low relevance for this study. Those studies were found to be not relevant for not being related to the focus of this present research, which included, but are not limited to social themes, governmental/policy studies, related to healthcare, sustainability focus or other unrelated aspects of the supply chains.

Those 33 documents were selected for full reading in order to create a literature overview and identify the current gaps within it. Content analysis is also conducted in those documents in order to categorize the papers, identify variables and define the main terms of the theme, providing an overall structure of the literature. Seuring and Gold (2012) conduct a content analysis in SCM literature and affirm that the structured and rule-governed procedures of qualitative content analysis compose a powerful tool to generate valid and reliable results from the literature. Similarly, Jain et al. (2010) claim that content analysis allows the researcher to define the nature of the content, find patterns, and estimate relationships among the analyzed literature. The content analysis is explored in section 2.

Regarding the supply chain, given its complexity, the utilization of simulation techniques to propose the supply chain redesign is usual (BUIL; PIERA; LASERNA, 2011; ER; MACCARTHY, 2006; FU-REN LIN; YU-HUA PAI, 2000; MARTINS et al., 2017). Towill (1993a, 1993b) suggests system dynamics as a tool for business processes redesign; Karagiannaki, Doukidis, and Pramatari (2014) make use of discrete event simulation (DES) to redesign a supply chain with RFID implementation; Ponte et al. (2016) utilize Agent-Based Modeling (ABS) to supply chain redesign in order to reduce the bullwhip effect.

The utilization of TOC and simulation though is more recent: Kaijun, Wang and Yuxia (2010) simulate the TOC's buffer management practices for inventory control; Wu Huang and Jenc (2012) study the replenishment frequency within the Theory of Constraints context; Costas et al. (2015) apply TOC's practices in the known Beer Game case; Gupta and Andersen (2018) utilize DES to apply TOC's performance indicators of TDD (throughput-dollar-days) and IDD (inventory-dollar-days) and analyzed their impacts on the SC. However, this model focus on the TDD and IDD performance measures and actions taken are at the manufacturing level of the supply chain, not the SC design or structure. Thus, this model does not apply the TOC supply chain solution, focusing instead in issues such as set-up times, maintenance planning, and production capacity. The application of the TOC in the supply chain is still limited though (COSTAS et al., 2015), with a clear gap regarding empirical studies to support the theory's practices (TSOU, 2013; WATSON; POLITO, 2003). This study then provides an empirical study from a real case by the utilization of computational simulation, defining System Dynamics (SD) as its modeling and simulation tool.

System Dynamics is chosen for this study for being known as a tool that observes systems from a macro level and is utilized for strategic decision making (LAW, 2014). According to Sterman (2000), the system dynamics (SD) is concerned with the behavior of complex systems and requires more than just technical tools for the creation of mathematical models. Pidd (2003) affirms that the SD is a set of tools and a simulation approach thought initially for the industrial environment. With one of its operation methods, the system dynamics makes use of its structural functionalities to develop a computer simulation model that utilizes quantitative data (PIDD, 2003). From the system dynamics modeling and the current state of the case will derive the validation of the model itself and from the validated model new models will be created to simulate the individual application of the steps of the TOC distribution/replenishment solution. At the end, once all steps have been applied, it will be able to evaluate the overall impacts of the whole TOC solution in the supply chain based on traditional financial measures as well as the TOC's performance measures. The gradual application of the steps will allow to assess individually each one of the TOC's policies, comparing them and measuring their contribution to the overall impact in the supply chain as whole.

In order to apply the TOC's steps it is necessary to change the SC design. This study aims to define what are the necessary changes in order to fully apply the TOC model and how long it takes to see the impacts in the supply chain. Also, to better understand all the impacts caused by this changes the CausalImpact technique is utilized. According to Brodersen et al. (2015) This technique allows to measure the causal impacts caused by an intervention in a temporal series, allowing to understand and compare the application of the TOC steps and the non-application of them. Therefore, the causal impacts to the supply chain caused by the changes required by the TOC solution is of interest as well, contributing to fill the gaps of empirical researches (GUPTA; BOYD, 2008; TSOU, 2013) and of evidences of the TOC solution application (IKEZIRI et al., 2019).

In a general sense, this study also aims to contribute to fulfill the gap of empirical studies of the TOC literature within the supply chain context as well as contribute with the application of the distribution/replenishment solution and the analysis of its impacts in the system as a whole. This study aims also to contribute and to be relevant to the enterprise context. The current global environment of the supply chains presents great challenges for the enterprises. Higher levels of productivity, responsiveness, quality and reliability combined with reduced costs have become the norm to ensure the survival of companies in an environment containing increases in demand, variability, and competition (MISHRA et al., 2012). However, many companies still face problems in their supply chains, such as lost sales, unavailability of many products, stocked products that are hard to sell, high investment on inventories with low turnover, and slow response time to changes in demand (MARGARETHA; BUDIASTUTI; SAHRONI, 2017).

To overcome the supply chain challenges many practices, tools, and techniques were developed in recent times, such as Just-in-Time, MRP and TOC (GUPTA; SNYDER, 2009). The TOC specifically has covered many problems in the enterprise context demonstrating proven empirical results such as increased levels of production while at the same time reducing inventory investment and cycle times (WATSON; POLITO, 2003). Mabin and Balderstone (2003) have analyzed a series of TOC applications in organizations and their respective improvements, as demonstrated in

Table 1.

Table 1 – Improvements from TOC application

Measurement	Number of evaluated works	Average improvement (%)
Lead time	34	70
Cycle time	14	65
Due date performance	13	44
Inventory	32	49
Revenue	20	83
Throughput	4	65
Profitability	7	116

Source: Mabin and Balderstone (2003).

Even though there are many studies demonstrating the benefits in applying TOC practices in production and factory levels, the studies regarding its application and impacts in supply chains are rather limited and, therefore, not fully reported and comprehended (COSTAS et al., 2015; GUPTA; SNYDER, 2009; IKEZIRI et al., 2019). Therefore, the relevance of this study within the enterprise context is to validate the aforementioned improvements of the application of TOC in the supply chain performance, providing guidance for its implementation and clarifying the expected results derived from it, based on a real case example. It also extends the TOC supply chain solution beyond the its initial context – retail and distribution (IKEZIRI et al., 2019) – to another strategic sector. The case's business market is at an strategic position in Brazil, representing 4,36% of the country's GDP in 2018 (WORLD BANK GROUP, c2019). This should also contribute to the development and adoption of the theory in real-world applications, further enhancing the supply chain management performance of enterprises.

TOC research within the SC perspective have been very specific, focusing on parts of the replenishment solution such as manufacturing level operations (GUPTA; ANDERSEN, 2018; TELLES et al., 2019), inventory impacts and improvements (CHANG; CHANG; HUANG, 2014; CHANG; CHANG; SUN, 2015), buffer management (TSOU, 2013), and replenishment frequency (WU et al., 2012; WU; LEE; TSAI, 2014). This research advances the studies of TOC in SCM, by providing a holistic view of its impacts in the supply chain and its links, analyzing not only its inventory levels, but also how well positioned are those inventories – using the IDD – and the SC throughput performance – the TDD. Those measurements are applied at each incremental step of the solution, being able to: a) assess them individually and synergistically; b) assess their causal effects probabilities and results at the overall system as well as at its components; and c) the time it takes from the application of the solution to the observed effects in the system.

Additionally, this work contributes to the company's case informing what impacts and results can be achieved through the TOC method, what is necessary to change in terms of supply chain design to apply the proposed policies and how long it would take to perceive the benefits of implementation. It can also contribute to other supply chain managers, providing a solid and empirical TOC-SCRS study, covering its implementation, the challenges, the difficulties and especially the expected improvements. Within the supply chain redesign, it aims to assert TOC's SC policies as a sound alternative to be considered in SC redesigns that aim for increased performance, just other know practices such as lean and JIT.

Having presented the academic justification of the research, the next section covers this study delimitations.

1.4 DELIMITATIONS

Once defined the aim to create a system dynamics model based on the studied case the delimitation to guide the work should be clarified as well. First, is not the intent of the work to create a generic model for future studies, in that sense, the proposed model will relate only to the defined case. Similarly, given the case complexity and its operations scale, this study will focus on the internal supply chain of the organization considering all the units located in Rio Grande do Sul state, but not including suppliers or any other external stakeholders. In that sense, it is also worth mentioning that the system comprises of an internal supply chain, meaning that all chain links are from the same organization, which might differ from the general supply chain. However, those supply chain links are all locally managed with independent and local KPI's as well, meaning that the SC behavior is comparable to a common supply chain structure of independent organizations.

Regarding the Theory of Constraints policies, this research focuses on the supply chain distribution/replenishment solution steps as proposed by Schragenheim (2010). It does not include in the system, the manufacturing steps proposed in the solution, as it is not part of the model. It is not its intent to analyze or apply any other of the theory's techniques that are not strictly included in the distribution solution, such as the thinking process, the critical chain project management, the focusing steps etc. Having defined the current delimitations, the next section will cover the work structure.

1.5 WORK STRUCTURE

This work is divided into three chapters: Introduction, Theoretical Background, and Methodological Procedures. In the Introduction, already presented, the initial discussion regarding the theme is conducted, the research aim and problem definition are clarified, the specific and general objectives are defined, and the study's delimitation is described. In the next section, the Theoretical Background is explored, where the main terms and concepts are defined, the relevant literature about the theme is studied through bibliometric and content analyses. Lastly, the section that covers the methodological procedures is presented derived from the goals, objectives, and delimitations of the research.

2 THEORETICAL BACKGROUND

This section presents the main theoretical concepts that ground this study. First, an overall perspective of the Theory of Constraints is elaborated. Later, focus is given into the study's main theme TOC within the supply chain. In order to explore the subject, both bibliometric analysis and content analysis are conducted. In the bibliometric analysis, it is possible to observe the evolution of the publications throughout time, the main journals and terms for those publications, and co-authorship and cluster analysis. In the content analysis, the selected studies derived from the systematic literature review are deeply analyzed, defining the main theoretical concepts, the types and categories of these studies and proving a comprehensive framework for TOC's application in the Supply Chain.

2.1 THEORY OF CONSTRAINTS

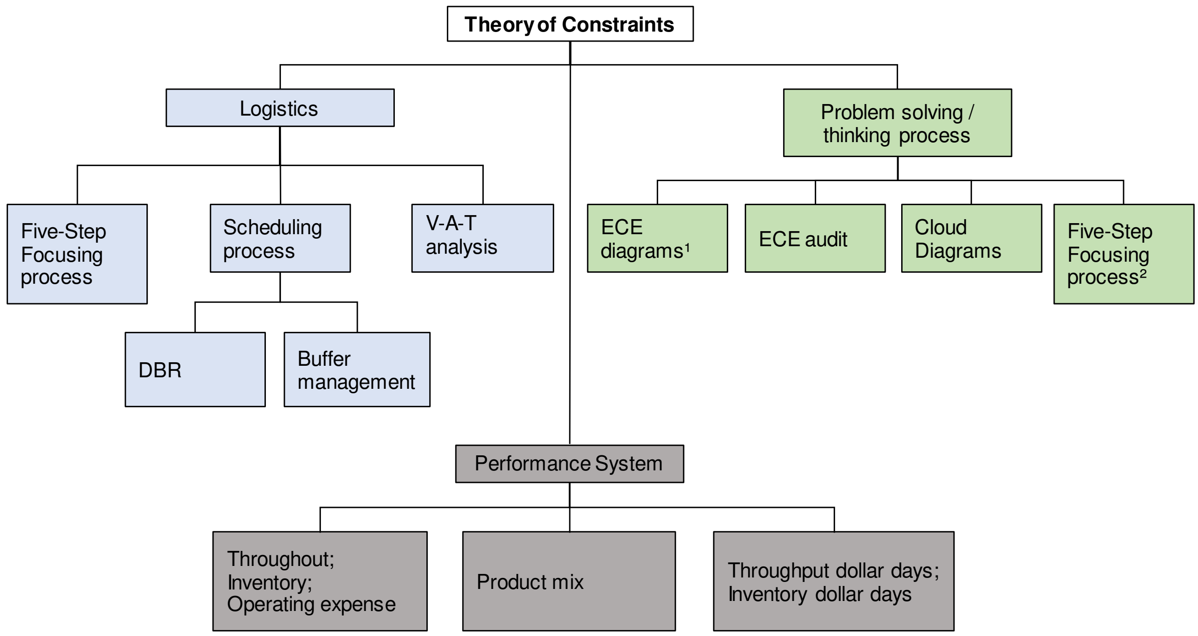
The Theory of Constraints is a management philosophy which asserts that constraints determine the performance of a system and that those constraints are opportunities for continuous improvement of the system (BLACKSTONE, 2001; PONTE et al., 2016; RAHMAN, 1998). TOC was originated from the Optimized Production Timetables (OPT) – a software for production schedule – in the late '70s (GUPTA, 2003). Since then, the theory has evolved being applied to many aspects of management in both strategic and operational levels (BASHIRI; TABRIZI, 2010) and in a wide range of fields as production operations, finance, project management, supply chain, marketing, among others (BLACKSTONE, 2001).

According to Spencer and Cox (1995), TOC consists of three paradigms:

a) logistics: consists of those elements which are utilized mainly in operations management for constraints management, production scheduling, and buffer placement;
b) performance measurements: developed to support the management of the constraints and to mitigate the conflicts that occur in the traditional performance measurement systems;
c) thinking process: aims to solve three questions faced by management what to change, to what to change to and how to cause the change.

Spencer and Cox (1995) provide a comprehensive overview of the Theory of Constraints, its three paradigms and their respective tools and methods as illustrated in Figure 5.

Figure 5 – Schematic of the Theory of Constraints



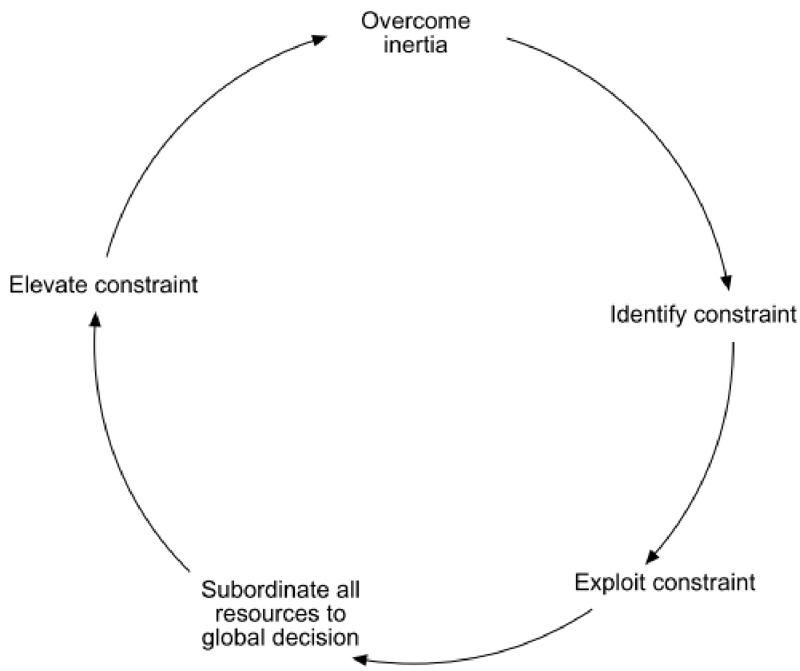
Notes:
1: ECE diagrams include any of the following: Current Reality Tree (CRT), Evaporating Clouds diagram (EC), Future Reality Tree (FRT), Prerequisite Reality Tree (PRT) and Transition Tree diagrams (TT).
2: When the five-focuding steps are applied outside the logistics field it belongs to the thinking process.

Source: Adapted from Spencer and Cox (1995).

In the logistics branch of TOC can be identified the five-focusing steps, the Drum-Buffer-Rope methodology and buffer management, and the V-A-T analysis. The DBR "synchronizes resources and material utilization in an organization" (TULASI; RAO, 2012), while the buffer management supports the decisions and tradeoffs between constraint protection and lead times (WATSON; BLACKSTONE; GARDINER, 2007). The V-A-T analysis is a classification method to identify the position of the buffers in a production line, having its name from the usual diagrams that describe production processes (SPENCER; COX, 1995). According to Rahman (1998), the logistics paradigm is a philosophy that builds the base of the TOC working principle of continuous improvement, through the application of the five-focusing steps.

The first of the five-focusing steps is the identification of the constraint. According to the TOC the constraints determine the performance of the system, therefore, management of the of a few focus points allows effective control of the whole system (WATSON; BLACKSTONE; GARDINER, 2007). The second step is deciding on how to exploit the constraint, aiming at making the constraint as effective as possible, reduce its effects and make everyone aware of it and its effects on the performance of the entire system (GUPTA, 2003; RAHMAN, 1998). The rate of throughput at the constraint limits the output of the system, so the third step consists of subordination of the system to the constraint. By adjusting the non-constraints components of the system to support maximum effectiveness of the constraint, wastes are eliminated and responsiveness is maximized since the system focus on the works that turn cash through sales in the near term (RAHMAN, 1998; WATSON; BLACKSTONE; GARDINER, 2007). The fourth step is to elevate the system's constraint, this can be achieved by adding more capacity to the constraint resource or off-loading part of its demand (GUPTA, 2003; WATSON; BLACKSTONE; GARDINER, 2007). The last step is a closing loop for the continuous improvement process, stating that if during the previous steps a constraint is broken, go back to step 1 and do not let the inertia become a constraint (GUPTA; SNYDER, 2009; RAHMAN, 1998). Figure 6 summarizes the five-focusing steps and the continuous improvement process.

Figure 6 – The five-focusing steps and the continuous improvement process



Source: Rahman (1998).

Following the TOC schematic depicted in Figure 5, other important part of the theory is related to its performance system. The Theory of Constraints criticizes the traditional accounting claiming that this method is obsessed by the need to reduce operational expense, or as TOC refers to, the cost world thinking (COLWYN JONES; DUGDALE, 1998). While traditional accounting focuses on cost reduction, the TOC, on the other hand, focuses on making money now and in the future (WATSON; BLACKSTONE; GARDINER, 2007). In that sense, the TOC proposes its own performance system. Composed by operational measures that are financial in nature, are easy to apply at any level of a company and ensure that local decisions are aligned with the profit goal of the system (GUPTA; SNYDER, 2009; NOREEN; SMITH; MACKEY, 1996). From the operational measures, we can derive the global (financial measures) as described in Frame 2.

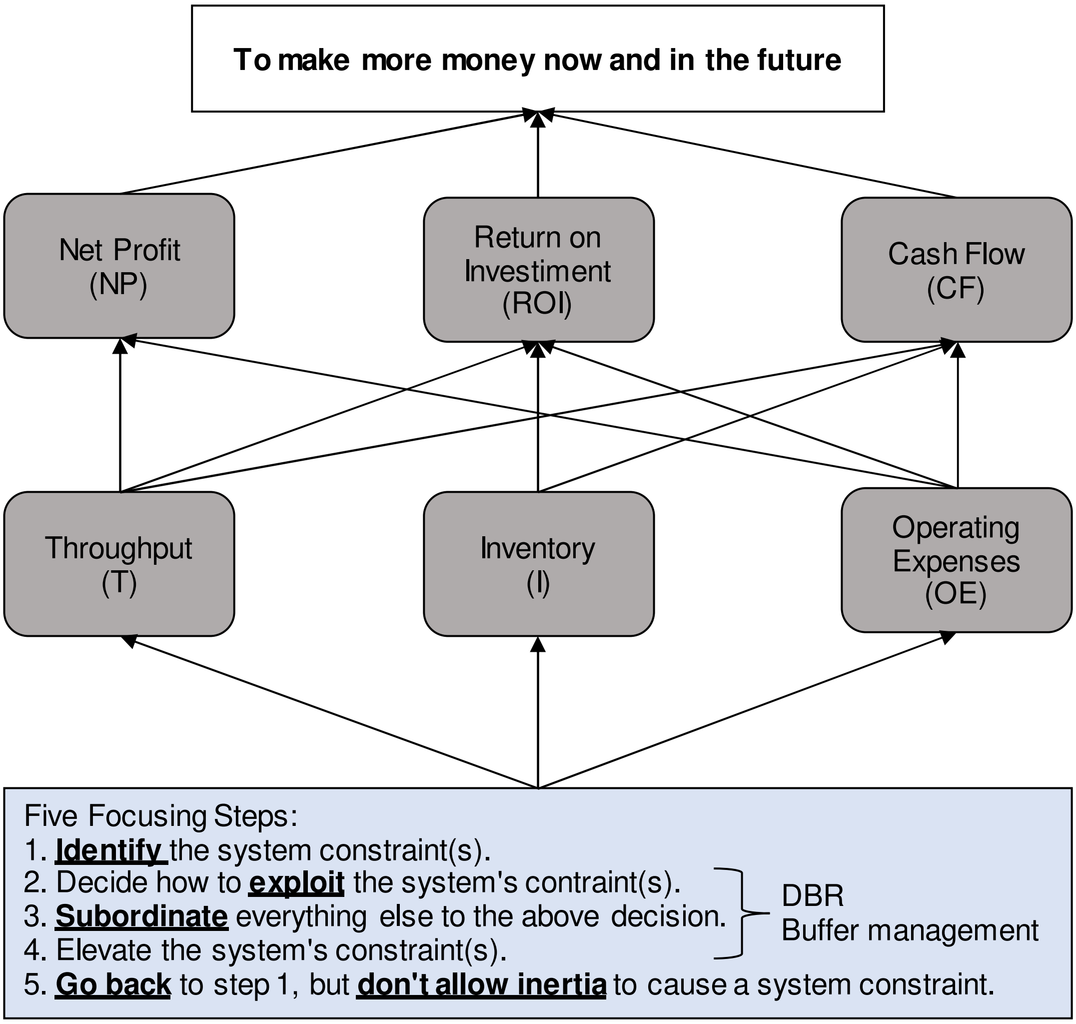
Frame 2 - TOC performance measures

Measure	**Acronym**	**Definition**
Operational measures		
Throughput	T	The proportion at which the system generates money through sales
Inventory	I	All the money invested in goods which the system aims to sell
Operational Expense	OE	All the money utilized to transform inventory in throughput
Global Measures		
Net Profit	NP	The throughput subtracted from the operational expenses NP = T - OE
Return Over Investment	ROI	A relative measure that represents the net profit over inventory ROI = NP/I
Cash Flow	CF	A survival “red line”, treated as an “on-off” type measurement

Source: Adapted from Rahman (1998).

The TOC’s performance measures and the logistics paradigm are connected and aligned with the theory’s goal to make more money now and in the future. Figure 7 illustrates this rationale through a framework.

Figure 7 – TOC framework



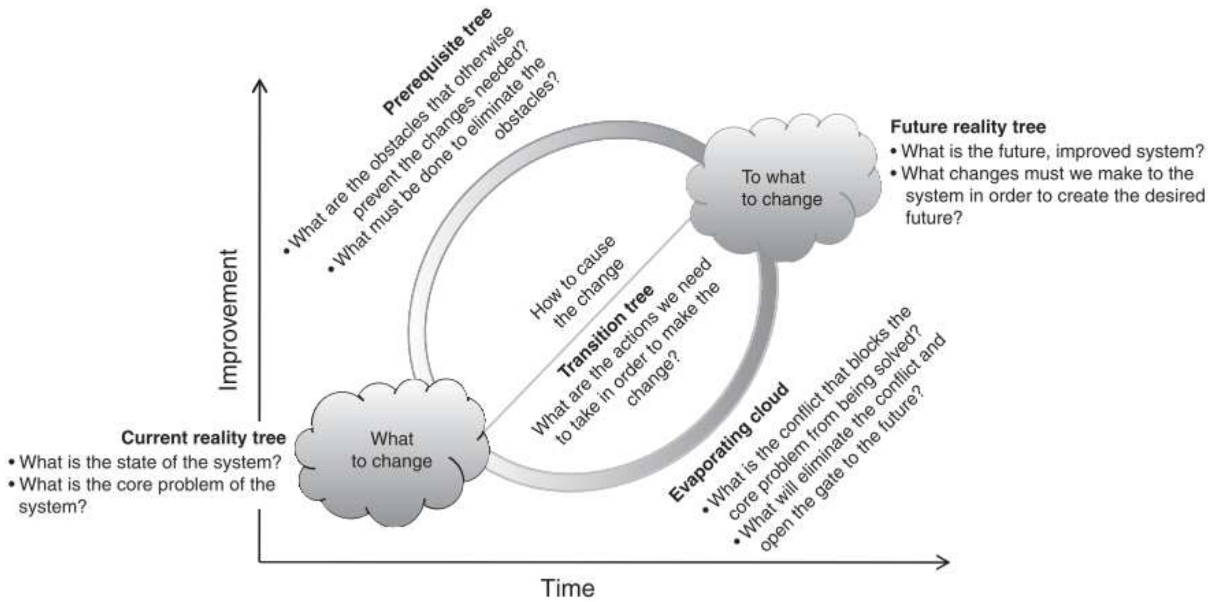
Source: Adapted from Gupta, Ko and Min (2002).

Other than the operational measures, the TOC performance measures also include the product mix decisions and the throughput and inventory dollar-days measures. In the TOC. The product mix decisions utilize the throughput and profit per-constraint per time period instead of the traditional usage of sales price, gross profit or gross margin for product mix prioritization (BUDD, 2013; SPENCER; COX, 1995). The throughput-dollar-days (TDD) “is a reliability measure that evaluates the faults in terms of commitment to clients” (BERNARDI DE SOUZA; PIRES, 2010) and the IDD is a measure to evaluate the stock value and the remaining time of it in a specific location, in other words, the excess of inventory (BERNARDI DE SOUZA; PIRES, 2010). The TDD is calculated as the selling price of a late sales order multiplied by the number of days it is late, while the IDD is the stock value multiplied by the days on hand (GUPTA; ANDERSEN, 2012, 2018).

The five focusing steps are generalized in this branch into a Process Of OnGoing Improvement (POOGI) driven by three simple questions: “what to change?”; “what to change to?”; and “how to cause the change?” (COLWYN JONES; DUGDALE, 1998). The main element of the thinking process is the effect-cause-effect (ECE) diagrams (SPENCER; COX, 1995). To achieve the necessary improvements the TOC utilizes its logical trees which are basically a set of diagrams to analyze effect-cause-effect relationships (BLACKSTONE, 2001). The Current Reality Tree (CRT), the Future Reality Tree (FRT), and the Transition Tree (TT) are logical diagrams based on sufficiency while the Evaporating Clouds (EC) and the Prerequisite Tree (PRT) are logic structures based on necessity (MABIN; DAVIES, 2010). More recently, the Strategic and Tactics Tree (S&T) has been included in TOC’s logical diagrams; the S&T is a graphical representation of the hierarchy between goals, objectives, intermediate objectives, and tactics which serves as a tool for complete synchronization and communication of the change process (SCHEINKOPF, 2010; WATSON; BLACKSTONE; GARDINER, 2007).

According to Watson, Blackstone, and Gardiner (2007), the application of the thinking process generally starts through the construction of the CRT to identify the core problem(s). Then, the EC is utilized to discover hidden assumptions that can be invalidated by the injections – a future action to eliminate the problem – that would structure the problem solution. The FRT is used to guarantee that, once the solution is implemented, unexpected negative outcomes (Negative Branches) do not occur – the negative branch reservation (NBR) is a sub-tree of the FRT that can be used to improve critical feedback and develop incomplete ideas. With the validated solution, the PRT identifies intermediate objectives to overcome obstacles during the solution implementation. Finally, the TT is derived from the PRT and the FRT to achieve a specific implementation plan for the proposed solution (WATSON; BLACKSTONE; GARDINER, 2007). Figure 8 demonstrates the thinking process tools and the relationships among them and with the POOGI.

Figure 8 – Thinking process application tools



Source: Scheinkopf (2010).

This section aimed at providing an overall comprehension of the TOC, its paradigms and its tools. The next sections intend to focus on the applications of the Theory of Constraints within the supply chain context.

2.2 TOC AND SUPPLY CHAIN MANAGEMENT

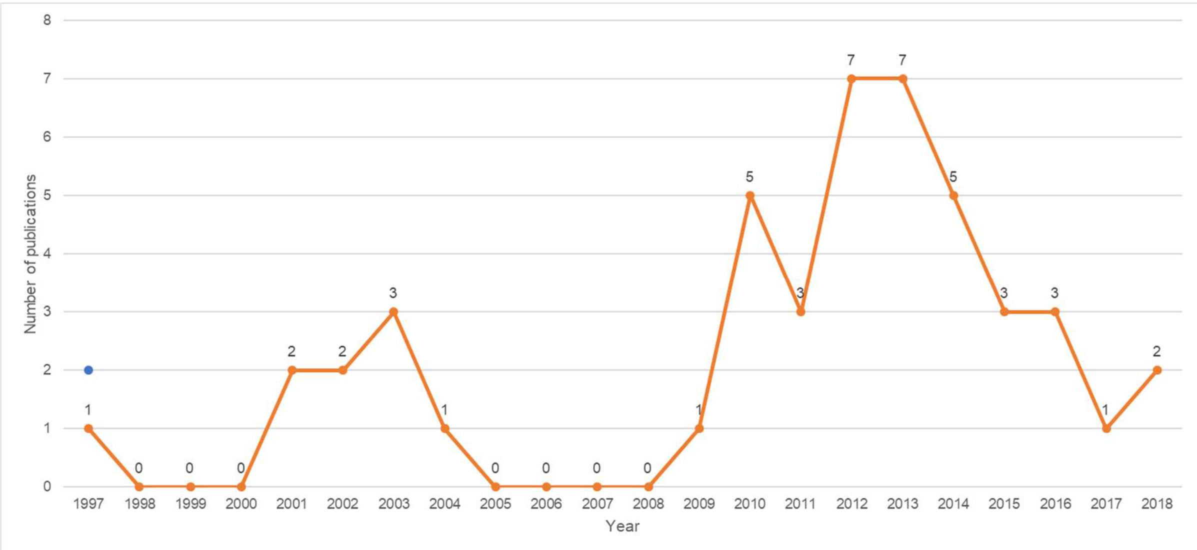
As previously stated, from the systematic literature review 46 documents were selected which are utilized for the descriptive analysis. After the exclusion of documents that were found to be not relevant for this study, 33 documents are selected for the content analysis. The descriptive part will basically contain a bibliometric analysis of the studies, while the content analysis structure the selected documents within logic categories for literature exploration and definition. The bibliometric analysis provides a general picture of a defined subject of research that can be categorized by papers, authors and journals (MERIGÓ; YANG, 2017), while the content analysis is utilized to generate valid and reliable results from the literature review (SEURING; GOLD, 2012).

2.2.1 Descriptive Analysis

During the SLR 46 studies were selected to be analyzed in respect to their publication distribution over time, the main journals that contribute to the theme, co-authorship analysis, and key-word network analysis.

The first analysis is the number of publications over the years. The full-time spam of the selected studies is utilized for this. Chart 1 provides the total number of publications by year. The theme is first discussed in the work of Pérez (1997) and is followed by a hiatus until 2001 where a few publications bring up the TOC and Supply Chain once again. A new hiatus follows from 2005 to 2008 and then an increase in publications happens, especially from 2010 to 2014. From that period, it seems that the number of publications concerning the TOC supply chain solution has decreased.

Chart 1 – Total number of publications by year

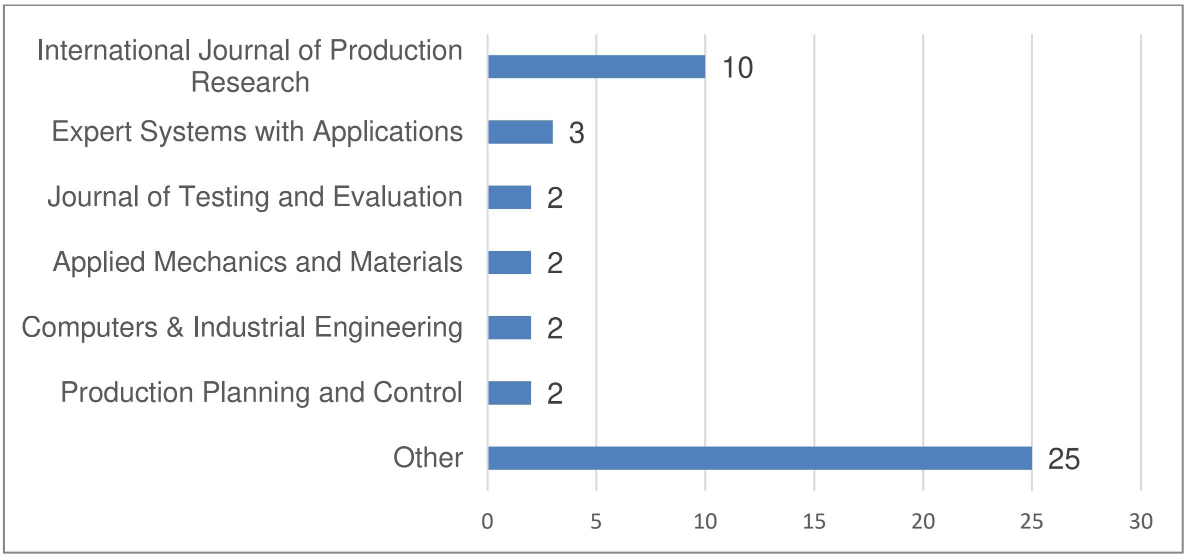


Source: The author (2020).

During the peak of publications regarding the subject, some major events can be mentioned, although is not the aim of this study to prove the relationship of the events to the publications. The publications reach their peak during the period of 2010 to 2014, right after the unfolding of the 2008 financial crisis (JOEL HAVEMANN, [s.d.]) and the European debt crisis in 2009 (“Timeline: The unfolding eurozone crisis - BBC News”, 2012). Then, the increasing interest of the theme can be linked to financial crisis periods as companies are challenged to face situations of high inventory, low turnover, and sudden demand changes (TSOU, 2013) and consequently themes such as Supply Chain Management become strategically important (COSTAS et al., 2015).

Regarding the periodicals that most contributed to the TOC Supply Chain Replenishment Solution, Chart 2 presents the number of publications by journals. In the chart, the journals with one publication only were aggregated in the label "Others". It is possible to notice that the International Journal of Production Research is the one who has more publications, which represents approximately 22% of the publications. However, the relevant publications of the theme are also widely spread, as 54% of the journals had published only one paper concerning the subject.

Chart 2 – Number of TOC and supply chain publications by journal



Source: The author (2020).

The main contributor, the International Journal of Production Research is published since 1961. It is an established, successful and leading journal with publications related to manufacturing, production, and operations management research. Currently, the journal has an impact factor of 3,199 according to the Journal Citation Index.

Going into further detail regarding the most relevant journals it is possible to double-cross with the distribution of those periodicals throughout the time, which is presented in Table 2. From the data it is possible to observe that in the period where most of the publications are concentrated – from 2010 to 2014 – is where most publications are spread in the "Other" journals categories, meaning that the main periodicals were not the ones to have more publications. In the mentioned period other journals accounted for 17 of the 27 publications, or 63%, more than the overall distribution of 54% in the “Others” category.

Table 2 – Yearly publications of TOC in supply chain by journal

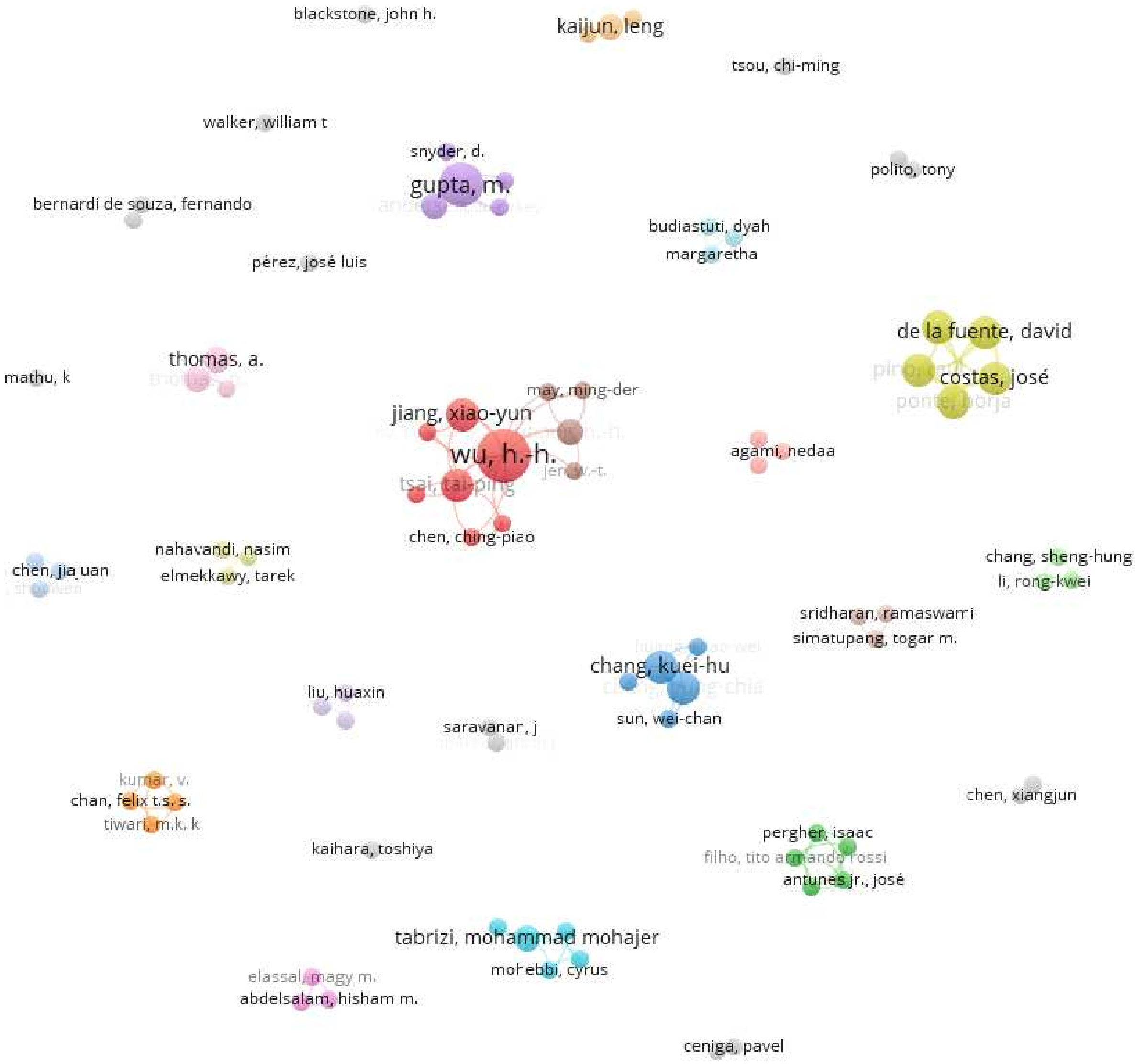
Year	International Journal of Production Research	Expert Systems with Applications	Applied Mechanics and Materials	Computers & Industrial Engineering	Journal of Testing and Evaluation	Production Planning and Control	Others	Total
1997	-	-	-	1	-	-	-	1
2001	1	-	-	-	-	-	1	2
2002	1	-	-	-	-	-	1	2
2003	3	-	-	-	-	-	-	3
2004	-	-	-	-	-	-	1	1
2009	1	-	-	-	-	-	-	1
2010	-	2	-	-	-	-	3	5
2011	-	-	-	-	-	1	2	3
2012	3	-	-	-	-	-	4	7
2013	-	-	1	-	-	-	6	7
2014	-	-	1	1	1	-	2	5
2015	-	1	-	-	1	-	1	3
2016	-	-	-	-	-	1	2	3
2017	-	-	-	-	-	-	1	1
2018	1	-	-	-	-	-	1	2
Total	**10**	**3**	**2**	**2**	**2**	**2**	**25**	**46**

Source: The author (2020).

Co-authorship analysis provides quantitative evidence to better comprehend the social patterns of scientific collaboration (BELLANCA, 2009), their structure and their clusters (PETERS; VAN RAAN, 1991). In order to conduct this analysis, graphical representations and bibliographic mappings are utilized as they provide a useful method to facilitate interpretation of large sets of data (VAN ECK; WALTMAN, 2010). Utilizing the *VOSviewer* software, the 46 studies are analyzed. According to Peters and van Rann (1991), the minimum threshold for the number of publications by authors is related to the size of data and its value should provide a good overview for the analysis; with a low threshold interpretation of data can be difficult, while a high threshold may result in an incomplete analysis. Since the data for the analysis comprises only 46 studies, the minimum number of documents of an author was set to

1, which includes all studies, but does not compromise the interpretation. The network of co-authorship is presented in Figure 9. In the co-authorship network, each author is represented by a label and a circle, the colors represent the clusters and the circle sizes relate to the importance according to the number of publications (COBO et al., 2011; VAN ECK; WALTMAN, 2010). The software's algorithm identified a total of 86 authors and 29 clusters.

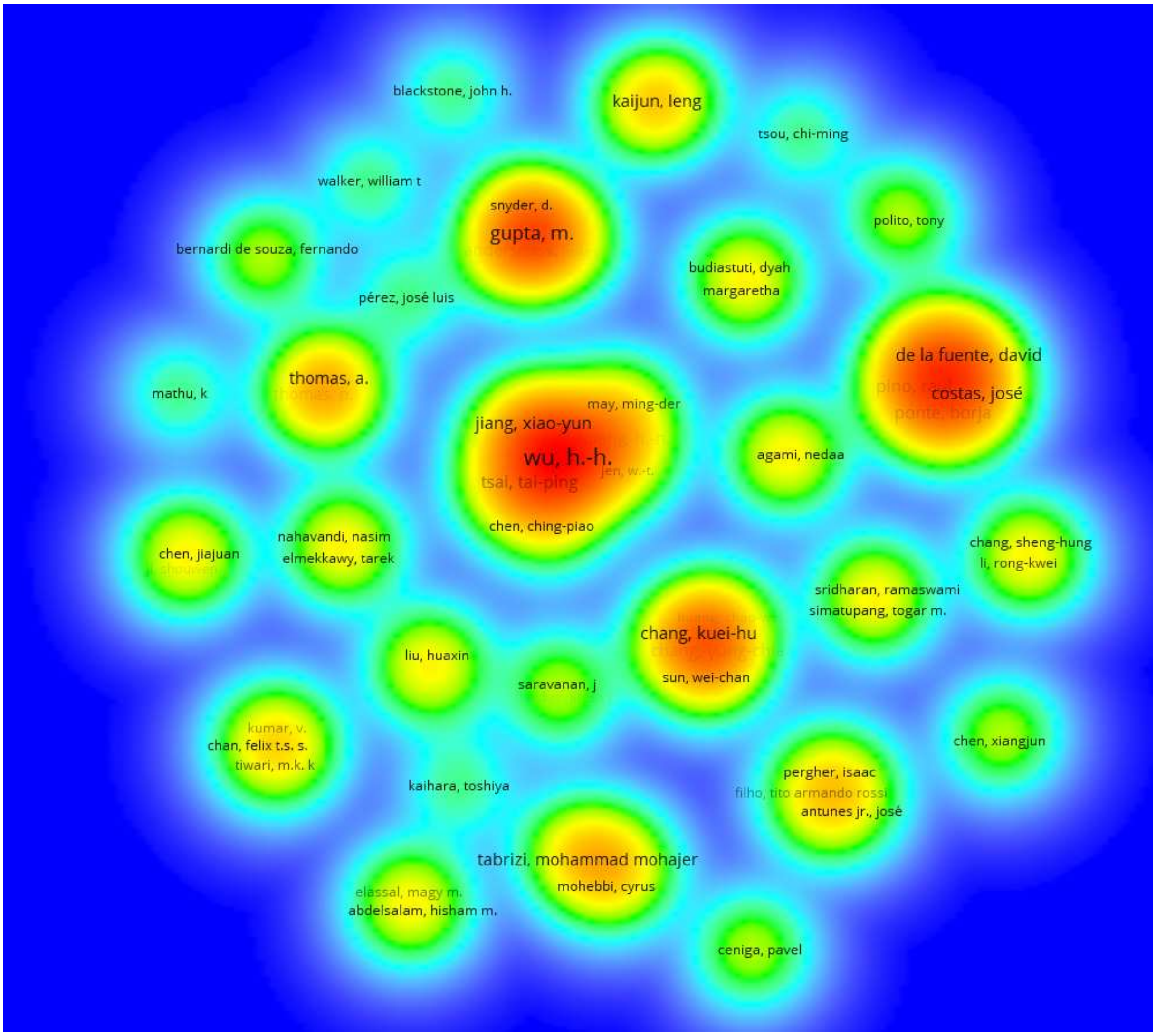
Figure 9 – TOC and SCM co-authorship network about TOC in SCM



Source: The author (2020).

Having identified the clusters, a density analysis is also presented in Figure 10. The density analysis is important to have an overview of the general structure of the network and to draw attention to the most important areas (VAN ECK; WALTMAN, 2010). It is similar to the network mapping, however, it displays colors that represents the density or importance of each point (COBO et al., 2011; VAN ECK; WALTMAN, 2010). In the figure, the redder is the circle the greater is the number of publications of the authors.

Figure 10 – TOC in SCM co-authorship density map



Source: The author (2020).

From those two figures, it is possible to identify the clusters that have contributed more to the TOC-SC theme. It is possible to identify four clusters that standout from the others. Those clusters are presented in Table 3. The clusters are ordered by number of publications and present author name, the number of documents for each one of the authors, the period of the publications and their respective country. It is possible to observe that Wu and Gupta are the authors with more publications, however, although Wu has more publications regarding the theme, Gupta has published more recently and before Wu as well; the latest publication from Wu found in the SLR was from 2014.

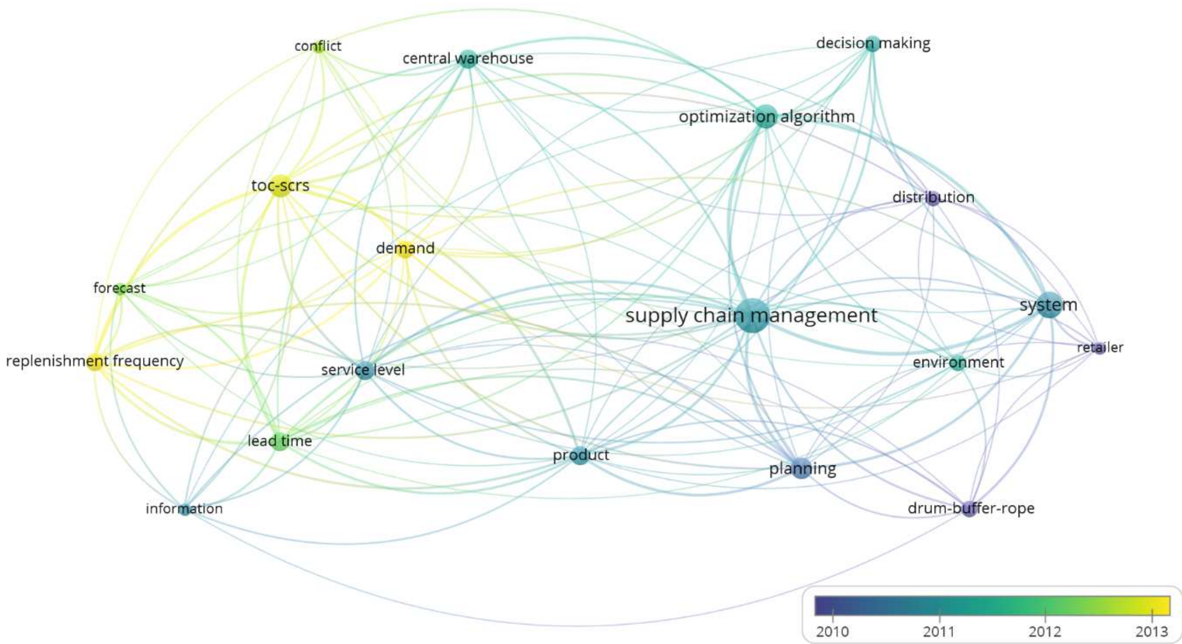
Table 3 – Co-authorship clusters details

Cluster	Author	Documents	Publication period	Country
1	Wu, Horng-Huei	7	2010 – 2014	Taiwan
	Jiang, Xiao-Yun	3		China
	Tsai, Tai-Ping	3		Taiwan
	Chen, Ching-Piao	1		Taiwan
	Hu, Huosheng	1		UK
	Lee, Amy H.I.	1		Taiwan
	Tsai, Chih-Hung	1		Taiwan
2	Costas, José	3	2015 – 2016	Portugal
	De La Fuente, David	3		Spain
	Pino, Raúl	3		Spain
	Ponte, Borja	3		Spain
	Puche, Julio	3		Spain
3	Gupta, Mahesh	5	2002 – 2018	USA
	Andersen, Soeren	2		Denmark
	Ko, Hyun-Jeung	1		USA
	Min, Hokey	1		USA
	Snyder, D.	1		USA
4	Chang, Kuei-Hu	3	2014 – 2015	Taiwan
	Chang, Yung-Chia	3		Taiwan
	Huang, Chao-Wei	1		Taiwan
	Lei, Yi-Chieh	1		Taiwan
	Sun, Wei-Chan	1		Taiwan

Source: The author (2020).

Other than the co-authorship analysis, a network of the terms is presented in Figure 11. The network is created from the terms of the titles and abstracts of the selected studies, with a binary counting method – if the term is presented or not in a specific study -, a minimum occurrence of a term set to 4 and keeping 60% of the most relevant terms based on the score calculated by the software. This analysis led to a network of 19 terms and 2 different clusters. Since a filtering is made at the occurrence of terms and only the most relevant ones are selected, the time-spam is adjusted to the period with more occurrences, hence 2010 to 2013, as seen in the figure. A thesaurus of terms was created to aggregate similar labels into equivalent terms and is presented in Appendix B.

Figure 11 – Network of terms in TOC SC publications through time



Source: The author (2020).

From the figure can be identified two clusters, one centered around “supply chain management” and another one centered around TOC Supply Chain Replenishment System (TOC-SCRS), both clusters are represented by the red and green circles, respectively. Although it is possible to observe that SCM is a more common term than TOC-SCRS in the literature, both terms are interconnected and the TOC supply chain replenishment system has received more attention recently. Some important terms were not found tough. In the network, terms such as empirical, performance measures, and inventory are missing, which might demonstrate that those were not the primary focus of current TOC SCM research. Thus, this work aims at a still unexplored research front.

Having presented a thorough descriptive analysis of the literature, next section aims to cover the content analysis.

2.2.2 Content Analysis

From the descriptive analysis, 33 documents were selected for the content analysis. Those 33 documents were also categorized according to their types and approaches, and the TOC distribution solution steps utilization (SCHRAGENHEIM, 2010). One additional category has been included for performance measurement from the TOC's proposition, as suggested by Bernardi de Souza and Pires (2010) and previously detailed in section 2.1 (see Frame 2 - TOC performance measures and Figure 7 – TOC framework). Frame 3 presents the structure of the content analysis.

Frame 3 – Content analysis categories

Analytical category	Description
STUDY TYPE	
Empirical	Presents practical application of TOC-SC concepts
Theoretical	Presents only theory or idealized problems
STUDY APPROACH	
Literature review	Study focus on systematic literature reviews
Optimization problem	Provides an optimization algorithm to maximize or minimize a specific variable
Simulation	Provides a simulation of problem utilizing TOC-SC concepts
Theory building/framework	Focus on providing a conceptual framework regarding TOC-SC
TOC DISTRIBUTION STEPS	
Aggregate stock at the highest level in the SC	Demonstrates evidence of the stock aggregation step of the TOC solution
Determine stock buffer sizes for chain locations	Demonstrates evidence of the determination of buffer sizes step of the TOC solution
Increase the frequency of replenishment	Demonstrates evidence of the increasing frequency replenishment step of the TOC solution
Manage the flow of inventories by buffer	Demonstrates evidence of the managing inventories by buffers step of the TOC solution
Use dynamic buffer management	Demonstrates evidence of the DBM step of the TOC solution
Set manufacturing priorities according to the PWH buffers	Demonstrates evidence of the manufacturing priorities step of the TOC solution
TOC PERFORMANCE MEASURES	
Measuring performance from an SCM perspective	Demonstrates evidence of supply chain management through the utilization of TOC performance measures

Source: The author (2020).

The work from Schragenhem (2010) was utilized as a base for the content analysis. The author provides a structured method for the TOC supply chain solution, composed of six steps. Therefore, all the other 32 documents were analyzed and categorized according to Schragenhem's proposition in order to identify the steps which are covered by the literature. In that sense, Frame 4 presents a summary of the TOC-Supply Chain / Distribution Solution proposed by Schragenhem (2010).

Frame 4 – TOC supply chain / distribution solution steps

Step	Description	Step Main Points
1	Aggregate Stock at the Highest Level in the Supply Chain: The Plant/Central Warehouse (PWH/CWH)	"(...) keep larger buffer stocks at the divergent point—where the stocks can be used to serve many different destinations—and use a pull replenishment mechanism triggered by sales at the end of the chain—the consumption point." "In order to have the product available at different locations, it is recommended to aggregate the inventory at the supplying source and, when necessary, build a PWH/CWH for that purpose." "We keep most of the stock (see Fig. 11-3) at the PWH/CWH by setting the buffer stock size high. According to the principles of statistics, this aggregation of inventory guarantees a more stable and responsive system than a system of keeping large inventories at the different consumption points (shops)." "When a given consumption point sells a unit, the consumed unit will be replenished as soon as possible from the PWH/CWH."
2	Determine Stock Buffer Sizes for All Chain Locations Based on Demand, Supply, and Replenishment Lead Time	"The stock buffer size is the maximum amount or quantity of inventory of an item held at a location in the supply chain to protect Throughput (T). The stock buffer size (limit) is dependent upon two different factors: 1. Demand rate — demand is the need for an item while the demand rate represents the amount demanded per time period (day, week, month, etc.). 2. Supply responsiveness — how quickly the consumed units can be replenished. The main factor here is the TOC replenishment (lead) time (RLT,)" "(...) the TOC RLT is comprised of three components: 1. Order lead time—the time it takes from the moment a unit is consumed until an order is issued to replenish it. 2. Production lead time—the time it takes the manufacturer/supplier from the moment he issues the order until he finishes producing it and puts it in inventory or ships it. 3. Transportation lead time—the time it takes to actually ship the finished product from the supplying point to the stocking location."
3	Increase the Frequency of Replenishment	"TOC takes a very different perspective, that of Throughput World thinking (a focus on making money now and in the future), in determining the direction and frequency of replenishment. It focuses on the additional T and return on inventory investment." "(...) by making the frequency of delivery higher, a better availability is created whereas the cost of shipments increases. By making the frequency lower, one will have to pay with either lower availability or with much higher inventory levels kept at the consumption points in order to cover for variations in demand."

Step	Description	Step Main Points
4	Manage the Flow of Inventories Using Buffers and Buffer Penetration	"The TOC logic is to define the required safety and constantly monitor how the safety is being used. This safety is called a buffer. In a distribution environment, the quantity of an SKU we would like to keep at the stock locations (including the PWH/CWH and RWHs) is defined as stock buffer size. The buffer size or limit for this SKU depends on the three questions of what, where, and when to ensure high availability to support T and low inventory investment with low associated OE." "Buffer penetration is defined as the number of missing units from the buffer divided by the stock buffer size expressed as a percentage. The number of units missing from the buffer is the stock buffer size minus what is on hand and already ordered." "The buffer penetration sets the color of the buffer according to the different zones: • Less than 33 percent buffer penetration: Green • Between 33 and 67 percent buffer penetration: Yellow • Between 67 and 100 percent buffer penetration: Red • 100 percent buffer penetration (being stocked out): Black"
5	Use Dynamic Buffer Management	"The TOC logic dynamically measures the actual usage of the stocks and readjusts the stock buffer sizes (maximum target for replenishment) accordingly. This method is referred to in TOC literature as Dynamic Buffer Management (DBM)." "The default recommendation for remaining in the green zone too long is to decrease the buffer size. The basic guideline is to decrease the buffer size by 33 percent (...)" "The guideline for relieving the TMR condition is to increase the buffer level by 33 per- cent. Both the definition of too long in a zone and the definitions of how much to decrease or increase the stock buffer level for each SKU are dependent on location, item, etc., and may differ across SKUs."
6	Set Manufacturing Priorities According to Urgency in the PWH Stock Buffers	"When manufacturers embrace the TOC replenishment/distribution solution, another source of demand has to be dealt with—consumption from the PWH back through the manufacturing process. For these PWH orders, the right priority for manufacturing should be set (not according to time) based on the priority of the SKU." "The best priority mechanism is to take the buffer penetration for the item at the PWH location (the VBP representing the physical stock at the PWH versus the buffer stock limit) as the priority for the replenishment manufacturing order, since the stock status at the PWH reflects the consumption from all downstream locations, and thus the total status of this item in the supply chain, eliminating the need for forecast."

Source: Adapted from Schragenheim (2010).

Before presenting the analysis of the studies, a few concepts identified in the content analysis will be defined. Many of the terms found have different descriptions, so this definition aims to generalize the main concepts that comprehend this study and, consequently, the Theory of Constraints replenishment/distribution solution. Frame 5 present those concepts and their definitions.

Frame 5 – TOC SC concepts definitions

Concept	Definition	Authors
TOC	An approach to continuous improvement of an enterprise, which asserts that constraints determine system performance. Global methodology that supports managers to focus on the most critical issues.	(BLACKSTONE, 2001; PONTE et al., 2016) (LENG; CHEN, 2012; WU et al., 2010)
Constraint	A focusing point around which a business can be organized or improved. Anything that inhibits a system from improving its performance according to the goal. Can be physical, non-physical and can be located internally or externally.	(BLACKSTONE, 2001) (BERNARDI DE SOUZA; PIRES, 2010) (SIMATUPANG; WRIGHT; SRIDHARAN, 2004)
DBR	A method for achieving effective SCM, used as a manufacturing planning and control mechanism. The drum is located at the bottleneck or constraint and is the system's pacemaker which sets the beat (production rate). The buffer protects the drum against demand variation in order to fully utilized the bottleneck. The rope acts as a release instrument that subordinates the system to the drum.	(PARSAEI; NAHAVANDI; ELMEKKAWY, 2012) (PONTE et al., 2016)
Buffer	Material queues, additional capacity and time allowances that are positioned at strategic locations to ensure that the constraint is fully utilized.	(WATSON; POLITO, 2003)
Performance measures	Indicators based on the idea that the purpose of a business is to make money now and in the future. Composed of financial (net profit, return-over-investment and cash-flow) and operational indicators (throughput, investment and operating expenses), as well as the TDD and IDD.	(GUPTA; ANDERSEN, 2018; PUCHE et al., 2016)

Concept	Definition	Authors
The Goal	To make money now and in the future.	(SIMATUPANG; WRIGHT; SRIDHARAN, 2004)
Distribution / replenishment system	A pull distribution method derived from the first three steps of the five focusing steps, that aims to ensure availability of the items at every sales point A solution based on decoupling points to reduce bullwhip effect and maintain inventory availability to consumers. A pull system where buyers and suppliers can apply collaboration through continuous replenishment of the inventory buffers. A production-distribution strategy composed of demand-pull and buffer management strategies.	(BERNARDI DE SOUZA; PIRES, 2010) (WU et al., 2010) (TSOU, 2013) (CHANG; CHANG; SUN, 2015; GUPTA; ANDERSEN, 2018)
SCM	A method that aims to create value to the whole SC network, instead of only to individual enterprises. A method that utilizes information technology to integrate suppliers, manufacturers, distributors, and retailers, seeking cooperation to obtain improved results for the supply chain as a whole. A method aimed to deliver the right product to the right place at the right time, in a cost effective way.	(AGAMI; SALEH; RASMY, 2012) (CHANG; CHANG; LEI, 2014) (FILHO et al., 2016)
Bullwhip effect	Demand amplification caused by downstream supply chain partners' demand variation. Effect caused by the combination of an upstream serial transmission of demand information between nodes of SC and a downstream delay in transit time.	(KAIJUN; WANG YUXIA, 2010; WU et al., 2010) (WALKER, 2002)

Source: The author (2020).

Having defined the main terms that concern this study, it is necessary to stratify the literature documents in accordance to their types – theoretical or empirical – and the approaches used by those studies – literature review, simulation, optimization problem, and theory building/framework – as proposed in Frame 3. Table 4 presents each of the 33 documents included in the content analysis. Theoretical studies comprise theory-based studies such as reviews and idealized problems, whilst empirical relate to studies based on real-world data and/or applications. For their types, it was possible to identify four general categories within the documents; literature reviews are studies that provide a comprehensive analysis of the literature at the time of publication; optimization problems proposed new algorithms to find better optimal solutions for defined problems, using techniques such as particle-swarm-optimization (PSO) and genetic algorithms; simulation includes general simulation problems with approaches such as discrete-event-simulation (DES), system dynamics (SD), agent-based-simulation (ABS), etc.; theory building/frameworks basically aim to propose new theoretical insights and frameworks to contribute to the body of literature.

Table 4 – Document types and approaches

Document	Type			Approach		
	Theoretical	*Empirical*	*Literature review*	*Optimization*	*Simulation*	*Theory building*
(PÉREZ, 1997)	X	-	X	-	-	-
(BLACKSTONE, 2001)	X	-	X	-	-	-
(KAIHARA, 2001)	X	-	-	-	X	-
(WALKER, 2002)	-	X	-	-	X	-
(WATSON; POLITO, 2003)	-	X	-	-	X	-
(YUAN; CHANG; LI, 2003)	X	-	-	-	X	-
(SIMATUPANG; WRIGHT; SRIDHARAN, 2004)	X	-	-	-	-	X
(BASHIRI; TABRIZI, 2010)	X	-	-	X	-	-
(BERNARDI DE SOUZA; PIRES, 2010)	X	-	X	-	-	-
(KAIJUN; WANG YUXIA, 2010)	X	-	-	-	X	-
(SCHRAGENHEIM, 2010)	X	-	-	-	-	X
(WU et al., 2010)	X	-	-	-	X	-
(AGAMI; SALEH; RASMY, 2012)	X	-	-	-	-	X
(GUPTA; ANDERSEN, 2012)	X	-	-	-	X	-
(LENG; CHEN, 2012)	-	X	-	X	-	-
(PARSAEI; NAHAVANDI; ELMEKKAWY, 2012)	X	-	-	-	X	-
(WU et al., 2012)	X	-	-	-	X	-
(JI; LI; CHEN, 2013)	X	-	-	-	X	-
(JIANG et al., 2013)	X	-	-	-	X	-
(JIANG; WU, 2013a)	X	-	-	X	-	-
(JIANG; WU, 2013b)	X	-	-	X	-	-
(SUN et al., 2013)	X	-	-	-	X	-
(TSOU, 2013)	X	-	-	-	X	-
(CHANG; CHANG; HUANG, 2014)	-	X	-	-	X	-
(CHANG; CHANG; LEI, 2014)	-	X	-	-	X	-
(WU; LEE; TSAI, 2014)	-	X	-	-	X	-
(CHANG; CHANG; SUN, 2015)	-	X	-	-	X	-
(COSTAS et al., 2015)	X	-	-	-	X	-
(FILHO et al., 2016)	-	X	-	-	X	-
(PONTE et al., 2016)	X	-	-	-	X	-
(PUCHE et al., 2016)	X	-	-	-	-	X
(MARGARETHA; BUDIASTUTI; SAHRONI, 2017)	-	X	-	-	X	-
(GUPTA; ANDERSEN, 2018)	X	-	-	-	X	-
Total	**24**	**9**	**3**	**4**	**22**	**4**

Source: The author (2020).

As it can be noted in Table 4 most of the literature is composed of theoretical studies and the most common approach is simulation. From the analyzed studies simulation is utilized in 66,7% of them, however most of them are based on theoretical or idealized problems, resulting in only 8 simulation studies with real-world applications. Walker (2002) is the first to present a study of such kind, utilizing TOC's Drum-Buffer-Rope for supply chain synchronization, with a study case of an electronic instrumentation factory in the USA. Watson and Polito (2003) use simulation to test if a TOC-based heuristic would improve the financial results of a company, utilizing data from a major US company. After those two, only 11 years later an empirical-simulation study is found in Chang, Chang and Huang (2014) where a TOC model is created and integrated with market demand forecast to improve the simple demand-pull Theory of Constraints' replenishment policy in a wafer foundry in Taiwan. Chang, Chang and Lei (2014) also conduct a study in a Taiwanese wafer foundry, simulating different buffer management policies for inventory replenishment. Wu, Lee and Tsai (2014) carry out a case study in a machinery factory, simulating scenarios to defined replenishment frequencies for different products with large variation of sales volume. Chang, Chang and Sun (2015) use again the wafer manufacturing case to simulate the TOC's demand-pull replenishment system and try to improve it by combining it with market demand forecast. Filho et al. (2016) simulate the application of TOC's concepts for management of logistics distribution in an automotive components factory. Finally, the study from Margaretha, Budiastuti and Sahroni (2017) applies TOC through simulation in a fast moving consumer goods company located in Indonesia. Table 5 demonstrates the studies' types and approaches distributions.

Table 5 – Studies' type and approach distribution

Approach	**Absolute**		**Relative**		**Total**
	Theoretical	*Empirical*	*Theoretical*	*Empirical*	
Simulation	14	8	42,4%	24,5%	66,7%
Theory building/framework	4	-	12,1%	-	12,1%
Optimization	3	1	9,1%	3,0%	12,1%
Literature review	3	-	9,1%	NA	9,1%
Total	24	9	72,7%	27,3%	100%

Source: The author (2020).

Empirical-simulation studies comprise a good part of the reviewed literature. Most of the studies address or focus on isolated parts of the whole solution in an unstructured way and do not clearly define the TOC's solution steps. In that sense, this work identifies which six steps of the solution – as proposed by Schragenheim (2010)

– can be found in each of the documents. Additionally, the analysis also includes the utilization of TOC's performance measures in supply-chain management as suggested by Bernardi de Souza and Pires (2010). During the content analysis, the documents were coded with the relevant steps only if they demonstrated clear relevance to the document context and objectives, so only mentioning a part of the step is not accounted in text coding. Table 6 exhibits the analysis, with Schragenheim's (2010) proposed steps numbered from 1 to 6 (see Frame 4 for their definitions) and PM column to represent TOC's performance measures.

Table 6 – Content analysis of TOC-SC solution steps

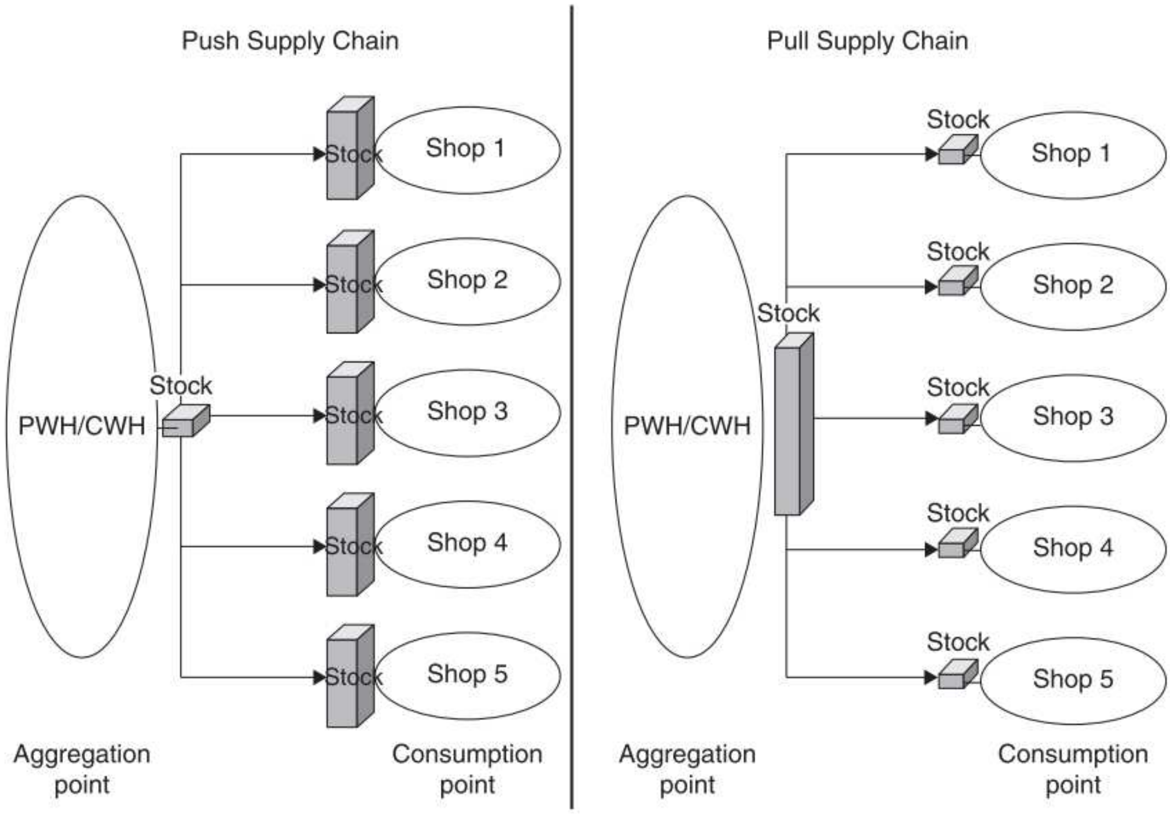
Document	**Steps**						
	1	*2*	*3*	*4*	*5*	*6*	*PM*
(PÉREZ, 1997)	-	-	-	-	-	-	-
(BLACKSTONE, 2001)	-	-	-	-	-	-	-
(KAIHARA, 2001)	-	-	-	-	-	-	-
(WALKER, 2002)	-	X	-	-	-	-	-
(WATSON; POLITO, 2003)	-	-	X	X	X	-	X
(YUAN; CHANG; LI, 2003)	X	X	-	X	X	-	-
(SIMATUPANG; WRIGHT; SRIDHARAN, 2004)	X	X	-	X	X	-	X
(BASHIRI; TABRIZI, 2010)	-	-	-	-	-	-	X
(BERNARDI DE SOUZA; PIRES, 2010)	X	X	X	X	X	X	X
(KAIJUN; WANG YUXIA, 2010)	X	X	-	X	X	-	-
(SCHRAGENHEIM, 2010)	**X**	**X**	**X**	**X**	**X**	**X**	**-**
(WU et al., 2010)	-	X	X	X	-	-	-
(AGAMI; SALEH; RASMY, 2012)	-	-	-	-	-	-	-
(GUPTA; ANDERSEN, 2012)	-	-	-	-	-	-	X
(LENG; CHEN, 2012)	-	-	-	-	-	-	-
(PARSAEI; NAHAVANDI; ELMEKKAWY, 2012)	-	X	-	-	-	-	-
(WU et al., 2012)	-	X	X	X	-	-	-
(JI; LI; CHEN, 2013)	X	-	-	-	-	-	-
(JIANG et al., 2013)	-	-	X	-	-	-	-
(JIANG; WU, 2013a)	-	-	-	-	X	-	-
(JIANG; WU, 2013b)	-	-	-	-	X	-	-
(SUN et al., 2013)	-	-	-	X	X	-	-
(TSOU, 2013)	-	-	-	X	X	-	-
(CHANG; CHANG; HUANG, 2014)	X	X	X	X	X	-	X
(CHANG; CHANG; LEI, 2014)	-	-	-	X	X	-	-
(WU; LEE; TSAI, 2014)	-	X	X	-	-	-	-
(CHANG; CHANG; SUN, 2015)	-	X	-	X	X	-	-
(COSTAS et al., 2015)	X	X	-	X	-	X	X
(FILHO et al., 2016)	-	-	-	X	-	-	-
(PONTE et al., 2016)	-	-	-	X	-	X	X
(PUCHE et al., 2016)	-	X	-	X	-	X	X
(MARGARETHA; BUDIASTUTI; SAHRONI, 2017)	X	X	-	X	-	-	-
(GUPTA; ANDERSEN, 2018)	-	-	-	-	-	-	X
Total	**9**	**15**	**8**	**18**	**13**	**5**	**10**

Source: The author (2020).

From the table it is possible to identify that steps 4, 2, and 5 are respectively the most commonly found within the selected documents. All those three steps relate to buffer management – buffer penetration, determination of buffer sizes, and DBM respectively –, meaning that buffer management is the most common approach of within the TOC-SCRS literature. Contrarily, steps 6, 3, and 1 – respectively, prioritization according to urgency in the PWH buffers, increase replenishment frequency, and stock aggregation at the highest level of the SC – are the least to be found within the literature. The performance measures topic is positioned in the middle of those two groups appearing in 10 different documents. It is possible to note that a few documents were not coded with any of the steps, meaning that the documents did not explicitly cover the analyzed steps. This does not mean that the document is not relevant to the topic tough, those documents were kept in the analysis as they may, nevertheless, provide relevant overall insights to the TOC-SCRS theme. Another important point is to mention that the work from Bernardi de Souza and Pires (2010) covers all the steps proposed by Schragenheim (2010) as well as the performance measures. However, Bernardi de Souza and Pires (2010) structured the TOC solution into five different steps – being performance measures one of those five – while Schragenheim (2010) uses six steps, not considering PM. In that sense, is believed that Schragenheim (2010) provides better segregation in his proposal and a more procedural view of the solution, proving more details about it, which facilitates the analysis and literature comparisons and therefore justifying the choice of his work rather than Bernardi de Souza and Pires's (2010).

The TOC supply chain replenishment system states that the forecast accuracy is dependent on the level of the distribution system – e.g. retailer, regional warehouse, central warehouse, or plant (KAIJUN; WANG YUXIA, 2010; YUAN; CHANG; LI, 2003). Therefore, the TOC-SCRS suggests stock aggregation at the source and the utilization of a plant warehouse (PWH) or a central warehouse (CWH) to have products available at different locations (BERNARDI DE SOUZA; PIRES, 2010). When the organization is a manufacturer, this point is referred to as the PWH and when the organization is a distributor then it is called CWH. Additionally, if transportation time from the PWH/CWH to the consumption point is considerably long, a regional warehouse (RWH) might be necessary between them in order to reduce lead times (SCHRAGENHEIM, 2010). In the TOC solution, the buffer stock size at the consumption point is kept to a minimum, consequently, the buffer stock at the PWH/CHW needs to be set to higher levels to assure that when a shop sells a unit, this unit is replaced as soon as possible by the PWH/CHW in a pull system supply chain (SCHRAGENHEIM, 2010). Statistically, this aggregation ensures more reliability in product replenishment than keeping stock at different consumption points (YUAN; CHANG; LI, 2003). Figure 12 demonstrates the change proposed by the TOC-SCRS.

Figure 12 – Aggregation at the PWH/CHW

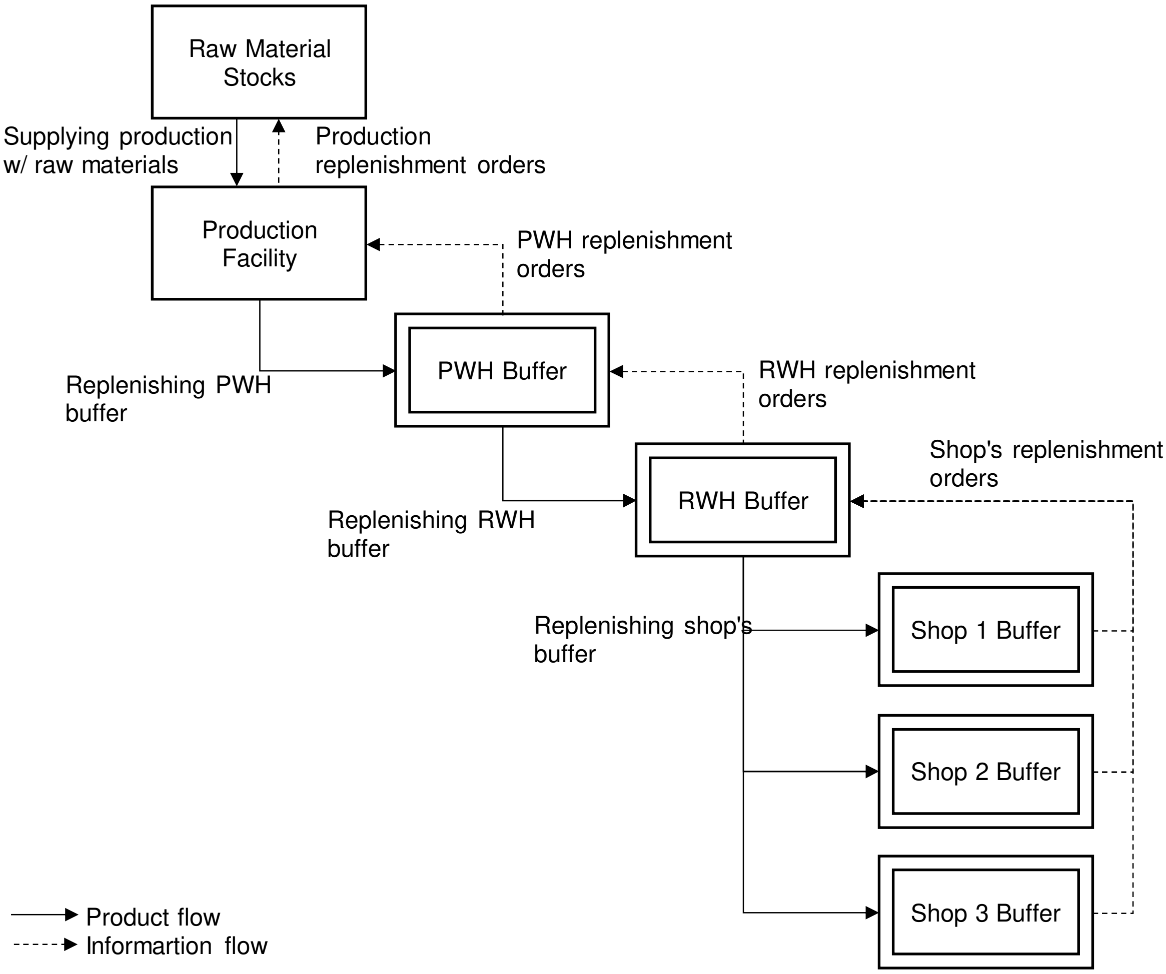


Source: Schragenheim (2010).

According to Simatupang; Wright, and Sridharan (2004), there are three focal points that keep buffer stock in the supply chain: the retailer or shops, the warehouse – in this case the RWH – , and the plant. The shops should have just stock to cover demand of costumers and replenishment time from the warehouse; the warehouse has stocks to satisfy the expected demand of the stores, considering the time it takes to reliably replenish the warehouse buffer with what was actually delivered to the shops – first aggregation level; Similarly, the plant holds enough stock to replenish what the warehouse has delivered – second point of aggregation (MARGARETHA;

BUDIASTUTI; SAHRONI, 2017; SIMATUPANG; WRIGHT; SRIDHARAN, 2004). Figure 13 depicts the schematic for replenishment within the supply chain according to the TOC proposal.

Figure 13 – Replenishment schematic within the TOC supply chain



Source: Adapted from Simatupang; Wright; and Sridharan (2004).

In that sense, the supply chain changes its operation to a pull system. The downstream node of the supply chain places an order to the upstream level based on what has been sold (CHANG; CHANG; HUANG, 2014), while each node, except the shops, manages its own buffer to ensure availability of the goods (COSTAS et al., 2015). This form of operation aims to satisfy the needs of the retailers' buffer stock, ensuring the throughput of all the supply chain (JI; LI; CHEN, 2013).

Following the inventory aggregation, the next step refers to the determination of the stock buffer sizes. Many mathematical methods have been created to determine the buffer sizes in the supply chain locations (KAIJUN; WANG YUXIA, 2010; YUAN; CHANG; LI, 2003), however, in TOC setting the exact buffer size is not an relevant issue as long as the buffer is monitored in a timely manner (YUAN; CHANG; LI, 2003). Basically, the buffer size is the maximum quantity of stock of an item, kept at each point of the supply chain to protect the throughput or, in other words, ensure that every potential customer will have its demand met (BERNARDI DE SOUZA; PIRES, 2010; CHANG; CHANG; HUANG, 2014; SCHRAGENHEIM, 2010).

According to Schragenheim (2010), the maximum stock buffer size is dependent on demand rate and supply responsiveness. The demand rate is the demand of an item per period (day, week, month, etc.). Supply responsiveness refers to how quickly consumed units can be replenished, represent by the replenishment lead time (RLT). Parsaei; Nahavandi; and Elmekkawy (2012), Simatupang; Wright; and Sridharan (2004), and Yuan; Chang; and Li (2003), add a safety factor to be considered to provide additional protection for unexpected demand and allowing buffer replenishment in time, without losing throughput. Additionally, Bernardi de Souza and Pires (2010) mention a few other variables may be considered in the buffer size determination, such as: average demand within replenishment time, fluctuations of demand, fluctuations of replenishment time, customer tolerance time, among others.

The replenishment lead time (RLT) has a major role in the buffer size determination. The TOC RLT has three components: order lead time (OLT), production lead time (PLT) and transportation lead time (TLT) (BERNARDI DE SOUZA; PIRES, 2010; SCHRAGENHEIM, 2010). The OLT refers to the time it takes to issue an order of an item from the moment of its consumption; the PLT is the time between the order issuing until its production has been finished; and the TLT is the time from actually shipping the item from the supplying point to the stocking location. The TOC solution aims to reduce the RLT to a minimum in order to generate desired effects such as reduction of stock required to cover demand during lead time at consumption points, less fluctuations in supply time, more accurate forecasts due to the reduced time interval needed, and increase overall responsiveness of the supply chain (BERNARDI DE SOUZA; PIRES, 2010; SCHRAGENHEIM, 2010). Although important, the RLT has not been much discussed within the literature. Many studies aim to create mathematical methods for buffer size determination and only consider RLT as part of the model, even though, as previously stated, this is not a critical point to the TOC solution. Such studies are those of Chang, Chang, and Sun (2015), Walker (2002), Wu et al. (2010), Wu, Huang, and Jen (2012), and Wu, Lee, and Tsai (2014).

TOC-SCRS states that items should be replenished based on actual consumption rather than forecasting. In order to do so, it is necessary to use replenishment policies based on either daily or the smallest economically feasible order period (WATSON; POLITO, 2003). The PWH is an important factor to accomplish this, as it allows the factory to cover replenishment orders directly from its stock without having to produce this specific item even when that item is available in other client's inventory (BERNARDI DE SOUZA; PIRES, 2010).

Increasing the replenishment frequency may be a challenge as suppliers are accustomed to supply large lot sizes and to pursue high usage of production capacity (CHANG; CHANG; HUANG, 2014). According to Schragenheim (2010), differently than the traditional perspective based on economies of scale, the TOC proposal focuses on the additional throughput (T) and the return over investment (ROI). The author claims that there is a tradeoff between the additional costs of increasing the frequency of shipments and the cost of having lower availability. Also, in many cases the frequent transportation will not cost more than the large-sized shipments as instead of having large quantities of few products one can have small quantities of many products. In most cases, the additional revenue obtained will compensate the incurred extra cost.

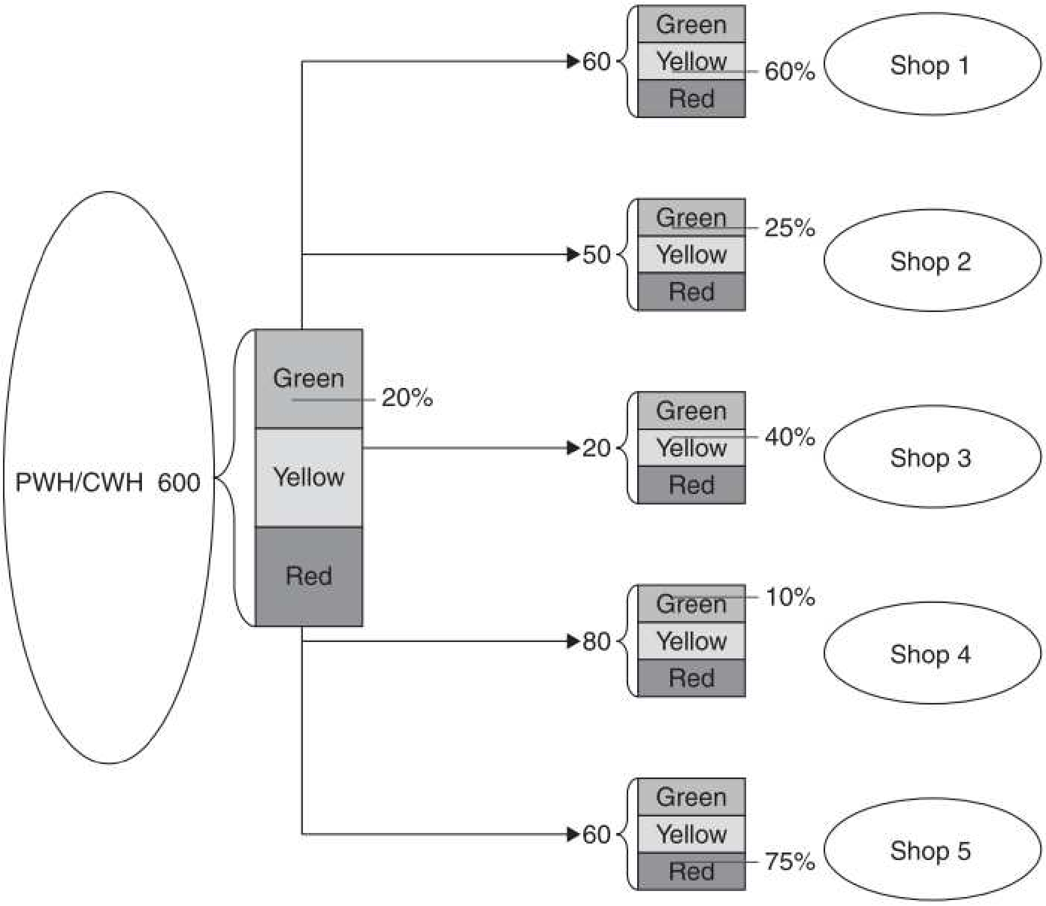
The benefits from increasing the replenishment frequency can be seen in the studies of Jiang et al. (2013) and Wu, Lee, and Tsai (2014). They propose to increase the replenishment frequency of high demand products and simulate the results. Jiang et al. (2013) utilizes an optimization algorithm to shorten the replenishment frequency based on each product demand, while Wu, Lee, and Tsai (2014) simulate an empirical case applying similar rules. Both report reduction of inventories and economic benefits while meeting demand requirements and considering capacity constraints, demonstrating the benefits of increasing the replenishment frequency. Concluded the discussion on the replenishment frequency, next TOC SC step refers to the inventory management and buffer penetration.

Buffer size reflects the pattern of the stock consumption level, therefore, buffer monitoring needs be constant at all time in order to make the decisions about the timing of production and replenishment (TSOU, 2013). In that sense, monitoring the buffer constantly should ensure that the flow of inventory within the supply chain is moved accordingly so that each SKU is replenished on time at the consumption points (PONTE et al., 2016; PUCHE et al., 2016). Thus, the buffer monitoring is a constant state of progression of the contents of the buffer (WATSON; POLITO, 2003).

Buffer monitoring is realized through the buffer penetration, which is the percentage relation between the missing units from the buffer and the stock buffer size (SCHRAGENHEIM, 2010). Usually, the buffers are divided into three distinct zones containing one third of the stock buffer size and colored differently as green, yellow and red (CHANG; CHANG; SUN, 2015; CHANG; CHANG; LEI, 2014; SIMATUPANG; WRIGHT; SRIDHARAN, 2004; YUAN; CHANG; LI, 2003). The colors are set according to the buffer penetration level: green is for less than 33%, yellow is when it is between 33 and 67%, and red when it is greater than 67% (SCHRAGENHEIM, 2010; YUAN; CHANG; LI, 2003). This color schematic serves as an indication of replenishment urgency (BERNARDI DE SOUZA; PIRES, 2010) and its model within the supply chain is depicted in Figure 14:

a) Green: means that the on-hand inventory is almost up its theoretical maximum;
b) Yellow: represents the intermediate level, where the normal on-hand inventory should remain
c) Red: indicates that there is a risk of not meeting the entire demand.

Figure 14 – Buffer penetration schematic for the supply chain



Source: Schragenheim (2010).

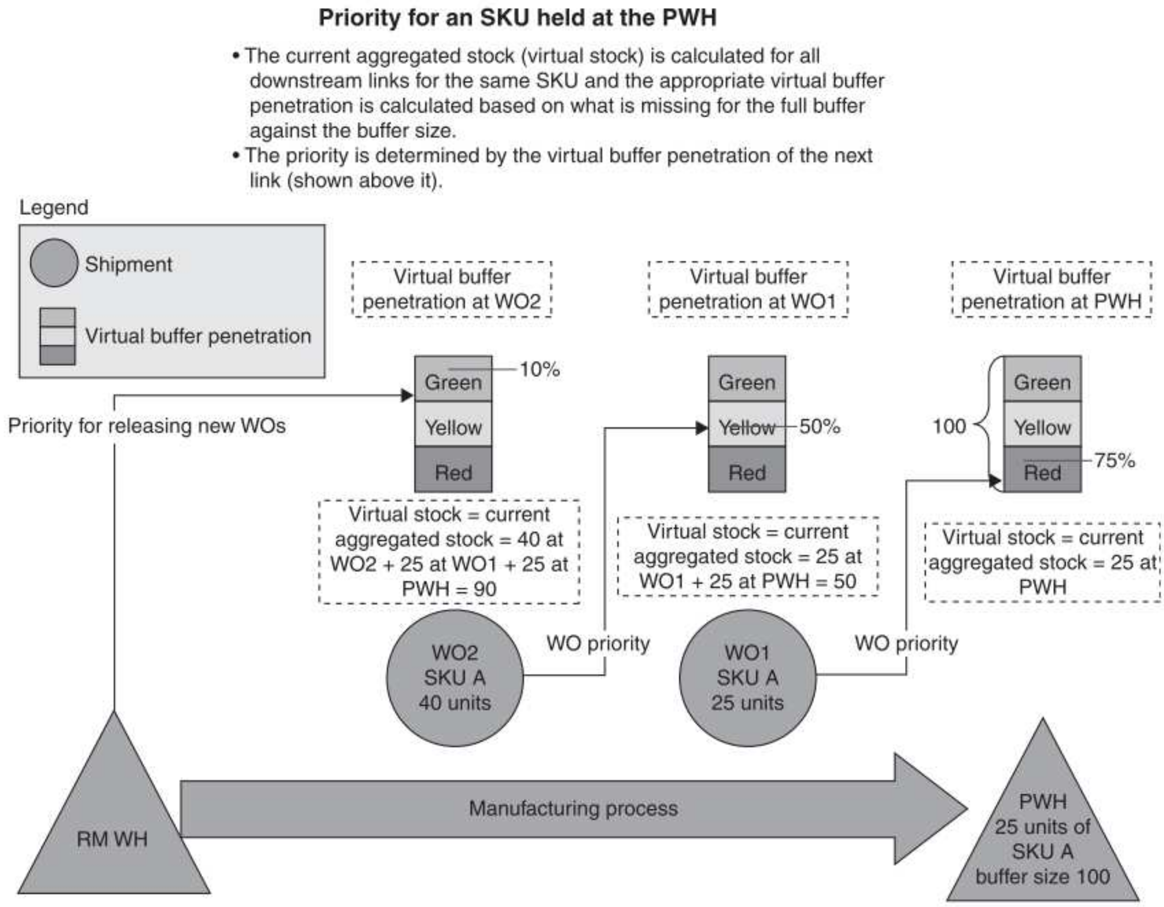
The different levels of buffer penetration also represent different actions to be taken. For instance, when the buffer is in the yellow zone it is necessary to have replenishment planned to send the buffer back to the green zone; if the penetration is in the red zone, then replenishment should be prioritized and speeded up to reach the green zone once again (SIMATUPANG; WRIGHT; SRIDHARAN, 2004).

The buffer penetration indicators also allow to implement the dynamic buffer management. The dynamic buffer management is a simple and straightforward technique which consists of monitoring the buffer through buffer penetration and adjusting the buffer size based on its behavior (TSOU, 2013).The TOC claims that buffer size must be altered based on the changes of the environment (WATSON; POLITO, 2003) and considers that the ideal levels should be reached throughout the time after this adjustments (YUAN; CHANG; LI, 2003). Basically, the dynamic buffer management rule states that over time the buffer should remain in the yellow zone and it must be altered if it is remaining in the red or green zones for long periods of time (BERNARDI DE SOUZA; PIRES, 2010). If the buffer indicates stays too long in the green zone it means that the buffer stock size is too high and can be reduced (SUN et al., 2013); if the buffer is often in the red zone it means that the buffer is too low and the risk of stock outs are likely to occur, meaning that the buffer size must be increased (CHANG; CHANG; HUANG, 2014; CHANG; CHANG; LEI, 2014). Those states can be nominated as Too Much Green (TMG) and Too Much Red (TMR), respectively (SCHRAGENHEIM, 2010).

As a basic rule, when a buffer is on TMG then the buffer size should be decreased in 33%, while if the buffer is on TMR it should be increased at the same rate (BERNARDI DE SOUZA; PIRES, 2010; SCHRAGENHEIM, 2010). Schragenheim (2010) also suggests a cooling period after any changes are made to buffer sizes so the system can readapt to the new buffer size. Under TMR conditions, this period can be a full replenishment time, while in TMG this time should be enough to let the inventory cross-over to the green level from above.

The last step refers to the manufacturing prioritization according to the PWH buffers. The top priority of the system using the TOC-SCRS solution is the SKUs that are within the red zone of the buffer penetration level (BERNARDI DE SOUZA; PIRES, 2010). However, another source of demand must be considered within the TOC solution – the consumption from the PWH back through the manufacturing process. The product order prioritization is set by the factory utilizing integrated information from all the downstream nodes of the supply chain (COSTAS et al., 2015; PONTE et al., 2016; PUCHE et al., 2016). According to Schragenheim (2010), the manufacturing priority should be set not according to time but rather based on the priority of the SKU. Therefore, the author suggests the utilization of the virtual buffer penetration (VBP) at the PWH location as the priority for the replenishment manufacturing order. The VBP is represented by the physical stock at the PHW divided by the buffer stock limit, reflecting the consumption from all downstream locations and, consequently, the general status of the SKU in the supply chain.

Figure 15 – Virtual buffer penetration example



Source: Schragenheim (2010).

In the example, the VBP at the PWH is 75% as there is 25 units in stock and the buffer limit is 100 units, consequently, the buffer penetration is in the red zone. In the factory, work order 1 (WO1) is for 25 units, increasing the VBP to 50% and 50 units in the aggregated stock, leaving the buffer in the yellow zone. WO2 consists of 40 units, which brings the aggregated stock to 90 units, 10% of VBP and almost to the limit of the green zone. The VBP provides a holistic system measure that aligns and synchronizes the manufacturing plant with the whole chain. The next section concludes the review of the TOC distribution solution, discussing the performance measures.

Beyond the TOC-SCRS, the TOC performance metrics are also of interest. According to the TOC perspective, collaborative performance metrics are required to guarantee that each supply chain component is doing what is supposed to do to create more throughput (SIMATUPANG; WRIGHT; SRIDHARAN, 2004). The basic TOC performance measures assume that the goal of the organization is to make money now and in the future (COSTAS et al., 2015). Those are divided in global measures and operational measures, and are detailed and explained in section 2.1 (refer to Frame 2 and Figure 7 for a structured comprehension).

Simatupang; Wright; and Sridharan (2004) state that each member of the SC should measure their performance related to the impact on the throughput, the inventory and the operating expenses of the whole SC, acting locally to ensure their maximization. However, it is necessary to monitor if all the members of the chain are aligned. To do so, throughput-dollar-days (TDD) and inventory-dollar-days (IDD) are other two indicators that allow individual supply chain nodes to function as a collaborative synergistic system (GUPTA; ANDERSEN, 2018). The TDD is calculated as *throughput value in dollars x number of delayed days*, the TDD is used to measure the replenishment policy effectiveness to respond to demand; the IDD formula is *value of inventory in dollars x number of days in stock* and represents the efficiency of a node of the supply chain within the time period (CHANG; CHANG; HUANG, 2014; GUPTA; ANDERSEN, 2018). According to Gupta and Andersen (2012), The TDD guarantees that deliveries are due on time and the IDD continuously promotes actions to inventory reduction. As the aim of the supply chain is to maximize the throughput, the TDD is the main priority and its target is zero. The IDD then functions as a secondary measure and its target should be minimized without compromising the TDD (BERNARDI DE SOUZA; PIRES, 2010).

The performance measure discussion concludes the theoretical background section. An overall view of the theory has been provided, followed by a focused view of the TOC within the supply chain context which explored the studies found in the systematic literature review and defined the concepts within the TOC-SCRS. The next section, then, aims to elucidate the steps regarding the methodology of the present study.

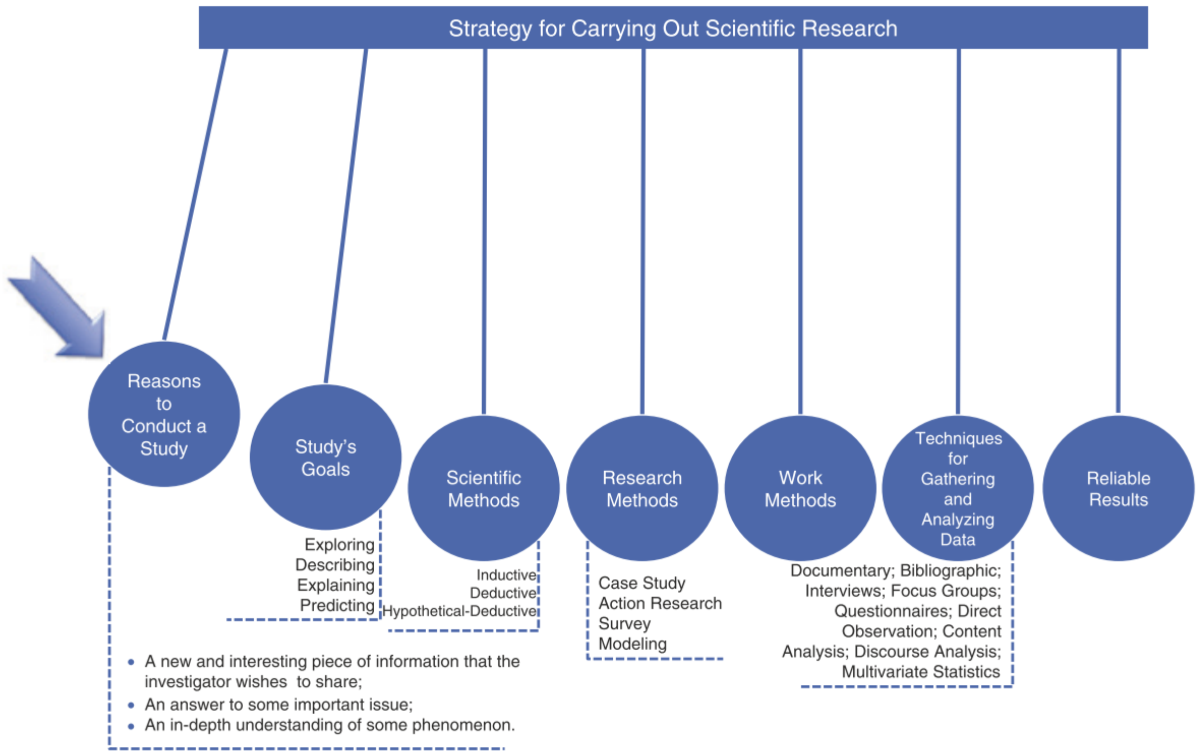
3 METHODOLOGICAL PROCEDURES

There are two factors that are essential in conducting successful research: rigor and relevance (DRESCH; LACERDA; ANTUNES JR., 2015). In that sense, the introduction section aimed to present the theme and the current scenario of the research clarifying its relevance. Consecutively, the Methodology section aims to delineate the research's rigor defining both research and work methodologies. Therefore, this section is unfolded in the Research Methodology and Work Methodology sub-sections.

3.1 RESEARCH METHODOLOGY

In order to ensure the reliability of the results of a research work, especially scientific research, the researcher must follow a defined procedure or sequence of steps (DRESCH; LACERDA; ANTUNES JR., 2015). Therefore, to illustrate those steps and its interdependencies Dresch, Lacerda and Antunes Jr. (2015) represent scientific research steps through the Newtown's Pendulum, as can be seen in Figure 16

Figure 16 – Pendulum for carrying out scientific research



Source: Dresch, Lacerda and Antunes Jr. (2015).

Having defined the reasons behind this study and its objectives, as presented in the Introduction Section, it is necessary to define its scientific methods. According to Saunders; Lewis and Thornhill (2012), there are three main research approaches: deductive, inductive and abductive. The laws and theories that form scientific knowledge are derived by induction based on experiments and observation (CHALMERS, 2013). Once this general knowledge is available it can be utilized to create predictions and explanation to certain phenomena, which constitutes the deductive process (CHALMERS, 2013). Lastly, the abduction process makes usage of data to explore a phenomenon and create a new or alter an existing theory, being tested subsequently based on new data collection (SAUNDERS; LEWIS; THORNHILL, 2012a). Therefore, this work utilizes mainly the deductive and abductive methods. The deductive process appears in the construction of the conceptual model and in the application of the TOC premises in the studied case. Meanwhile, the abductive process is shown from the exploration of the different proposed scenarios by the case and by the theory to be tested.

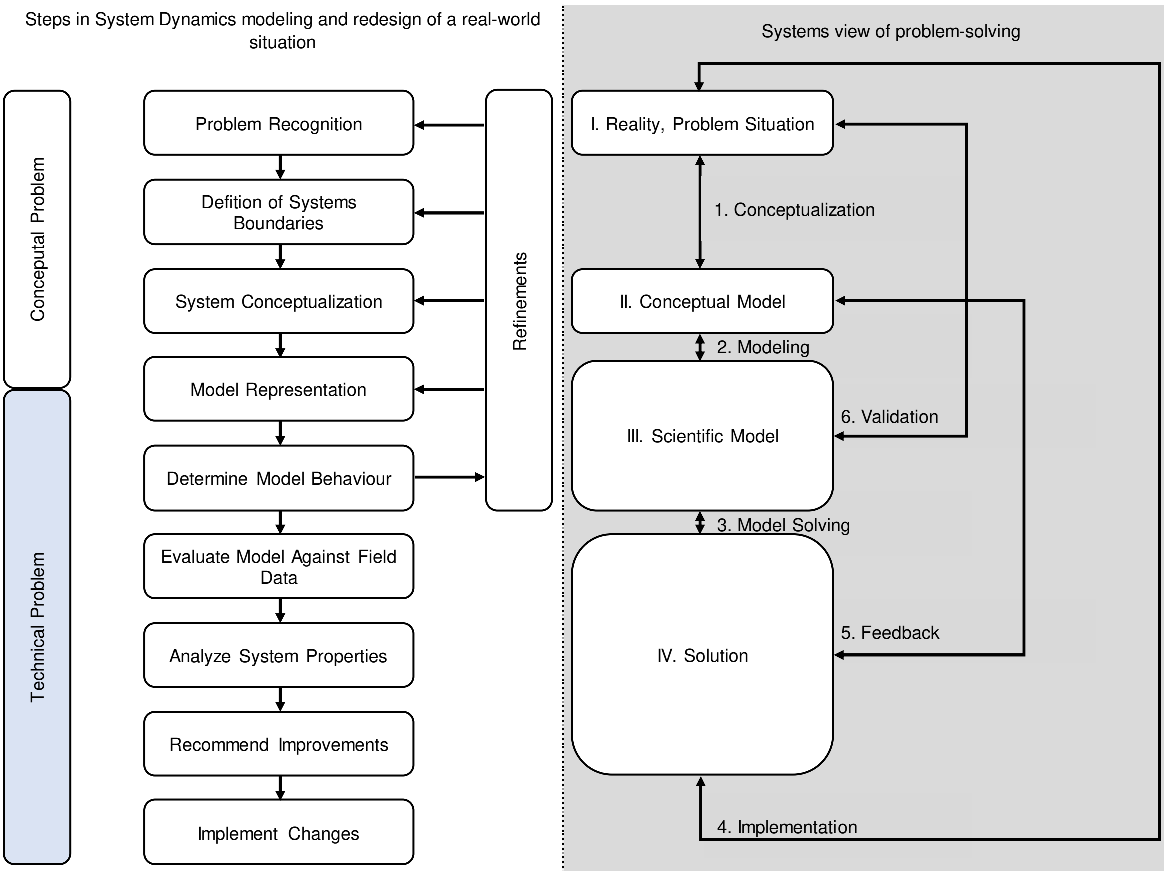
Following the steps to carry out scientific research, after the scientific method delineation the next step comprises the research methods. According to Dresch, Lacerda and Antunes Jr. (2015), it is important to define and justify the research method to ensure that the investigation provides a reasonable answer to the defined problem. The proper utilization of a research method supports the recognition of the study by the scientific community, providing evidence that the work is reliable and valid for the body of knowledge (DRESCH; LACERDA; ANTUNES, 2015). Given the aim of this work and the complex scenario of the studied case, modeling presents itself as a sound research method as it allows for better comprehension of complex problems (PIDD, 2003). Additionally, through computational simulation it is possible to address, in an exploratory way, complex problem situations where frequent transformation occurs (PIDD, 2003). Pidd (2003), also points out that computational simulation allows to find reasonable answers quickly and relative low costs when compared to real world experimentation. Systems dynamics is then proposed as a simulation tool for the representation of complex systems, which allows to find better ways to operate this defined system and comprehend the consequences of the changes (PIDD, 2003).

The quantitative modeling serves as a base for Operational Research (BERTRAND; FRANSOO, 2002). According to Bertrand and Fransoo (2002), within the OR universe, quantitative modeling research can be classified as empirical or axiomatic and as descriptive or normative. The axiomatic research aims to find solutions that provide insights about the problem structure, while the empirical research intends to find adequacy among between the observations and actions applied in the real world and the ones applied in the model. Additionally, the normative research has its interests in developing policies, strategies and actions that improve the results found in the literature, while the descriptive research analyzes a model that leads to the comprehension and explanation of the characteristics of the model itself (BERTRAND; FRANSOO, 2002). In that sense, this research can be classified as empirical-normative. Having delineated the research method, next section presents and explains the work methodology.

3.2 WORK METHODOLOGY

The work method, presented in a logical and structured format, is important to ensure the replicability of the study (MENTZER; FLINT, 1997). The work method should be constituted by a sequence of logical steps to reach the research's goals, ensuring clarity and transparency throughout the process (DRESCH; LACERDA; ANTUNES JR., 2015). The proposed work method for this work is based on the studies of Mitroff et al. (1974) and Towill (1993a). Both methods are similar and are presented comparatively in Figure 17.

Figure 17 – Work methodology comparison



Source: Mitroff et al. (1974) and Towill (1993a).

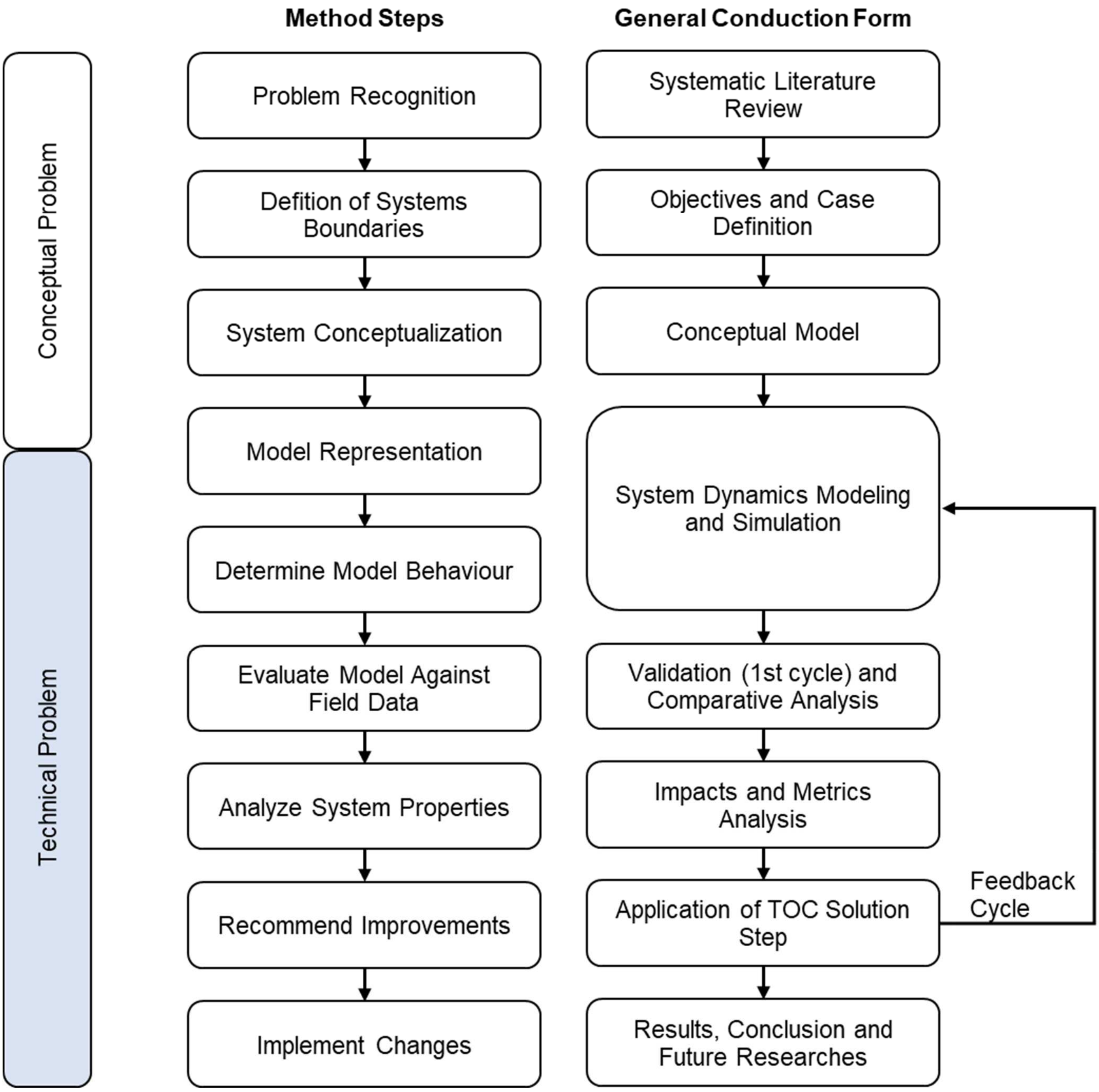
Towill (1993a) proposes the utilization of a step-by-step method to apply System Dynamics in the redesign of real-world situations. The separation of the method in a conceptual part and technical one is suggested, although the parts overlap during the model representation. In the conceptual phase the researcher aims to establish his own perceptions about the problem, during this phase he is not yet willing to use resources in the systems redesign. However, at the moment when the results start to be generated and it becomes possible to conduct data analysis, the problem is defined as technical (TOWILL, 1993c).

Mitroff et al. (1974) present a similar method described as a systems view for problem-solving. The conceptualization begins from a real problem to create a scientific model, this model generates solutions that must be implemented in the real-world in order to solve the defined problem. Additionally, the generated solution may create feedbacks for the conceptual model which generates a new scientific model and, consequently, new solutions, forming a virtuous cycle (MITROFF et al., 1974).

For this research though, the feedback cycle returns to the simulation model, in order to generate new results for the simulated scenario.

The work methodology steps are then presented step-by-step in Figure 18, along with the conduction form for each one of the suggested steps.

Figure 18 – Work Method



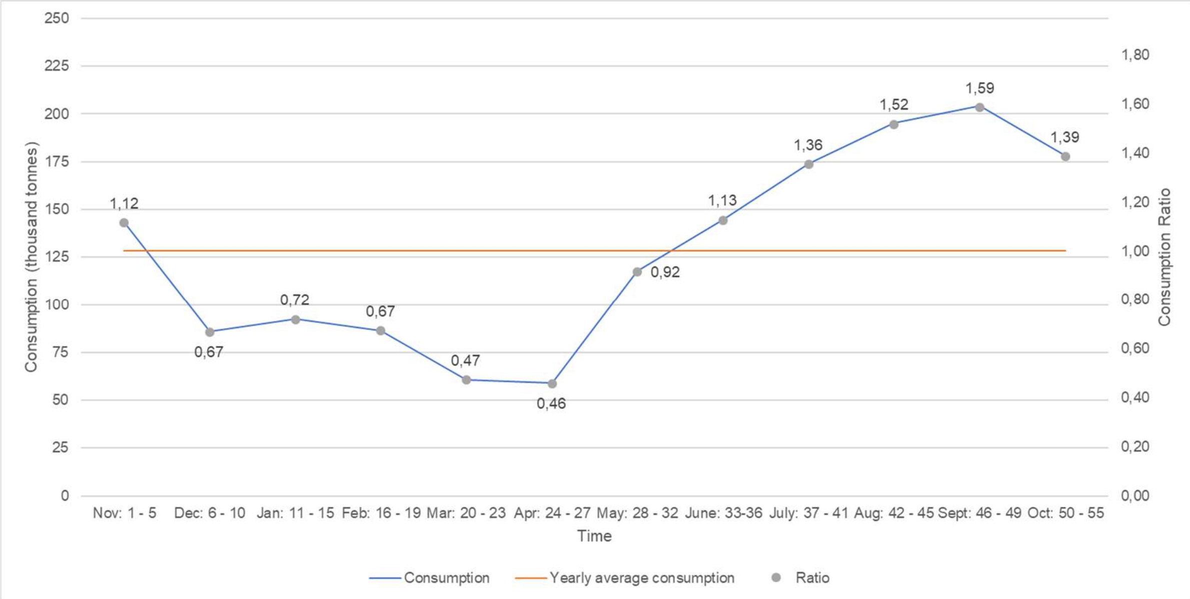
Source: The author (2020).

The problem recognition phase is conducted by the systematic literature review, as already presented. The definition of the system boundaries is highly dependent on the research's objectives and the data that will be available from the case studied. Once the boundaries of the system have been defined, the conceptual model will be created depicting the actual state of the case and serving as the base model for the system dynamics modeling. The model representation and its behavior are created in the SD model and computational simulation, utilizing the Stella software. In the first cycle, a validation of the model with real-world data is conducted, then for the following cycles, a comparative analysis takes place to measure the impacts in performance, in comparison to the base model. The analysis of the system's properties is achieved by the tracking of previously defined metrics. The recommend improvements phase prepares the model to the application of one of the steps of the TOC solution, creating a feedback cycle as proposed by Mitroff et al. (1974) which is only concluded when all the solution steps are applied. Once the steps are all applied, the results, conclusions, and future study possibilities are discussed. It is important to mention that the application of the TOC steps will be represented only by the simulation model and therefore will not be applied in the empirical case. After defining the work method, the next section will cover the phase of data collection and data analysis.

3.3 CASE OVERVIEW

This section aims to clarify the case of study providing an overview of the system under analysis and the delimitation of its boundaries. As stated in the introduction, the case under study comprises a multinational chemical industry supply chain, which has facilities in eleven different Brazilian states. The company is a market-share leader of the sector, competing with other big players. This research focuses on the international supply chain of this company, considering its forecasting process and raw-material replenishment planning. The market the company is in is seasonal, having its high season from July to September. This seasonality can be observed through Chart 3, which presents the raw-material consumption, the yearly average consumption and the consumption ratio (month's consumption divided by average consumption) by time. The time is presented in months and the simulations model time. From that it is possible to note that in September the peak consumption is achieved, which represents 1,59 consumption ratio, almost 60% higher than the average consumption.

Chart 3 – Case's consumption time series



Source: the author (2020).

Currently, around 80% of the raw material is imported from other countries – mostly from Europe – and transported by sea. Those raw-materials are generally commodities and the available supply option within the country comes from the company's biggest competitor – which has a limited supply for the market. The company is willing to increase the raw-material importation ratio, however, the long lead-times, the constant delays, and the inaccuracy of its forecasting process constraints the company to do so and achieve a competitive edge.

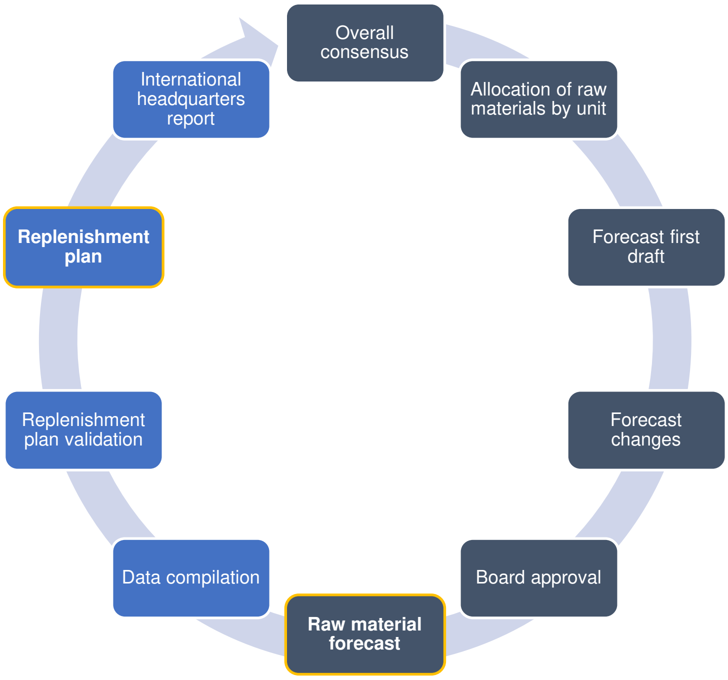
The replenishment process is coordinated by the S&OP (sales and operations) team which serves as a common connection between operations and the commercial team. The S&OP team receives a forecast plan created by market intelligence and sales teams which serves as a base for the replenishment plan. The forecast plan demonstrates the expected consumption of raw-materials based on estimated product sales; hence the forecast is already presented in raw-materials and not in final products. The S&OP team is responsible for coordinating the S&OP meetings where a general consensus is achieved on the forecast and replenishment plans. Overall, the S&OP team aims to have the right raw material at the right place. Figure 19 below depicts the structure of the S&OP team and its relationship with other company departments.

Figure 19 – Sales & Operations team and its connections

Source: the author (2020).

The forecast and replenishment plans are reviewed monthly in a structured way through the S&OP meetings. First, there is a consensus where all the stakeholders agree with a sales and delivery plan, based on market analysis and the past performed deliveries and sales. Then this consensus on the sales is allocated into raw-materials for each of the units spread throughout the country, creating a first version of the raw-material delivery forecast (i.e. delivery forecast or only forecast). This version might be challenged by the supply, logistics or operations teams and changed accordingly. After those alterations, the final forecast is approved by the board and then the final version for the month is created. Based on this latter version of the forecast, the S&OP team compiles the current inventory levels and the goods in transit to prepare the re-ordering of the raw materials, i.e. the replenishment plan. This plan is also validated by the operations, logistics, and supply teams in order to form the replenishment plan final version. This version is also shared with the headquarters in Europe. This cycle is replicated each month with a specific calendar, always reviewing the forthcoming months. Figure 20 illustrates the planning cycle.

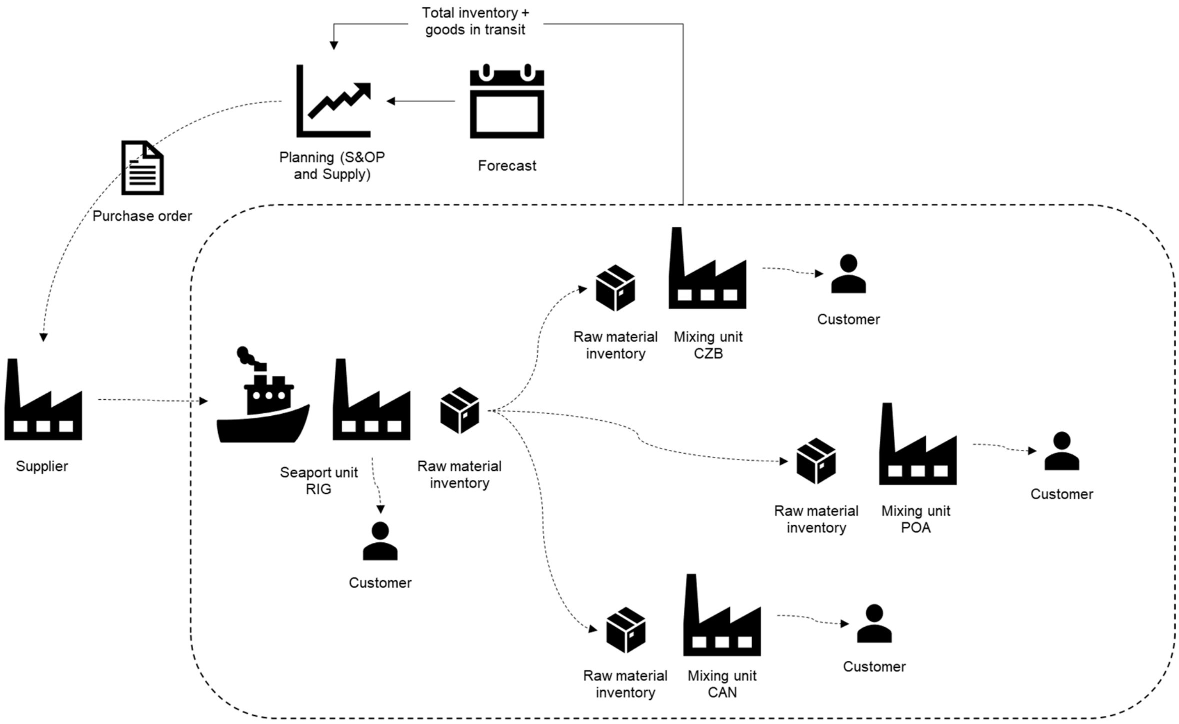
Figure 20 – Forecast and planning cycle



Source: the author (2020).

The forecast and replenishment plan are conducted for all the units in the country. The unit's management is divided between production (total of five) and mixing units (total of 24). The mixing units are then divided again into three other management structures according to their regional location. For this research, the focus will be on the Rio Grande do Sul state units given its representativeness in sales for the whole company. The state is the company's most representative state, accounting for 28% of the total sales volume, while the second greatest state has approximately 17%, the third 15%, and other 9 states the remaining 39%. There are four units in the state located in four different cities, being one of them a production unit with its own seaport – referred as RIG – and the other three being mixing units – referred as CAN, CZB, and POA. Usually, the seaport unit transfers raw materials to the mixing units, although depending on the material, some mixing units might receive the material directly from a supplier and transfer to any other requesting unit. During a one-year period, around 780 thousands of tonnes were transferred between those four units. Figure 21 provides an overall view of the described system that aids in the understanding of the case's supply chain.

Figure 21 – Rich picture of the analyzed supply chain.



Source: the author (2020).

The raw material forecast accuracy in the research period was around 60% while the raw material replenishment plan accuracy was around 56%. The forecast accuracy compares the forecasted consumption (by sales orders) of raw materials with the actual ones, while the replenishment plan accuracy measures how many raw materials were replenished in the necessary or expected date or time. The delays of raw materials or the lack of raw material inventory usually causes delays in sales orders. A recent research conducted with customers demonstrated that both customer satisfaction levels and customer fidelity have decreased in comparison to the previous year. One of the main reasons pointed by the customers was problems related to product delivery. It is estimated that the company lost 30 million dollars in sales margins due to those issues.

The whole planning process utilizes a few tools for the operations and reporting, such as Microsoft Excel; two different business intelligence (B.I.) tools for reporting, KPI tracking, and data extraction; Microsoft Sharepoint to gather data, manage the knowledge database, and get inputs from other areas; and the company's ERP. With many different areas, the company is highly departmentalized, and each area has its roles and responsibilities and the communication between those is basically through meetings and e-mails. Such departmentalization can be exemplified by the planning areas; other than the S&OP area, there is also the fulfilment area which is responsible for the mid-term replenishment plan (recurring to the national suppliers when there is a shortage of raw material, for instance) and also to schedule and reschedule product deliveries with customers; also each unit has a production planning and control (PPC) responsible which in accordance to the fulfilment planning schedules the weekly production of the units. Each of those planning areas (S&OP, fulfilment, and PPC) have different line managers and their own set of KPIs and targets.

For the sake of this research, the system's boundaries are delimited as the raw material planning and forecasting for the Rio Grande do Sul state described above. Thus, the following sections will present the data collection and data analysis processes that comprise the work method.

3.4 DATA COLLECTION

The data collection and data analysis phases are essential to ensure the operationalization of the research and work methods defined by the researcher (DRESCH; LACERDA; ANTUNES JR., 2015). Dresch; Lacerda and Antunes Jr., (2015) state that before the selection of a technique to conduct the research, the researcher must consider the data to be collected, as well as the way it is to be obtained: how, when and who may provide the required data. The systematic literature review is the first data collection to be realized and is based on the protocol form presented in Appendix A and fully explained in section 1.3.

The model conceptualization phase requires data collection as well. Within this phase, a real case is studied and the data collection is led by the researcher in the field. In this part two specialists from Sales & Operations team and one from fulfillment team were consulted, one of them provided an overall view of the planning and forecasting processes. The second one was appointed by the first specialist and provided a deeper understanding of the department activities as well as key data of replenishment of raw materials such as forecasts, replenishment plans, and raw material consumption. The fulfillment specialist was consulted once – based on the recommendation of the other two specialists due to his position and time within the company – in order to provide data on the sales order deliveries and delays. The consulted specialists and their profiles are presented in the frame below.

Frame 6 – Company's specialists consulted

Position	**Company time**	**Education background**
Senior S&OP coordinator	9 years	Business administration at Unisinos University
S&OP coordinator	10 years	Production engineering at Federal University of Rio Grande do Sul
Fulfillment coordinator	9 years	Chemical engineering at Federal University of Rio Grande

Source: the author (2020).

Ideally, all the data from production and raw material planning would be supported by sales data and the delays would be accounted in the sales orders. However, during data collection it was noted that the company does not have a good record of the sales orders delays. Two problems emerged regarding the sales orders dates of delivery. The first one is that the initial date at the sales order is commonly not relevant as the customer does not yet have a specific date to receive the products. The sales orders can be created even six months prior to the delivery date; therefore, the sales teams usually provide an irrelevant delivery date. Later, the fulfillment team contacts the customers to agree on an expected delivery date. As raw materials delays occur consequently changing to the sales orders delivery plan the fulfillment team contacts the costumer again to negotiate a new delivery date. All those changes in delivery date are not registered, the only record kept is the most recent delivery date meaning that at each interaction the former delivery date is lost. Therefore, the initial delivery date inputted in the system is not accurate and all the further changes to those delivery dates are lost, so delivery delays are difficult to track. In that sense the data collection and the model limit itself to consider only the raw material supply and replenishment systems, not accounting the sales operations.

The sources of data are varied. The second specialist provided various spreadsheets from the S&OP, supply, and logistics teams, access to those teams' knowledge databases – company's teams websites found in the intranet – and their business intelligence (B.I.) pages. Additionally, the company's ERP was also consulted. Therefore, data sources are the company's ERP database, logistics, S&OP,

and supply department data, as well as the direct observation of the researcher. This information was then compiled and followed by another two interviews with the company's S&OP specialists to come to a consensus of the structured data and the conceptual model validation. The data collection is then composed of five different techniques, respectively bibliographic, documentary, direct observation, and interviews (SAUNDERS; LEWIS; THORNHILL, 2012b). The frame below presents the variables collected, a brief description of them and their sources.

Frame 7 – Collected variables and sources

Variable	Description	Source
Batch premise	Provides the minimum order batch per raw material	Supply knowledge database
Unload premise	Provides the expected unload time at the seaport according to the raw material packaging type (either bulk or container)	S&OP knowledge database
Forecast accuracy	KPI that compares the forecasted raw material consumption against the real consumption	S&OP B.I.
Order time historical data	The actual raw material ordering time	Supply spreadsheet database
Order time premise	The expected time to issue a raw material order	Specialist
Origin premise	Provides the general supplying country and seaport by raw material	Supply knowledge database
Queue time historical data	The actual raw material queue time	Supply spreadsheet database
Raw material consumption	The real consumption of raw materials	ERP system
Raw material entries	The actual entries of purchased raw materials	ERP System
Raw material forecast	The expected consumption of raw materials (derived from the expected sales)	S&OP knowledge database
Raw material inventory position	The monthly inventory position by raw material and unit	ERP system
Release time historical data	The actual raw material release time	Supply spreadsheet database
Replenishment accuracy	KPI that measures the raw material expected deliveries against the real deliveries	S&OP B.I.
Seaport queue time premise	Provides the expected queue time at the receiving seaport	Logistics knowledge database
Seaport release time premise	Provides the expected liberation time of raw materials at the receiving seaport	Logistics knowledge database
Supply premise	Provides the replenishment strategy by unit and raw material	S&OP knowledge database
Transit time historical data	The actual raw material transit time	Supply spreadsheet database
Transit time premise	Provides the expected transit time by origin (country and seaport)	S&OP knowledge database

Source: the author (2020).

The variables above are used in order to construct the system dynamics model. All the time-varying variables (raw material forecast, consumption, inventory positions, and time historical data) had a dataset of one year, ranging from the 1st of November 2018 to 31st October 2019. As stated, this research aims to simulate four plants of the mentioned company, therefore all the data collected regarded only those plants. The seaport unit is referred to as RIG, while the other three mixing units can be referred to as CAN, POA, and CZB. A total of 29 different raw materials are imported for those units and 28 will be part of this research[1]. Having detailed the data collection, the next section covers the data analysis of the research.

3.5 DATA ANALYSIS

The data analysis can be defined as the phase where the researcher interprets the collected data to find the results of the study (DRESCH; LACERDA; ANTUNES JR., 2015). In the problem recognition and the definition of the system boundaries content analysis is utilized derived from the systematic literature review. From the data generated from the documents, observations and the interviews follow a content analysis of those, in order to conceptualize the system, represent the model and define its behaviors. This data is then inputted in a conceptual model without randomness for the verification phase. The verification is suggested by Sterman (2000) and aims to verify if the model behaves as the real system does. Next, randomness is added in the model by the cumulative probability distributions derived from the real data of the lead times – please refer to Appendices F, G, and H for those distributions. Those distributions are coded directly in Stella built-in functions. For the model validation, confidence intervals of the average inventory position are defined using Stella's sensitivity analysis with multiple runs and compared with the real data found in the data collection. For those a significance level of 5% is used and the maximum error allowed is set to 10% based on the real case values. A t test is conducted to verify that the number of runs in the sensitivity analysis is enough. The validation process is detailed later in the model section.

[1] One specific raw material had to be excluded from the analysis as a suggestion of the S&OP specialist due to reporting inconsistencies between the forecast data, the ERP consumption information, and the supply data.

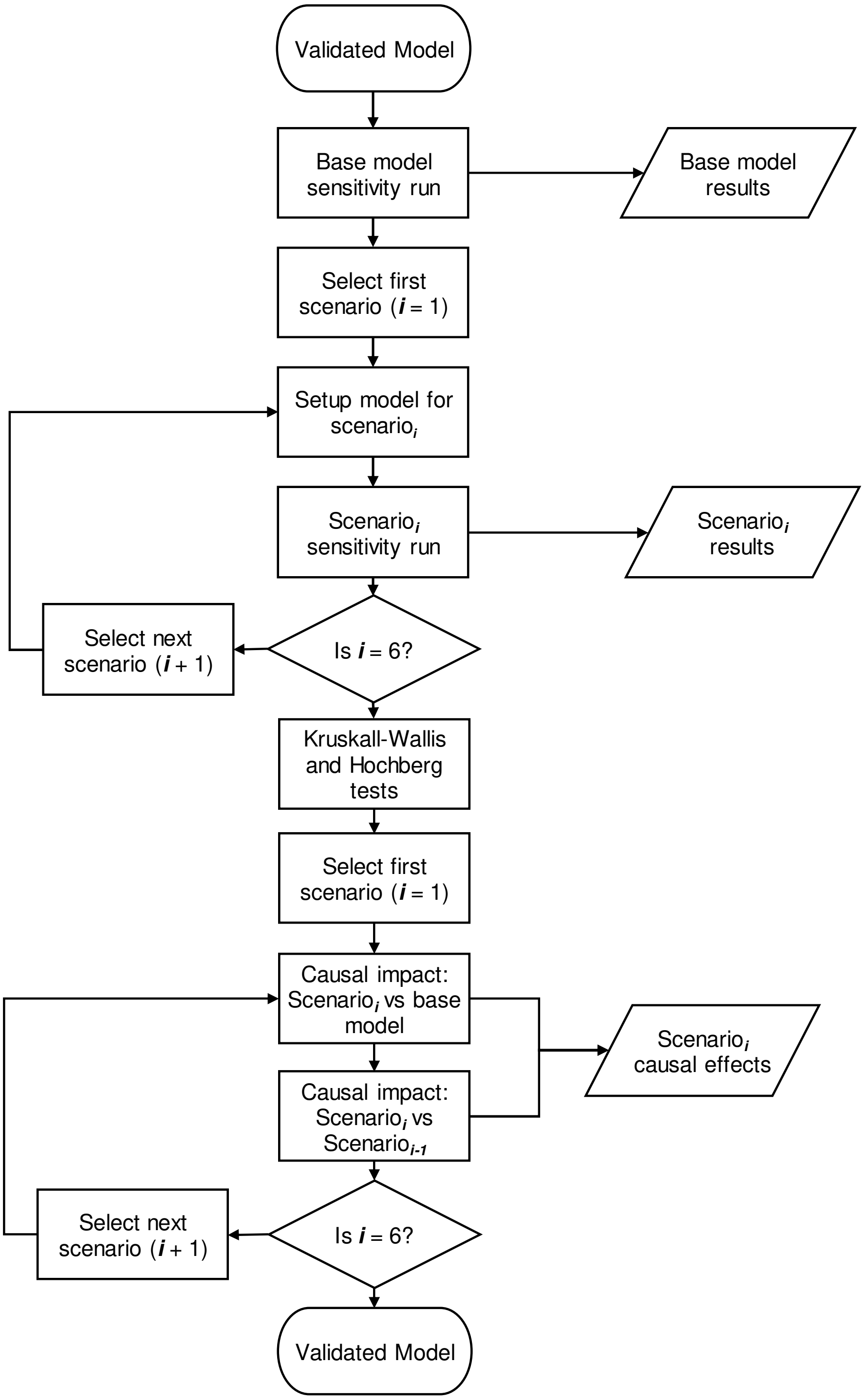
Once the model is validated, the TOC solution steps are applied in a logical sequence and the results are recorded for each one of those iterations. In order to evaluate the results from the TOC application the total inventory, inventory at the mixing units, inventory at the seaport unit, the throughput-dollar-days (TDD), and the inventory-dollar-days (IDD) are monitored. Regarding the unit of measurement, both TDD and IDD are in dollars and the inventories in tonnes.

As specified in the data collection section, since there is no accurate control of the sales orders delays, a proxy variable is utilized to account for the TDD. A proxy is a variable that is used to replace an unmeasurable or unobservable variable, although not a direct measure of the desired variable, a good proxy is strongly related to the variable of interest (LEWIS-BECK; BRYMAN; FUTING LIAO, 2004). Based on the specialists a good proxy for the sales orders delays is the raw material delays. Since the company has a make-to-order production system, any unexpected delay of raw materials can cause a direct delay in sales.

In order to evaluate the impacts of the TOC, at each iteration of the application of the distribution solution steps the results of the mentioned variables are be computed and compared to the previous result and the base model. The interest variables are defined as the throughput-dollar-days (TDD), the inventory-dollar-days (IDD), the inventory levels (at the CWH, at the shops, and at the whole SC). With the model results first, descriptive statistics are presented, both for the base model and the implementation of the steps. Then, a Shapiro-Wilk test (SHAPIRO; WILK, 1965) is conducted to check for data normality. The results show non-normal distributions. Therefore, the Kruskal-Wallis test is realized to check if there is any significative change between the scenarios. Since the Kruskal-Wallis test only informs that at least one of the scenarios is different, not indicating which are the different ones, the analysis is complemented with the Hochberg test (HOCHBERG, 1988). This test is utilized for multiple scenario comparison, providing the pairwise significances at each combination between the observed groups. Those groups are represented in the case by the base model and the created scenarios that apply the TOC's steps.

Finally, causal impact analysis – as proposed by (BRODERSEN et al., 2015) – is utilized to analyze the system properties and recommend improvements. According to Brodersen et al (2015), a causal inference may be understood as intervention or data treatment realized in a temporal series. The causal impact is the difference between the observed data with a given treatment – the implementation of one of the TOC solution steps – and the unobserved data values that would result from the series if no treatment was realized (ANTONAKIS et al., 2010). Figure 22 summarizes the steps for data analysis and the iteration process to simulate scenarios.

Figure 22 – Data analysis process flowchart



Source: The author (2020).

The scenarios defined for the analyses are shown in Frame 8. From the frame, it is possible to note which TOC steps are being applied, which model variables are used or not, and whether the buffer if based on the forecast (FB) or not (not FB). The buffer determination and the replenishment lead time are separated as individual variables. For those scenarios, the sensitivity runs are conducted with 30 multiple runs per simulation, resulting in a total of 210 simulation runs. The results for each scenario were exported to an Excel file and R was used in order to organize, summarize, and structure the results data for analysis.

Frame 8 – Simulation scenarios and model variables

		Model variables / parameters						
Scenario	**Description**	**TOC step used**	**Stock aggregation**	**TOC Buffer**	**TOC RLT**	**Buffer penetration**	**Dynamic Buffer**	**Buffer type**
Base	Base model	-	✗	✗	✗	✗	✗	FB
1	Stock Aggregation at the SC highest level	1	✓	✗	✗	✗	✗	FB
2	Determination of buffer sizes and replenishment lead time	1 and 2	✓	✓	✓	✗	✗	Not FB
3	Buffer penetration	1, 2, and 4	✓	✓	✓	✓	✗	Not FB
4	Dynamic Buffers	1, 2, 4, and 5	✓	✓	✓	✓	✓	Not FB
5	Forecast-based buffers	1 and 2	✓	✓	✓	✗	✗	FB
6	Hybrid model to deal with seasonality	1, 2, 4, and 5	✓	✓	✓	✓ (during low season)	✓ (during low season)	FB (during high season)

Source: the author (2020).

Also, it is important to mention that there was no expected disturbance on the demand, capacity expansion, significative technological improvement, or any other impactful initiative during the data colletion. The data analysis concludes the methodological procedures. The next section describes and details the model construction.

4 MODEL CONSTRUCTION

In this section, the construction process of the system dynamics model is described. For the model construction, the four units are created as well as the variables such as the raw material replenishment, the raw material consumption, and the transfers between the units. Initially, all the data collected serves as a direct input to the model, so no randomness is yet set. This step is conducted to verify the model behavior, which is done by comparing the final inventory position of the raw materials in the systems against the real data found in the company's ERP. Later, the planning process module of the system is created, which aims to simulate the forecasting and replenishment process of the company. During this phase, variation is added to the model through the lead times, based on the cumulative distribution function of the historical supply data, thus creating the base model. Finally, the base model is validated in Stella utilizing the confidence intervals of the average inventory of raw materials and comparing those to the real data.

The TOC steps application are created in the model as parameters, therefore in order to run a simulation with or without a specific TOC step is just a matter of adjusting the respective parameters. Therefore, the same model is utilized for the base model and all of the necessary scenarios are simulated by adjusting the respective parameters, assuring replicability of the base values or any required scenario at any moment.

The next section covers the conceptualization of system, the creation of the internal supply chain module and the initial model verification.

4.1 SYSTEM CONCEPTUALIZATION

As previously stated, the model will simulate the planning and replenishment of raw material of four units. The biggest unit is a production unit that has its own seaport, while the other ones are mixing units. The seaport unit is referred to as RIG, while the other three mixing units can be referred to as CAN, POA, and CZB. The raw material forecast starts the whole planning process. This forecast demonstrates the expected consumptions in tonnes for at least the next six months and is detailed by raw material and unit. At each planning cycle, the forecast is updated and a new month added to it. The forecast is exemplified in Figure 23 – Raw material forecast schematic.

Figure 23 – Raw material forecast schematic

Reference month	JAN	FEB	MAR	APR	MAY	JUNE	JULY	AUG	SEPT	OCT	NOV	DEC
01/01/2019	108.900	111.500	76.404	97.132	142.773	221.520	-	-	-	-	-	-
01/02/2019	107.254	120.500	80.889	88.159	134.292	254.159	348.444	-	-	-	-	-
01/03/2019	107.254	96.852	116.500	114.889	183.938	302.609	346.825	358.795	-	-	-	-
01/04/2019	107.254	96.852	109.067	122.726	185.361	311.022	356.801	382.006	326.411	-	-	-
01/05/2019	107.254	96.852	109.067	104.260	170.306	278.997	332.176	354.729	309.369	265.370	-	-
01/06/2019	107.254	96.852	109.067	104.260	183.879	288.592	306.642	348.613	317.145	259.836	136.130	-
01/07/2019	107.254	96.852	109.067	104.260	183.879	269.799	306.801	338.364	323.114	262.061	137.424	112.143
01/08/2019	107.254	96.852	109.067	104.260	183.879	269.799	289.049	350.364	336.126	263.320	133.396	129.589
01/09/2019	107.254	96.852	109.067	104.260	183.879	269.799	289.049	327.415	329.250	266.896	151.844	85.278
01/10/2019	107.254	96.852	109.067	104.260	183.879	269.799	289.049	327.415	297.516	277.665	170.253	100.211
01/11/2019	107.254	96.852	109.067	104.260	183.879	269.799	289.049	327.415	297.516	278.070	172.473	116.261
01/12/2019	107.254	96.852	109.067	104.260	183.879	269.799	289.049	327.415	297.516	278.070	184.195	119.409

Legends:

Forecast	Realized

Source: the author (2020).

From the forecasted quantities, a measure called "raw material exposure" is calculated. The exposure is calculated at raw material (RM) level and is an estimation of future lacks of material inventory, which should be replenished from a re-order. The variable is defined as:

$$Exposure_{rm\,fm} = \left|\sum_{fm=1}^{6} Forecasted\ Consumption_{rm\,fm} - Realized\ Month\ Sales_{RM}\right| - (Ongoing\ Purchases_{rm} + Inventory\ on\ hand_{rm}) \tag{1}$$

Where:

$rm = raw\ material;$

$fm = forecast\ month.$

The exposure is calculated then for all the forecasted months. A positive exposure value for a raw material means that a re-order is likely to be issued to replenish the inventory in the future month. Additionally, an estimation of the lead time is also calculated in order to check if a re-order should be requested in the ongoing month. This lead time estimation is based on a series of assumptions based on the raw materials, then if the raw material exposition in a future month is positive and the expected delivery of that material is in the same month, a replenishment requisition is created by the S&OP team. This purchase requisition is sent to the supply team in order to create and negotiate the raw material acquisition with the suppliers.

The first premise to calculate the expected lead time is the supply premise. This premise defines for each raw material its supplying unit, i.e. the unit that is responsible for supplying that material to other units when necessary. Since RIG has its own seaport and is the biggest unit of the region, most materials are supplied through this unit. However, other plants can be suppliers of a few materials as well, even though they necessarily need to arrive first at the RIG seaport. Thus, the plants that are supplied by the supplying unit need to issue a replenishment order to have the material transferred and available to them. Since the plants are all within the same state the transfer lead time is of one week, with little variation as long as the supplying plant has the inventory in hand. The replenishment frequency does not follow a predefined rule, and it varies according to the units and the materials, they can be daily depending on the demand or more sparse. Usually, all units keep extra inventory in their possession. Summing up, the supply premise defines which unit aggregates the inventory of that specific raw material. Frame 9 lists the raw materials and how they are supplied. It shows, for instance, that the raw material DAP GR is supplied by an external supplier at the RIG unit and then the RIG unit supplies that raw material for the other units.

Frame 9 – Raw material supply premise

Raw Material	Supplied by			
	RIG	CAN	CZB	POA
DAP GR	Supplier	RIG	RIG	RIG
KCL GR	Supplier	RIG	RIG	RIG
KRISTA K	CAN	Supplier	CAN	CAN
KRISTA MAG	CAN	Supplier	CAN	CAN
KRISTA MAP	CAN	Supplier	CAN	CAN
KRISTA MKP	CAN	Supplier	CAN	CAN
KRISTA SOP GR	POA	POA	POA	Supplier
KRISTA SOP ST	CAN	Supplier	CAN	CAN
KRISTALON 06 12 36	CAN	Supplier	CAN	CAN
KRISTALON 13 40 13	CAN	Supplier	CAN	CAN
KRISTALON 15 05 30	CAN	Supplier	CAN	CAN
NAM	POA	POA	POA	Supplier
NIP GR	POA	POA	POA	Supplier
PG MIX 14 16 18	CAN	Supplier	CAN	CAN
SAM GR	Supplier	RIG	RIG	RIG
SAM STD	Supplier	RIG	RIG	RIG
SSP GR	Supplier	RIG	RIG	RIG
TSP GR	Supplier	RIG	RIG	RIG
UREIA ADBLUE	CAN	Supplier	CAN	CAN
UREIA GR	Supplier	RIG	RIG	RIG
YBELA AXAN	Supplier	RIG	RIG	RIG
YLIVA NITRABOR	Supplier	RIG	RIG	RIG
YMILA 13 24 12	Supplier	RIG	RIG	RIG
YMILA 16 16 16	Supplier	RIG	RIG	RIG
YMILA 19 04 19	Supplier	RIG	RIG	RIG
YMILA 21 07 14	Supplier	RIG	RIG	RIG
YTERA CALCINIT	CAN	Supplier	CAN	CAN
YVERA 40	Supplier	RIG	RIG	RIG

Source: the author (2020).

The forecast quantities from other units are aggregated at the supplying unit as well. With the supplying unit defined, it is necessary to calculate the estimation of arrival for each raw material. This estimation is based on complementary premises as the order lead time, the transit lead time from the origin to the seaport, the queuing time in the seaport, the unload time in the seaport, and the liberation time of the raw material at the seaport. The order lead time is estimated as two weeks. All the remaining lead times are based on each raw material supply origin and supply method. The supply method is either bulk or container. The supply origin is the usual country and seaport which is utilized by the raw material supplier to ship its product. Table 7 demonstrates the raw materials supply method, origins, and transit lead times.

Table 7 – Material origin premise and transit time

Raw Material	Packaging Type	Country / Seaport Origin	Transit Time (days)	Transit Time (weeks)
DAP GR	Bulk	Morocco - Jorf Lasfar / Safi	15	2
KCL GR	Bulk	Russian	25	4
KRISTA K	Container	Israel & Jordan	40	6
KRISTA MAG	Container	Poland - Dgynia	47	7
KRISTA MAP	Container	China - Chongqing / Shangai	65	9
KRISTA MKP	Container	China - Chongqing / Shangai	65	9
KRISTA SOP GR	Container	Belgium - Antwerp	25	4
KRISTA SOP ST	Container	Belgium - Tessenderlo	55	8
KRISTALON 06 12 36	Container	Netherlands - Vlaardingen	68	10
KRISTALON 13 40 13	Container	Netherlands - Vlaardingen	68	10
KRISTALON 15 05 30	Container	Netherlands - Vlaardingen	68	10
NAM	Bulk	Russia	25	4
NIP GR	Container	Chile	30	4
PG MIX 14 16 18	Container	Netherlands - Vlaardingen	68	10
SAM GR	Bulk	China - Tianjing	45	6
SAM STD	Bulk	China - Tianjing	45	6
SSP GR	Bulk	Israel	22	3
TSP GR	Bulk	Morocco - Jorf Lasfar / Safi	15	2
UREIA ADBLUE	Container	Russia	42	6
UREIA GR	Bulk	Qatar	45	6
YBELA AXAN	Bulk	Netherlands - Sluiskil / Terneuzen	21	3
YLIVA NITRABOR	Bulk	Norway - Porsgrunn	23	3
YMILA 13 24 12	Bulk	Finland	33	5
YMILA 16 16 16	Bulk	Norway - Porsgrunn	23	3
YMILA 19 04 19	Bulk	Norway - Porsgrunn	23	3
YMILA 21 07 14	Bulk	Norway - Porsgrunn	23	3
YTERA CALCINIT	Container	Colombia & Norway	40	6
YVERA 40	Bulk	Netherlands - Sluiskil / Terneuzen	21	3

Source: the author (2020).

Once the raw materials arrive at the seaport destination the ships wait in the seaport “queue” to be able to unload its load, and once the material is unloaded it is necessary to wait for the release of the documentation. All of those three lead times depend on the packaging type of the material. They are all summed up to form what will be called from now on the port time processing. The seaport processing time premise is the same for all the raw materials, even though they might spend different times queuing or unloading.

Table 8 – Port processing time

Raw Material	Packaging type	Queue time (days)	Unload time (days)	Release time (days)	Total time (days)	Total time (weeks)
DAP GR	Bulk	7	4	2	13	2
KCL GR	Bulk	7	4	2	13	2
KRISTA K	Container	-	1	12	13	2
KRISTA MAG	Container	-	1	12	13	2
KRISTA MAP	Container	-	1	12	13	2
KRISTA MKP	Container	-	1	12	13	2
KRISTA SOP GR	Container	-	1	12	13	2
KRISTA SOP ST	Container	-	1	12	13	2
KRISTALON 06 12 36	Container	-	1	12	13	2
KRISTALON 13 40 13	Container	-	1	12	13	2
KRISTALON 15 05 30	Container	-	1	12	13	2
NAM	Bulk	7	4	2	13	2
NIP GR	Container	-	1	12	13	2
PG MIX 14 16 18	Container	-	1	12	13	2
SAM GR	Bulk	7	4	2	13	2
SAM STD	Bulk	7	4	2	13	2
SSP GR	Bulk	7	4	2	13	2
TSP GR	Bulk	7	4	2	13	2
UREIA ADBLUE	Container	-	1	12	13	2
UREIA GR	Bulk	7	4	2	13	2
YBELA AXAN	Bulk	7	4	2	13	2
YLIVA NITRABOR	Bulk	7	4	2	13	2
YMILA 13 24 12	Bulk	7	4	2	13	2
YMILA 16 16 16	Bulk	7	4	2	13	2
YMILA 19 04 19	Bulk	7	4	2	13	2
YMILA 21 07 14	Bulk	7	4	2	13	2
YTERA CALCINIT	Container	-	1	12	13	2
YVERA 40	Bulk	7	4	2	13	2

Source: the author (2020).

From the table above it is possible to observe that the expected seaport processing time is 13 days. Since the model uses weeks as its time unit, the 13 days are rounded to 2 weeks. Finally, as only RIG has its own seaport, if the supplying unit of that specific raw material is not RIG, the material has yet to be transferred to the supplying unit which adds one more week to the expected lead time. Thus, the total expected lead time is defined by the company as:

$$\begin{aligned} Expected\ LT = \ & Order\ LT + Transit\ Time_{rm} + Port\ Processing\ Time_{rm} \\ & + \ Seaport\ Transfer\ Time_{unit} \end{aligned} \tag{2}$$

Where:

$rm = raw\ material\ in\ ton;$

$unit = destination\ unit.$

Then, as stated previously if the expected lead time is equal to or less than raw material exposure in the forecasted month a purchase requisition is created for that material. All those requisitions form the replenishment plan. However, the requisition quantity is not the same as the raw material exposure, besides the raw material exposures, it is also necessary to account for the supplying batch sizes as well as an additional measure of safety. Both are defined for each raw material, while the order batch is defined by the suppliers – which also affect the minimum batch, as at least one batch must be procured – the safety measures are defined by the S&OP and supply teams. The safety measure basically relates to the criticality of the material – e.g. if it can be found within the country market, how easily it can be replaced, for which products it is used, etc. – and it consists of three levels. Each level defines an extra quantity to be purchased for each raw material at each re-order. Level 1 will consider the forecasted exposure plus the next month's forecast after the exposure for that material; level 2 will considerer the exposure plus the next two forecasted months after the exposure; and level 3, the exposure plus the next three months forecasted quantities after exposure. A material without the safety factor will only consider the raw exposure. Even though those levels are generally defined, they may change depending on the current situation or through time. Table 9 presents the safety factors and the batch premises (in thousands of tonnes) for each raw material.

Table 9 – Safety factor and batch premise

Material	Safety Factor	Batch Premise
DAP GR	-	5.000
KCL GR	1	4.000
KRISTA K	-	24
KRISTA MAG	-	21
KRISTA MAP	-	28
KRISTA MKP	2	24
KRISTA SOP GR	3	4.000
KRISTA SOP ST	-	24,5
KRISTALON 06 12 36	-	24
KRISTALON 13 40 13	-	24
KRISTALON 15 05 30	-	24
NAM	-	4.000
NIP GR	1	24
PG MIX 14 16 18	-	24
SAM GR	-	4.000
SAM STD	-	4.000
SSP GR	-	5.000
TSP GR	1	4.000
UREIA ADBLUE	1	28
UREIA GR	-	4.000
YBELA AXAN	1	500
YLIVA NITRABOR	3	500
YMILA 13 24 12	3	500
YMILA 16 16 16	1	500
YMILA 19 04 19	1	500
YMILA 21 07 14	3	500
YTERA CALCINIT	-	500
YVERA 40	-	500

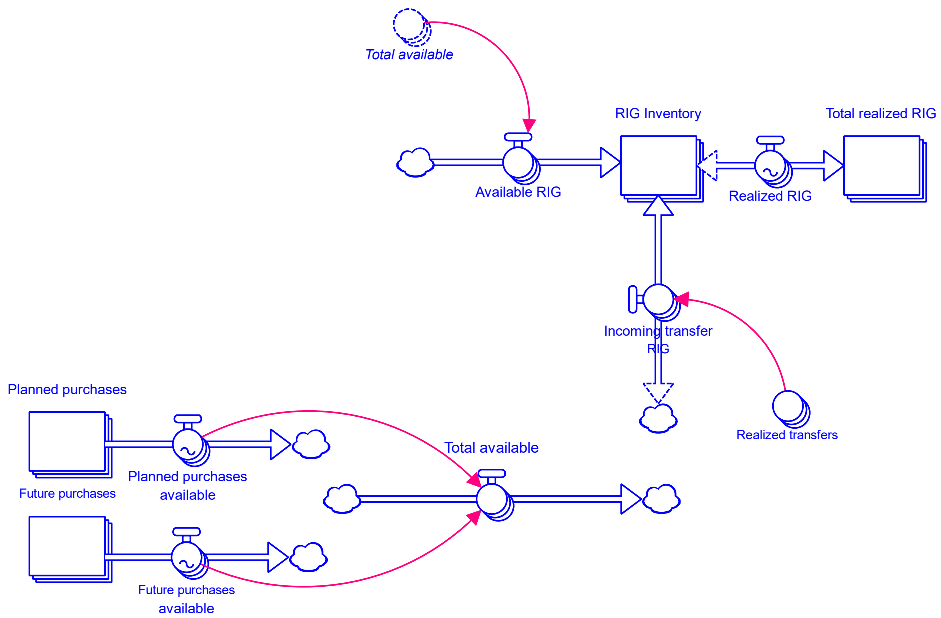
Source: the author (2020).

Having provided an overall comprehension of the current supply chain planning system of the company, the model construction is presented next. In the following section, the internal supply chain module with a brief model verification is described.

4.2 THE INTERNAL SUPPLY CHAIN MODULE

The model construction was started by the creation of the internal supply chain of the company. The model has the initial time unit as weeks, starting at 0 and ending at 55 – approximately one year. The delta time (DT) is set to 1, as a week is enough to capture the main impacts on the system, especially regarding replenishment delays as a one-week delay might incur in production planning rescheduling and a late sale. The selected integration method is Euler, as recommended by the software creator in order to use discrete objects and the software's built-in functions. The initial data required for the initial construction are the starting period inventory position by raw material and unit, the total raw material purchases (entries) for the simulation period by raw material and unit, the raw material consumption in the period by raw material and unit, and the raw material transfers between units. All this information was collected in the company's ERP, all the goods movements (entries, consumption, and transfers) are recorded daily and then are aggregated into weeks. The raw material purchases are split into planned purchases and future purchases. The planned purchases represent all those purchases that were already made before starting period of the simulation, i.e. the goods-in-transit or committed purchases. The future purchases are all those purchases that are concluded after the starting point of the simulation. This step is important when the TOC is implemented, as the model will be able to keep the already committed purchases and not consider the "future" ones derived from the actual replenishment policy. Figure 24 depicts this initial model for the RIG unit.

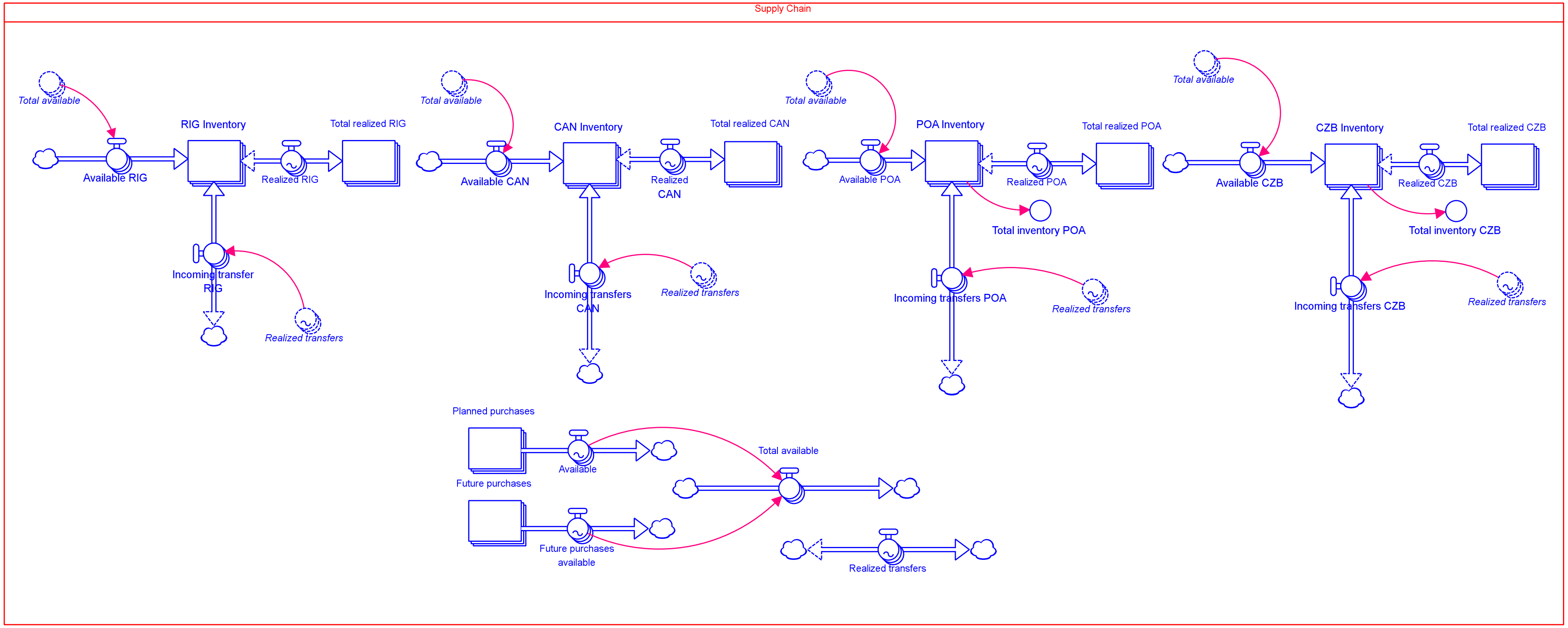
Figure 24 – Internal supply chain for the RIG unit



Source: the author (2020).

The variables above are arrayed by raw material except for the “realized transfers” which is arrayed by raw material and unit. They are uploaded in Stella in a excel spreadsheet. The variables “realized transfers”, “available”, “future purchases available”, and “realized RIG” are also graphical variables (i.e. time-varying). The purchase inventories are created in order to know how much raw material purchases are committed and will be used later. The “realized RIG” refers to the raw material consumption and is defined as a bi-flow to compute for the system’s issuing reversals – caused, for instance, by operational errors. The same logic is applied for unit transfers. The “total available” sums any purchases – planned and future – made that arrived at the specific time of the simulation then connecting to the units, as demonstrated in the “available RIG”, meaning that purchased raw material is available to enter in the unit inventory. The “incoming transfer” replies the values uploaded in the “realized transfers” variable, however, it will be utilized later for the TOC steps application. Finally, the “total realized RIG” is utilized to measure the cumulative raw material consumption. The same logic is applied for all the other units, forming the initial version of the model. Figure 25 – Basic supply chain model demonstrates the model including the remaining units.

Figure 25 – Basic supply chain model



Source: the author (2020).

From this point, a verification of the model is conducted. Assuming the model has the initial inventory positions, the entries of raw materials, and the raw material consumption, the final inventory position should match the ones found in the company's ERP. This is basically a verification step to check if the model is behaving accordingly. Other than the mentioned movements, there are other movements that were not included in the model, such as inventory corrections, loss of material, material weighing divergences, reversals not concluded in the ERP, etc. For this verification we compute the data from the model, add those excluded values found in the ERP system and compare it to the final position of stock in the ERP. This process is demonstrated in Table 10.

Table 10 – Inventory position (in thousand tons) for model verification

Material	Initial inventory	Other movements	Final inventory (ERP)	Final inventory (model)	Model + other	Total Error
KCL GR	44.793	839	35.692	34.852	35.692	-
YMILA 16 16 16	9.456	-120	23.666	23.787	23.666	-
UREIA GR	8.658	3.049	12.879	9.830	12.879	-
SSP GR	3.980	421	10.479	10.058	10.479	-
YMILA 19 04 19	-	39	10.065	10.026	10.065	-
YMILA 13 24 12	8.669	640	9.759	9.119	9.759	-
YLIVA NITRABOR	4.713	203	9.104	8.901	9.104	-
SAM GR	2.973	50	9.129	9.015	9.065	0,70%
YVERA 40	425	222	8.667	8.445	8.667	-
YBELA AXAN	8.454	-34	7.701	7.735	7.701	-
TSP GR	22.377	1.222	7.546	6.323	7.546	-
YMILA 21 07 14	138	242	3.307	3.065	3.307	-
SAM STD	4.278	-184	3.056	3.239	3.056	-
NAM	-	-114	1.429	1.542	1.428	0,07%
KRISTA SOP GR	263	12	1.045	1.033	1.045	-
UREIA ADBLUE	683	-3	420	423	420	-
DAP GR	4.474	119	224	105	224	-
YTERA CALCINIT	52	-	107	107	107	-
NIP GR	193	-6	86	92	86	-
PG MIX 14 16 18	49	1	85	84	85	-
KRISTALON 13 40 13	11	-	55	55	55	-
KRISTA K	134	-1	48	49	48	0,01%
KRISTA MKP	14	-	34	34	34	-
KRISTALON 06 12 36	30	-	20	20	20	-
KRISTALON 15 05 30	31	-	19	19	19	0,03%
KRISTA SOP ST	1	-2	9	11	9	0,05%
KRISTA MAG	7	-	7	7	7	-
KRISTA MAP	49	-	2	2	2	-
Total	**187.249**	**13.119**	**252.970**	**239.785**	**252.904**	**0,03%**

Source: the author (2020).

The error is calculated based on the "Model + other" – which represents the final inventory of the model plus the other movements – divided by the final inventory at the

ERP system. The error level, as expected is very low with a total error of 0,03%. Only a few materials present errors, which are likely to be related to rounding numbers, as the data inputs of the models are in thousand tonnes while the ERP computes those in tonnes or kilograms. Having defined the model basic supply, the following section describes the conceptualization and construction of the planning and replenishment model.

4.3 PLANNING AND REPLENISHMENT MODULE

In order to replicate into the model all those rules, logics, and premises from the replenishment plan, first, the forecast is uploaded in Stella in an Excel spreadsheet. The Forecast is defined as time-varying and arrayed by units, raw materials, and the forecasting month, therefore a three-dimension array (denoted in Stella as $Forecast[Units; RawMaterial; Forecasting\ Month]$). The forecasting month array is necessary in order to replicate the forecasting alterations at each month. It has 12 values representing each one month, ranging from F1811 to F1910, being that the first two digits are the forecast year and the last two the forecast month. Each time unit can have up to six forecast months which are updated at each planning cycle, i.e. at each month, thus the reason to create an array. The forecast month array is also useful later to determine the expected lead time or estimated time of arrival of the materials, which is used together with the model time units – for the comparison of months and the model time units please see APPENDIX C – MODEL TIME UNITS TABLE. The logic behind the forecast variable is exemplified in Table 11.

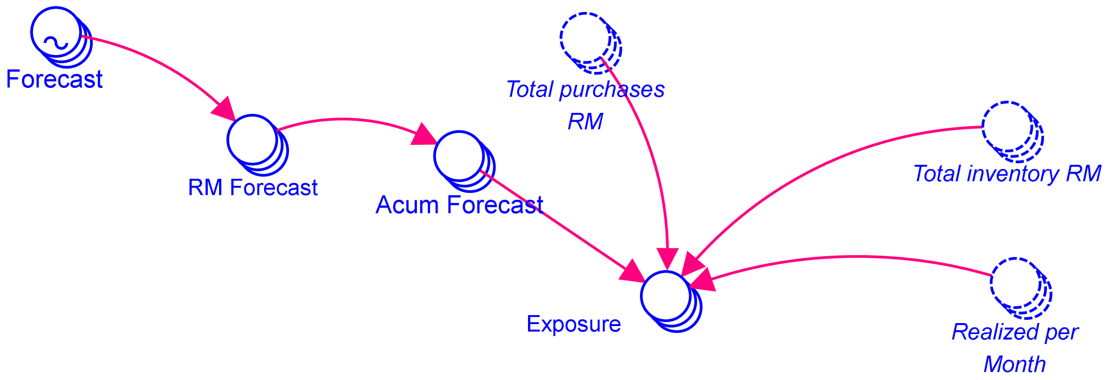
Table 11 – Forecast variable example

Raw Material	Week	Current Month	Unit	Forecast month	Quantity
KCL GR	5	November	CAN	F1811	67.747
KCL GR	5	November	CAN	F1812	33.018
KCL GR	5	November	CAN	F1901	10.160
KCL GR	5	November	CAN	F1902	7.498
KCL GR	5	November	CAN	F1903	9.477
KCL GR	5	November	CAN	F1904	13.066
KCL GR	6	December	CAN	F1811	2.279
KCL GR	6	December	CAN	F1812	3.414
KCL GR	6	December	CAN	F1901	3.608
KCL GR	6	December	CAN	F1902	11.993
KCL GR	6	December	CAN	F1903	7.010
KCL GR	6	December	CAN	F1903	12.015

Source: the author (2020).

Other than the forecast variable, another variable that aggregates the forecast by raw material – “forecast RM” – is created along with the accumulated forecast for the next 1 to 6 months – “accum forecast”. Those variables are then utilized to calculate the exposure in the model. The exposure variable is also arrayed by raw material and forecast month. Also the variables total purchases for raw materials, total inventory of raw materials, and total realized consumption per month – those are metrics created in a metrics module, please refer to Appendix D for further details– are created in order to calculate the raw material exposure, as defined in equation (1).

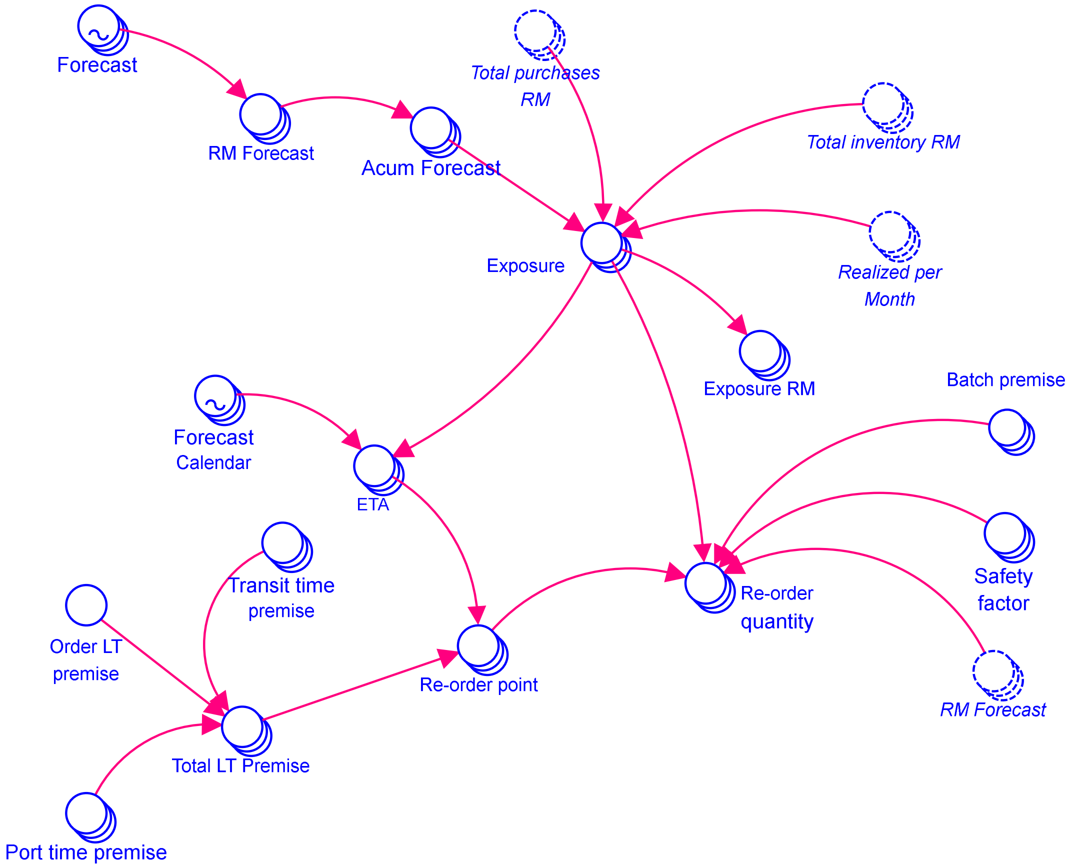
Figure 26 – Raw material exposure model representation



Source: the author (2020).

Then, in order to calculate the estimated time of arrival or the expected lead time another variable called forecast calendar is created. This variable is utilized to measure how much time the model has to make a replenishment re-order in for a given material in a given forecast month. Then the forecast calendar is time-varying and arrayed by forecast month which represents how many weeks are left to the future forecast months. Since the planning process is executed once per month and the forecast considers a whole month and not weeks, the time between two months is considered to be the difference between the end of the ongoing month and the beginning of the future month. Please refer to Appendix E for the details on the forecast month and the model time units. Figure 27 presents the re-ordering model representation.

Figure 27 – Re-ordering model representation



Source: the author (2020).

The ETA is equal to the forecast calendar if the exposure for the raw material at the forecasting month is greater than zero, otherwise it is always zero. The lead time premises are also included and the “Total LT Premise” sums up all of those premises. The “Re-order point” variable is a binary variable that denotes if a material should be re-ordered or not. In order to simulate the company’s replenishment plan, the “Re-order point” points out for a replenishment need only if the expected time of arrival (ETA) is less than or equal to the total lead time premise. It is important to note that the lead time premise considers the difference between the end of the current month and the beginning of the forecasted month, which provides some margin for delays – please see Appendix E for further details. Also the “Re-order point” is not active (equals 0) if the “ETA” is zero – i.e. no exposure – and it accumulates all raw material exposures up to the forecasting month where the expected lead time is greater than the “ETA”. To better illustrate this logic, the “Re-order point” code is presented as follows:

```
IF (ETA[RawMaterial;Forecasting_month] <= Total_LT_Premise[RawMaterial]
        AND NOT( ETA[RawMaterial;Forecasting_month] = 0)
        AND ETA[RawMaterial; Forecasting_month+1] > Total_LT_Premise[RawMaterial] )
THEN 1
ELSE 0
```

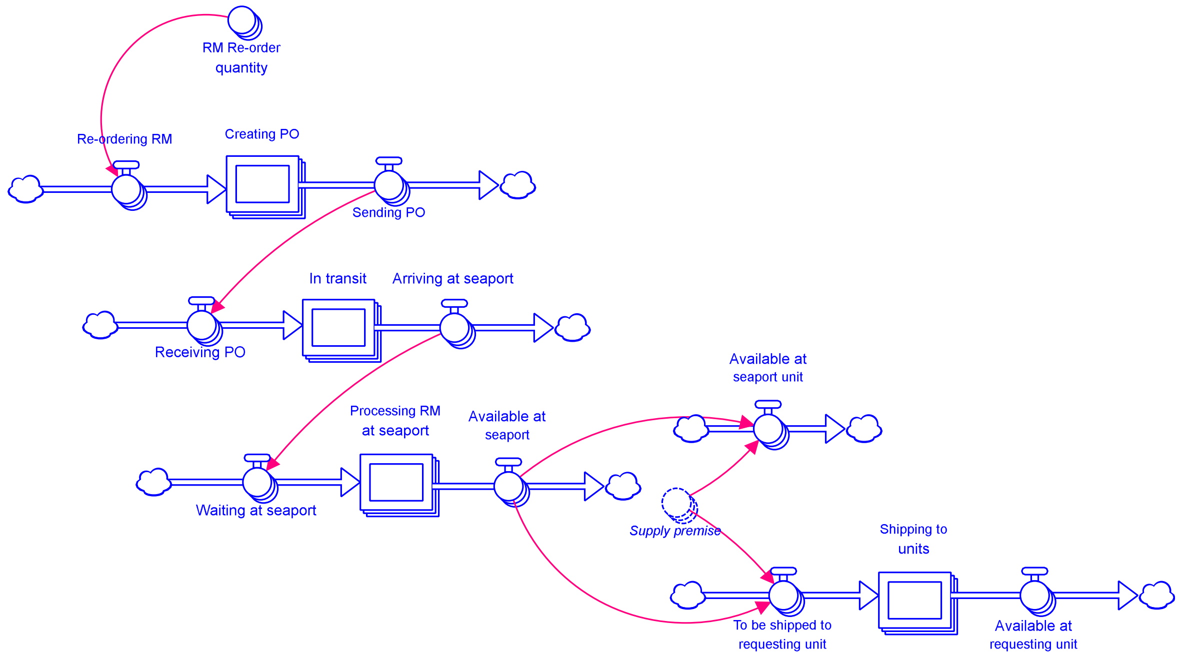
If the "Re-order point" equals to one, then the re-order quantity uses the exposure, the batch premise, the safety factor and the raw material forecast to create to request a replenishment for the raw material. The re-order quantity is the exposure material plus the additional inventory for the safety factor In order to explicit the calculation behind the re-order quantity, the following code is presented:

```
IF "Re-order_point" = 1
THEN
        IF ( Safety_factor [RawMaterial] = 1)
                THEN (INT ((Exposure [RawMaterial; Forecasting_month] + RM_Forecast
                [RawMaterial; Forecasting_month]) / Batch_premise [RawMaterial]) + 1) *
                Batch_premise [RawMaterial]
                ELSE
        IF Safety_factor [RawMaterial] = 2
                THEN (INT ((Exposure [RawMaterial; Forecasting_month] + RM_Forecast
                [RawMaterial; Forecasting_month + 1] + RM_Forecast [RawMaterial;
                Forecasting_month + 2]) / Batch_premise [RawMaterial]) + 1) *
                Batch_premise[RawMaterial]
                ELSE
        IF Safety_factor [RawMaterial] = 3
                THEN (INT ((Exposure [RawMaterial; Forecasting_month] + RM_Forecast
                [RawMaterial; Forecasting_month + 1] + RM_Forecast [RawMaterial;
                Forecasting_month + 2] + RM_Forecast [RawMaterial; Forecasting_month + 3])
                / Batch_premise [RawMaterial]) + 1) * Batch_premise[RawMaterial]
        ELSE (INT ((Exposure [RawMaterial; Forecasting_month]) / Batch_premise
        [RawMaterial]) + 1) * Batch_premise [RawMaterial]
ELSE 0
```

Then, the process of purchasing, delivering, and processing the raw material at the seaport is created. Once the material is processed at the seaport – i.e. has waited in the queue, unloaded and had its documentation released – it goes either straight to

RIG inventory or is shipped to any other supplying unit, as defined in the supply premise.

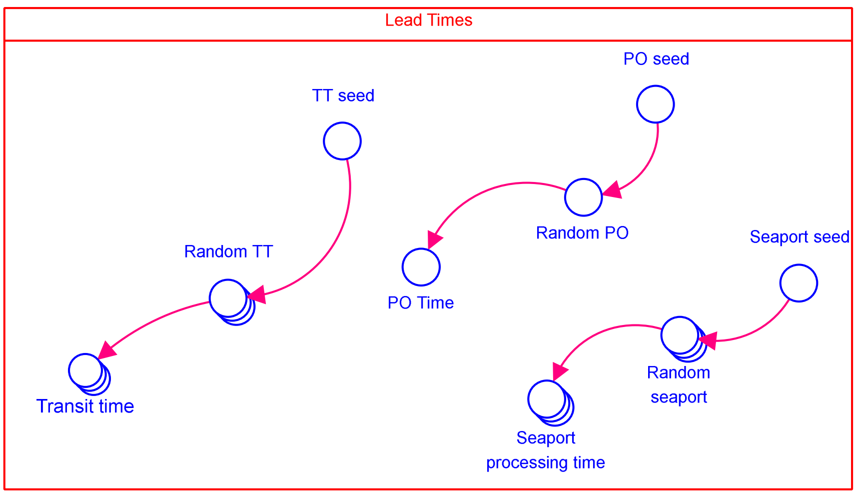
Figure 28 – Ordering raw material and seaport processing



Source: the author (2020).

All the lead time variables are created as ovens in order to have the order wait for their lead times. The model also simulates those lead times and they are inserted in its own module, as illustrated in Figure 29Figure 29.

Figure 29 – Lead times module

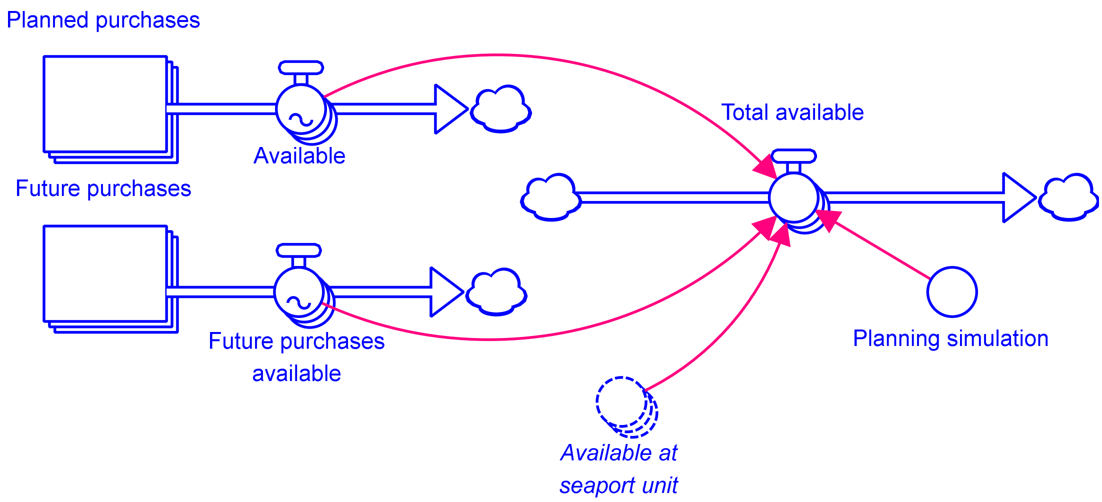


Source: the author (2020).

To simulate the lead times for order the order time, transit time, and seaport processing time the historical data of purchase orders are used. This historical data set has the one-year period of the model and was found in a supply team spreadsheet. For purchase orders, the difference between the purchase requisition and the purchase order is calculated, forming the order time. All the observations are separated and their probability range distribution is calculated – see Appendix F for order time distributions. A similar process is executed for the transit time and seaport time, except those are calculated individually for each raw material – see Appendix G and Appendix H, respectively, for more details on those distributions. In order to model the randomness of such variables, the connectors Random TT, Random PO, and Random seaport are created. Those create a random variable from 0,00 to 1,00, which is the probability of a certain time to occur, according to the probability functions created.

Finally, in order to have those purchases created in the planning simulation model to actually replenish the internal supply chain, the purchase model of the internal supply chain is slightly altered. A "Planning simulation" binary variable is created in order to turn on or turn off the part of the planning simulation. When this variable is set to 1, all the material flow on "Future purchases" is not considered anymore and the system starts to include the flows generated by the planning simulation. Figure 30 demonstrates this alteration.

Figure 30 – Incoming purchases



Source: the author (2020).

With the variability included in the system through the planning and replenishment module and its lead times the next section will demonstrate the inclusion of the TOC SC concepts in the model.

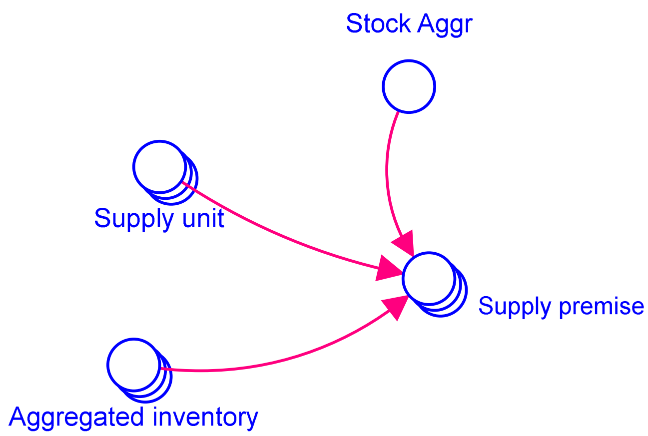
4.4 MODELING THE TOC STEPS

In this section, the construction of the simulation model to apply the TOC solution steps is presented.

4.4.1 Aggregating Stocks

The first step in the TOC supply chain solution is the aggregation of stocks at the highest point of the supply chain. In order to create this behaviour in the system two main alterations are necessary. First, the supply premise described in section 4.1 – see Frame 9 – is set always as the seaport unit (RIG). Second, due to the supply premise changes it is also required to change the transfers and re-order between the units. Therefore, a parameter variable for the stock aggregation is created in the model as a binary that controls whether the aggregation is being used or not. When this parameter is set to 1 then the supply premise is overwritten and RIG is set as the unit that supplies the materials for the other plants. Demonstrates this variable.

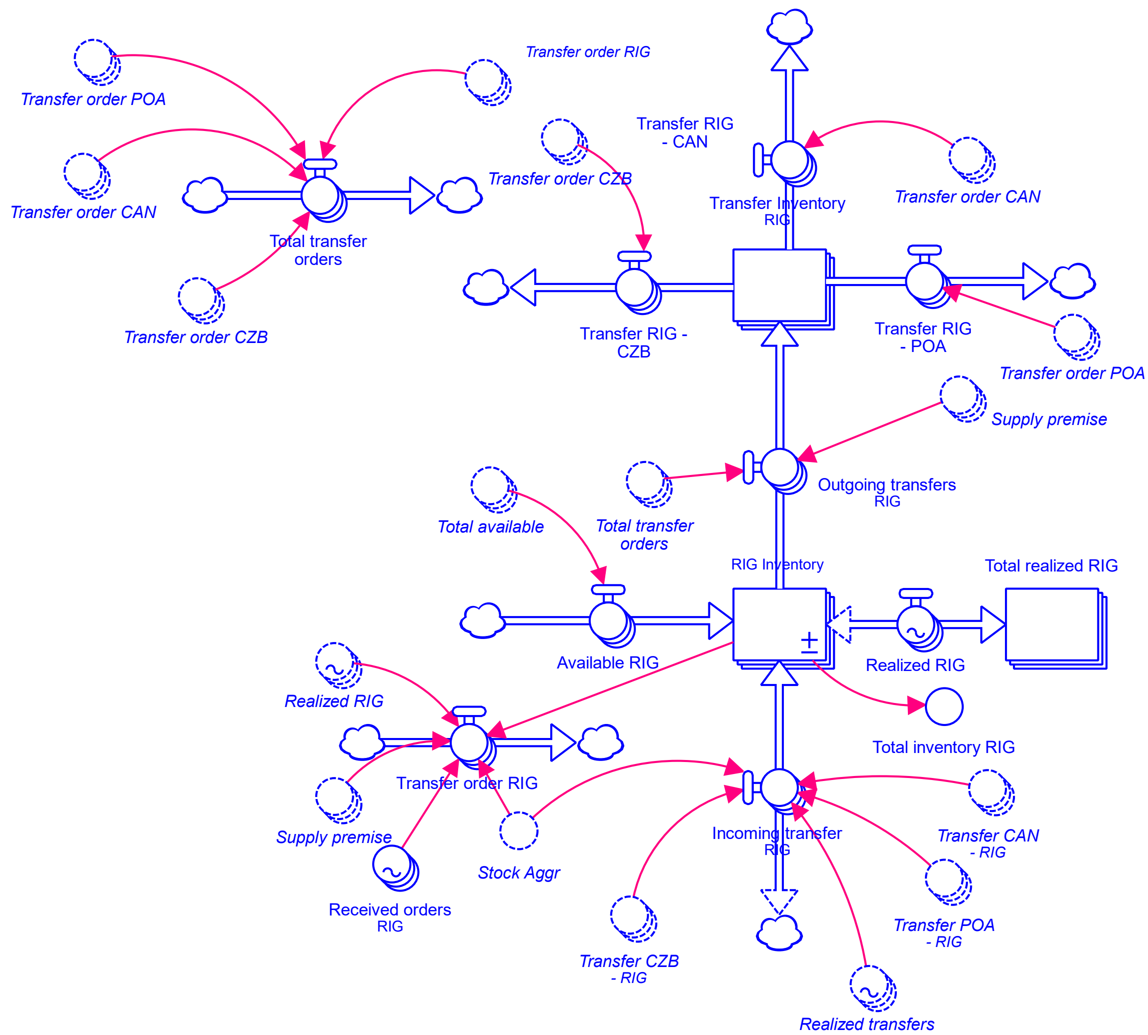
Figure 31 – Stock aggregation variable



Source: the author (2020).

Then the logic for requesting a re-order between units is created. The transfer orders are based upon the inventory held at the unit and the received sales orders. As an MTO production, the sales orders are received at least two weeks before delivery. The received orders converter is created in order to store these sales orders. This parameter is equal to the realized sales data, delayed by two weeks – representing the minimum time for a sales order to be received and fulfilled. A transfer order arrayed flow is created for each unit, representing the quantity the unit is requesting of each raw material. The transfer order quantity is calculated at each DT as the difference between received sales orders for the next two weeks and the inventory at hand in the unit. Therefore, each unit only requests the necessary quantity to cover its sales orders. All those transfer orders are summed into a total sales order flow that then is used to transfer the required raw material stock from the supplying unit to the requesting unit. Figure 32 exhibits the internal supply chain with the transfers for stock aggregation setup.

Figure 32 – Internal supply chain with transfer orders



Source: the author (2020).

The outgoing transfer flow is created to simulate an outgoing material from the supplying unit inventory to the transfer inventory. From the transfer inventory then the raw materials are “send” to the requesting unit – represented the transfer flows for each unit – and available in the incoming transfer flow of the respective unit. In that sense, the transfer orders are available one week after the request, which is the real lead time for such transfers. The next section covers the modeling of buffer sizes and the TOC RLT and described.

4.4.2 Determining Buffer Sizes Based on Demand, Supply, and The Replenishment Lead

To create the remaining steps of the TOC another module needs to be created and some alterations are to be made in the planning module. A few binary parameters are created in order to control the TOC steps application. For this step specifically the parameters created are the TOC buffer and the TOC RLT. The TOC size is defined as proposed by Youngman (2009):

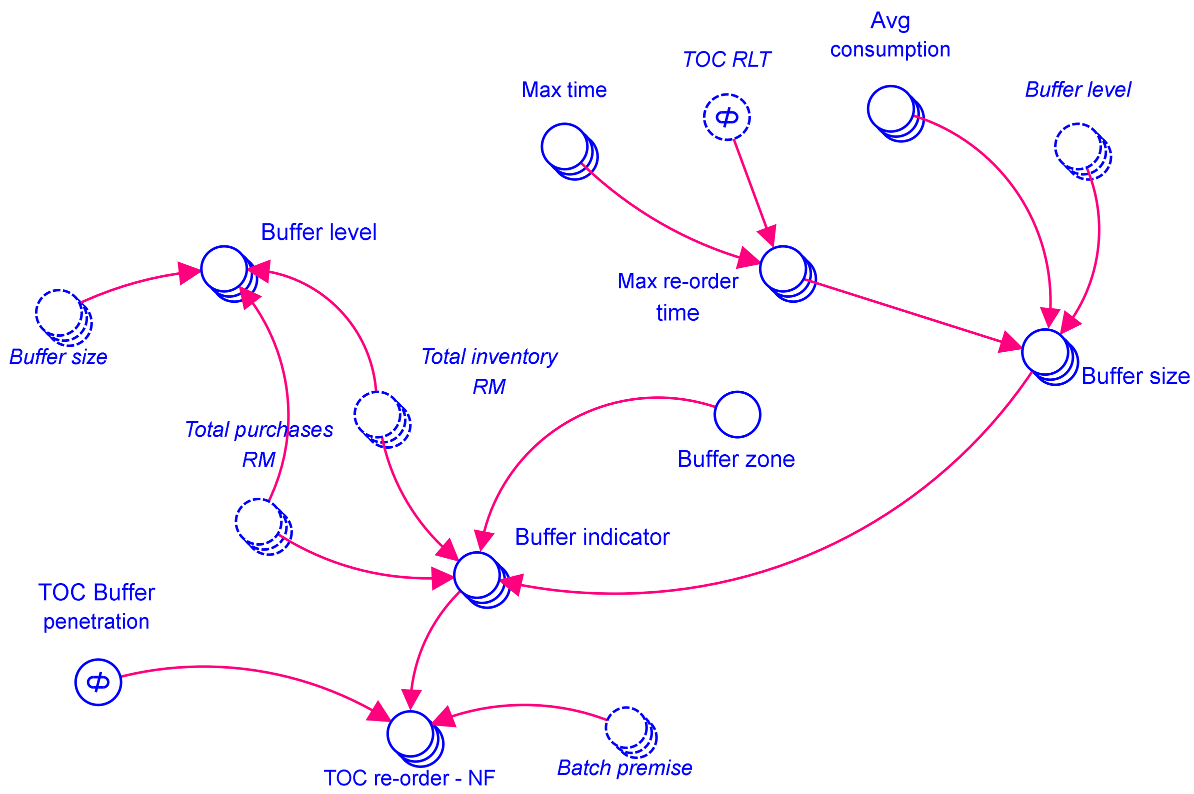
$$\begin{aligned} Buffer\ size = \ & Maximum\ re - order\ time * \ average\ comsumption \\ & + measure\ of\ safety \end{aligned} \tag{3}$$

The measure of safety is usually defined as 50%. The maximum time is calculated based on the historical supply data, while the weekly average consumption of the raw materials. Both variables are uploaded in the model by raw material in an excel spreadsheet. Then to simulate the replenishment lead time reduction proposed by the TOC, when the TOC RLT parameter is set to 1 there is no time from the identification of replenishment and the creation of the re-order; therefore, the RLT is 0 and the re-order is set directly to in transit, meaning that the supplier is already processing that order. It is important to note that, in this step, the model still uses the forecast to know when to issue a re-order. It only uses the buffer size in order to determine the re-order quantity. Having described the buffer sizing, the management of inventory using buffer penetration is presented next.

4.4.3 Managing Inventory Using Buffer Penetration

When the buffer penetration is used, the ordering process no longer uses the forecast. Once again, a few alterations are made and the TOC buffer penetration binary parameter is created. This parameter sets the utilization of the TOC re-order and overwrites any other orders based on the forecast. Figure 33 presents this part of the model as well as some components from the buffer size determination.

Figure 33 – Buffer penetration modeling



Source: the author (2020).

The buffer indicator is the main component in this part. This converter calculates the actual level of buffer penetration and issues a re-order if the level is smaller then the inventory in hand plus the open purchase orders. The buffer penetration level is the inventory on hand plus the already ordered units, described as a percentage of the buffer size. If the penetration level is smaller than 1, then a re-order must be issued. The “TOC re-order – NF” (NF meaning no-forecast) calculates the quantity necessary to replenish the buffer considering the batch premises for each raw material, then representing a re-order issue. This quantity is then sent back to the planning module in order to purchase the raw material. The following step is to use dynamic buffers, which is described on the next section.

4.4.4 Using Dynamic Buffers

The utilization of dynamic buffers is inputted in the system in a straightforward way. A binary variable parameter is created, if set to one the buffer size may change. Then we change the buffer size variable to simulate the Dynamic Buffer step of TOC. In order to measure the buffer penetration, the buffer level variable is created. The buffer level is represented as a percentage of the stock in hand plus the orders already issued divided by the current buffer level. The buffer size code is then altered to the following:

IF Dynamic_buffer = 0
*THEN ("Max_re-order_time" * Avg_consumption) * 1,5*
ELSE
IF (DELAY (Buffer_level; 1; 1) > 0,66 AND DELAY (Buffer_level; 2; 1) > 0,66 AND DELAY (Buffer_level; 3; 1) > 0,66 AND DELAY (Buffer_level; 4; 1) > 0,66)
*THEN ((("Max_re-order_time"*Avg_consumption)*1,5)*0,67)*
ELSE
IF (DELAY (Buffer_level; 1; 1) < 0,34 AND DELAY (Buffer_level; 2; 1) > 0,34 AND DELAY (Buffer_level; 3; 1) > 0,34 AND DELAY (Buffer_level; 4; 1) > 0,34)
*THEN ((("Max_re-order_time" * Avg_consumption) * 1,5) * 1,33)*
*ELSE ("Max_re-order_time"*Avg_consumption) * 1,5*

The logic above states that if the dynamic buffer parameter is zero, the buffer size is as described previously. Otherwise, it will monitor the buffer levels during the last four weeks and decrease the buffer size in one third if the buffer level was greater than 66% during that time; it will keep increase the buffer size by one third if the buffer level was smaller than 34% for the last four weeks; it will keep the buffer size the same for as long as the two other conditions are not met. With the application of the dynamic buffer, all of the TOC steps that were possible to be used in the cased were created. Since the model does not consider the manufacturing part of the system, the manufacturing prioritization step can’t be applied. Regarding the increase of the replenishment frequency, although it is not directly applied in the model, it occurs is a consequence of the aggregation of stocks and the utilization of the TOC buffers. The replenishment frequency will be covered in detail in the data analysis section. In the next section, a hybrid solution considering the case specificities and the TOC solution is described and modeled.

4.4.5 Creating a Hybrid Solution Utilizing Buffers and Forecast

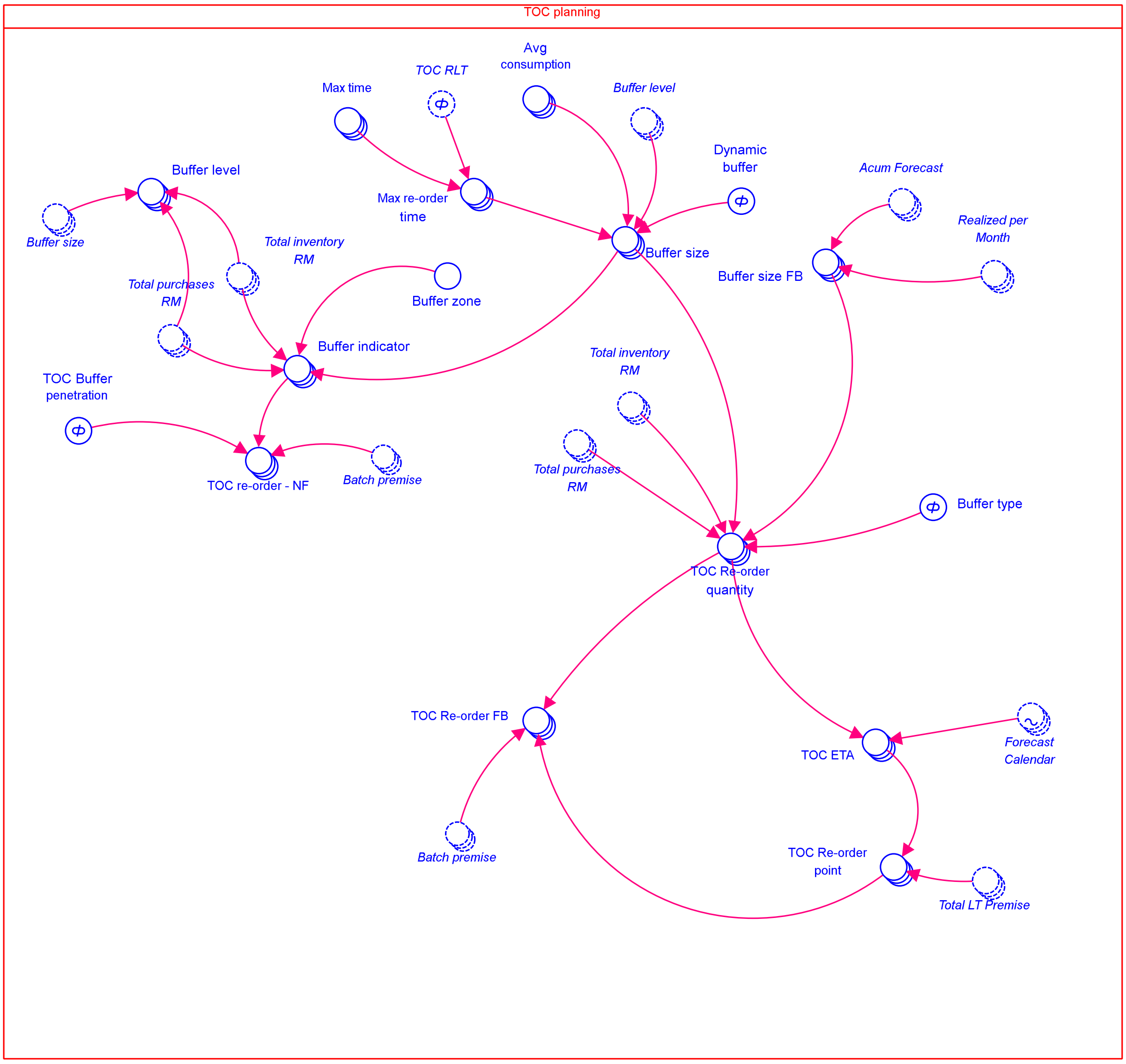
A hybrid model that uses the TOC buffer management and some information from the forecast is also proposed. This model is created to measure if it is possible to use the forecast information in conjunction with the TOC solution to achieve better results than the proposed steps and to deal with seasonality from the case. Schragenheim (2010) affirms that TOC's DBM does not handle well seasonality in demand and even proposes a few techniques to improve the method. This method is rather simplistic tough, consisting of disabling the dynamic buffer and stocking up prior to high seasons and the opposite to deal with sudden decreases of demand. In order to foresee seasonality patterns then, the forecast is still used. The current model creates a hybrid solution utilizing TOC solution steps and drawing information from the forecast.

The main change regards the buffer size and the re-ordering point. To do so a "buffer size FB" (forecast-based) is created. This buffer size is set according to the accumulated forecast of the forecast month and only replenished if the estimated time of arrival is smaller than or equal to the remaining time to that specific month. This re-order point is quite similar to the one that is utilized in the model currently. The buffer size is defined as:

$$Buffer\ size\ FB = \left|\sum_{fm=1}^{6} Forecasted\ Consumption_{rm\ fm} - Realized\ Month\ Sales_{RM}\right| * 1{,}5 \qquad (4)$$

Then if the buffer size is smaller than the inventory in hand and the raw material already ordered must be issued to replenish the buffer. In the model, the TOC re-order based on the forecast is calculated based on the quantity necessary to replenish the buffer plus the estimated time of arrival of the material for that future month. This follows the same logic as in the planning module and is with the TOC as well. Along with the other TOC steps described, this part composes the TOC planning module, as shown in Figure 34.

Figure 34 – TOC planning module



Source: the author (2020).

The presentation of the TOC planning module concludes all the modeling logic created. An additional module, however, is necessary in order to have the TOC performance measure, as well as many other indicators of inventory and consumption. Then, the performance measures module is presented next.

4.4.6 Performance Measures

Three main indicators are used to analyze the model and its results. From the TOC, the TDD and IDD are the main. Additionally, inventories also receive special attention and are tracked by the average stock positions. The TDD measures how much throughput the system is losing per day due to delayed orders, while the IDD measures how well the inventories are positioned (the right material at the right time). The main goal is to minimize the TDD while keeping the IDD as low as possible. In the model, the TDD and the IDD are calculated as:

$$TDD = Price_{rm} * Unmet\ demand_{rm} * order\ delay_{rm} * 7 \tag{5}$$

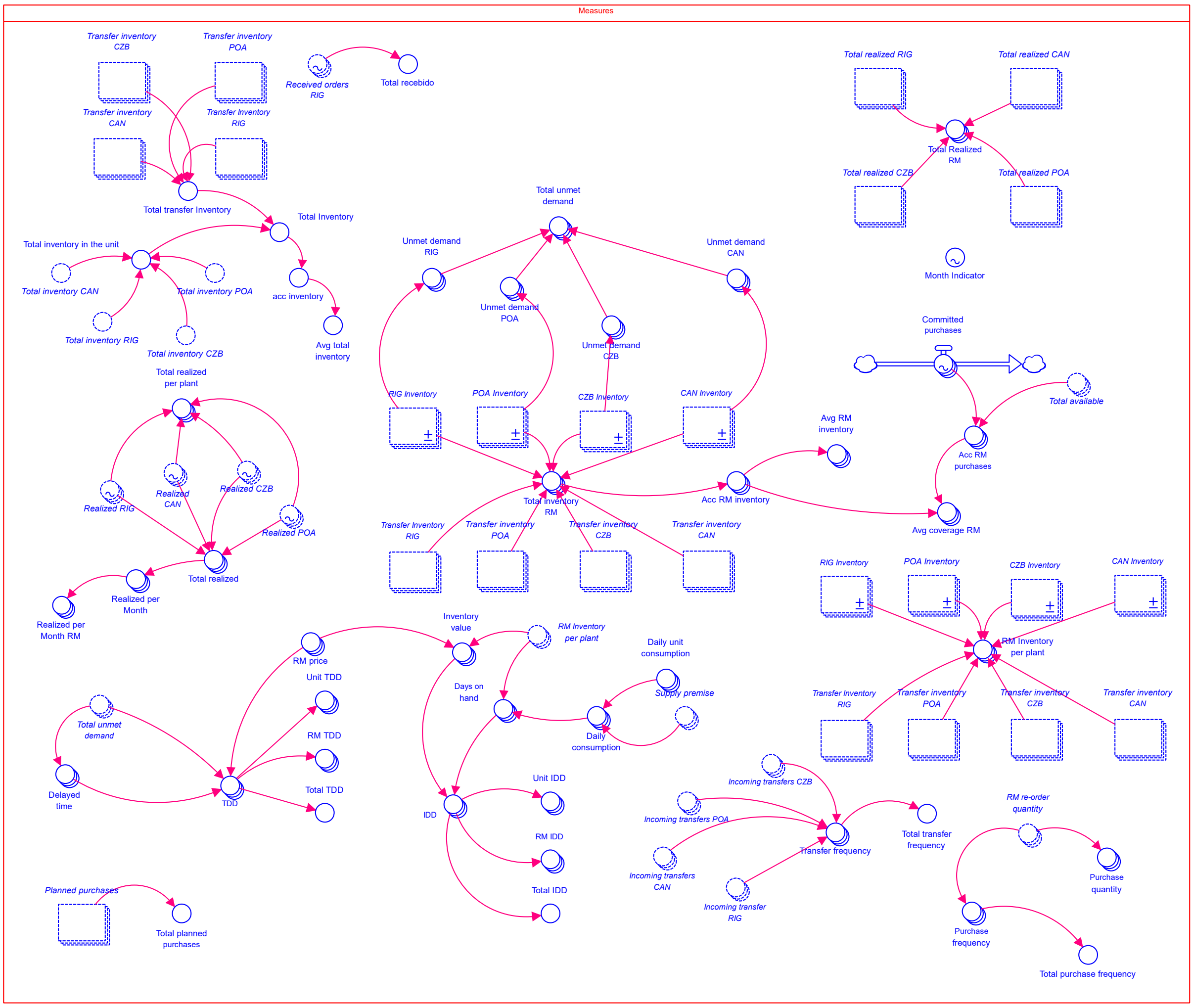
$$IDD = Days\ of\ inventory\ in\ hand_{rm} * Price_{rm} \tag{6}$$

Where:

$rm = raw\ material.$

It can be noted that the TDD has to be multiplied by 7 as the unmet demand can be only be measured in weeks. Since the IDD can be measured in days due to the average daily consumption is uploaded in the model in days. All those measures are used for analysis, verification, and validation purposes and need to be tracked in different layers of raw materials and units, which lead to several converters.

Figure 35 – Measures module



Source: the author (2020).

The measures module finishes the construction of the model. For an overall view of the model please refer to Appendix I.

4.5 MODEL VALIDATION

In order to validate the model, the final average stock position is utilized with all TOC parameters set to 0. The total inventory is validated as well as the main raw materials that compose the model. The raw materials are selected based on their purchase volume ratio compared to the total volume of purchases and the number of observations available (i.e. the number of purchase orders). The selection criteria per raw material are therefore defined as volume % of total purchases of at least 5% and a minimum of 15 observations available. These criteria lead to the selection of 6 materials to be validated: KCL GR, UREIA GR, YBELA AXAN. YMILA 16 16 16, TSP GR, and SAM GR. Table 12 exhibits the criteria for all raw materials; those marked in light blue are selected materials.

Table 12 – Observations and purchase volumes by raw material

Raw material	# Observations	Purchase volume	Volume % of total
KCL GR	84	549.377,14	37%
UREIA GR	50	263.782,00	18%
YTERA CALCINIT	26	2.196,00	0%
YBELA AXAN	23	106.640,00	7%
UREIA ADBLUE	21	3.772,00	0%
YMILA 16 16 16	20	124.908,44	8%
TSP GR	17	94.952,00	6%
SAM GR	15	69.673,68	5%
SSP GR	14	84.000,00	6%
KRISTA K	11	312,00	0%
YLIVA NITRABOR	9	30.054,00	2%
YMILA 13 24 12	9	44.630,00	3%
YMILA 19 04 19	8	28.643,00	2%
YVERA 40	8	33.041,00	2%
KRISTALON 06 12 36	8	216,00	0%
PG MIX 14 16 18	6	144,00	0%
KRISTA SOP ST	4	98,00	0%
YMILA 21 07 14	3	13.220,00	1%
KRISTA SOP GR	3	1.056,00	0%
KRISTA MKP	3	72,00	0%
NAM	3	12.751,00	1%
NIP GR	3	1.008,00	0%
DAP GR	3	8.796,00	1%
KRISTA MAG	3	69,00	0%
KRISTA MAP	3	82,50	0%
KRISTALON 13 40 13	3	72,00	0%
KRISTALON 15 05 30	2	48,00	0%
SAM STD	1	4.400,00	0%
Total	**363**	**14.78.013,755**	100%

Source: the author (2020).

Having defined the variables to validate the model, a sensitivity analysis is conducted in Stella with 30 different runs to find the final (week 55) average stock positions. The final stock position is used as the delays caused intentionally by the system can diverge from the real values. For example, an order can arrive 2 weeks later in simulation and the stocks positions would not be comparable in the same week. If this happens with a high-volume order, it might be significant in the overall result. However, the average position at the end of the year should be very likely to be comparable, providing a good measure for validation. The mean, standard deviation, and confidence intervals are computed by Stella and set to a 5% significance. Additionally, the t-student test is conducted in the data in order to verify the error and to check if the sample size is adequate, again 5% significance is used. The maximum error allowed is 10% of the real result. Table 13 demonstrates all those calculations.

Table 13 – Model validation results

Result variable	Real result	Mean result	Standard deviation	Lower bound	Upper bound	t	Error	Max error allowed	n
Total Inventory	195.356	200.497	13.487	166.000	219.000	2,0452	5.036	97.678	0
KCL GR	65.022	64.422	8.109	46.100	77.300	2,0452	3.028	6.502	7
SAM GR	8.774	8.221	1.252	5.780	10.800	2,0452	467	877	9
TSP GR	16.535	22.095	3.016	14.900	26.800	2,0452	1.126	1.653	14
UREIA GR	19.494	18.418	5.148	8.830	27.800	2,0452	1.922	1.949	29
YBELA AXAN	16.818	18.788	1.206	16.300	20.600	2,0452	450	1.682	2
YMILA 16 16 16	17.744	16.518	1.871	11.300	18.300	2,0452	699	1.774	5

Source: the author (2020).

From the table above, it is possible to observe that all the real results are within the confidence bounds of the model. No error is greater than the defined maximum error and from the sample size (n) calculation the greater value is of 29 for one raw material, as there were 30 samples the number of experiments is enough. Therefore, it is possible to consider the model validated. Appendix I present the charts from Stella for all the results as well as their confidence intervals and means.

5 ANALYSIS OF THE RESULTS

This section covers the analysis of the results found in the model. In order to observe the results of the TOC application, seven scenarios are created and simulated procedurally for each TOC solution step application plus two hybrid proposals. This hybrid solution is described in section 4.4.5. In the last scenario, in order to deal with seasonality, during the high season the traditional TOC buffers are “turned-off” and the forecast based buffers are used instead. So, the scenario uses the traditional TOC approach part of the time and the research proposed approach for the other part. The simulation results are generated through the sensibility run function of *Stella*, which simulates and compares multiple runs of the defined model and scenario. In the simulations, the analyzed variable results are throughput-dollar-days (TDD), inventory-dollar-days (IDD), and inventory position. Additionally, the purchase and transfer frequency are also assessed to estimate the any impacts in those variables. The six initial scenarios and the model variables used to setup them are the same as described in the data analysis section.

First, the results of the base model are presented utilizing a descriptive analysis. Next, the results of the scenarios are also described for the TDD, IDD, inventory – both at the CWH and the “shops” –, and purchase frequency. These are presented in descriptive statistics followed by statistical significance tests to determine if the results are initially statistically significant or not. Finally, the distributions are compared and the causal impacts analysis is conducted. Hence, being possible to measure the causal effects, how long it takes to observe the effects in the system, and if they are statistically significant or not. All the comparisons are made to the base model and between scenarios as well.

5.1 BASE MODEL RESULTS AND DESCRIPTIVE ANALYSIS

The base model results are the ones to be compared with results of the other scenarios. Therefore, a descriptive analysis is realized for these results, as presented in Table 14. From this it is possible to establish the ground truth of the simulation and the base comparison. Beside the total TDD and IDD of the system, the inventory is analyzed in its integrity, as well as the amount in the central warehouse (CWH) – the supplying unit for the case, i.e., the RIG unit – and the shops – in the case, all the other units. The sum column provides the aggregated value of the variable during the total time period.

Table 14 – Base model descriptive statistics

Variable	Mean	Standard Deviation	Minimum	1st quartile	3rd quartile	Maximum	Sum
TDD	501.669	604.235	-	55.208	648.198	2.567.107	27.591.846
IDD	7.384.706	3.116.739	2.521.564	5.064.310	8.448.708	14.974.969	406.158.857
Total Inventory	213.367	63.971	126.603	163.292	256.469	336.459	11.735.213
CWH Inventory	149.757	57.030	74.270	102.861	191.637	277.428	8.236.676
Shop Inventory	63.609	16.285	33.307	52.915	75.398	104.346	3.498.537

Source: the author (2020).

The values for TDD and IDD are in $ and the inventory in thousands of tonnes. From the data presented, it is possible to note the high values of delayed orders represented by the TDD. A total sum of 27,5 million dollars in the throughput-dollar-days seems high. Especially considering the high levels of inventory, shown in the 11,7 million tonnes of total inventory and the $ 406 million of inventory-dollar-days. Also, the CHW has approximately 70% of both the mean and the sum of the total inventory, so most inventory is kept at the RIG unit and only 30% is kept at the other three units.

The normality of these results is also checked through the Shapiro-Wilk test with 5% significance. Table 15 presents the tests resulting values of the test statistics (W) and p-value for each variable. Given that the p-values are all below the significance level of 0,05, it is not possible to affirm that the data is normally distributed. Therefore, for the comparison of the scenarios non-parametric tests will be necessary.

Table 15 – Shapiro-Wilk results for the results

Variable	W	p-value
TDD	0,7794	0,0000
IDD	0,9197	0,0013
Total inventory	0,8991	0,0002
CWH inventory	0,9068	0,0004
Shop inventory	0,9513	0,0262

Source: the author (2020).

5.2 SCENARIO COMPARISON

In order to have a general overview of the application of the TOC steps in the model, following on the previous analyses descriptive statistics are used again to complement results. After the descriptive analysis presentation, multiple comparison tests are conducted to check for statistical significances among the scenarios. Thus, the first descriptive analysis concerns the impacts of TOC application in terms of the TDD and IDD, which is presented in Table 16. In the table the descriptive statistics are presented, as well as the percentual mean difference between the respective scenario and the base model scenario. These analyses are then followed by the same comparison for the inventories and the purchase frequency.

Table 16 – Scenarios descriptive analysis for TDD and IDD

Scenario	Var.	Mean	Standard Deviation	Minimum	1st quartile	3rd quartile	Maximum	Sum	% mean diff.
Base	TDD	501.670	604.235	-	55.208	648.198	2.567.108	27.591.847	-
Base	IDD	7.384.707	3.116.739	2.521.564	5.064.311	8.448.709	14.974.969	406.158.858	-
1	TDD	193.068	220.780	1.250	29.035	274.767	738.433	10.618.725	-62%
1	IDD	4.479.555	2.334.657	1.495.035	2.893.247	5.923.281	11.268.154	246.375.550	-39%
2	TDD	182.284	170.778	1.250	14.400	293.461	551.291	10.025.595	-64%
2	IDD	9.227.213	4.792.996	2.331.623	4.625.740	13.787.214	16.239.031	507.496.726	25%
3	TDD	574.932	626.478	1.250	33.205	1.229.271	2.129.896	31.621.247	15%
3	IDD	6.361.947	3.591.123	922.311	2.265.843	9.466.318	11.671.744	349.907.088	-14%
4	TDD	901.526	990.289	1.250	37.113	1.880.859	3.464.344	49.583.943	80%
4	IDD	4.104.588	2.584.922	334.504	1.114.536	5.918.391	7.821.569	225.752.325	-44%
5	TDD	40.651	53.761	-	4.882	55.873	200.627	2.235.824	-92%
5	IDD	8.747.799	5.933.853	2.148.634	4.127.950	12.798.994	21.791.406	481.128.918	18%
6	TDD	67.668	91.595	-	5.906	71.796	353.476	3.721.721	-87%
6	IDD	13.331.604	3.819.707	4.985.657	11.847.073	15.631.702	21.853.624	733.238.213	81%

Source: the author (2020).

From the data presented above, it is possible to have an initial perception of the impacts of the TOC's implementation on the system. Scenarios 1, and 2 present an incremental decrease in the TDD. Scenario 1 – the aggregation of stocks – present the highest improvement in the IDD. Therefore, the stock aggregation presents more inventory accuracy – the right stock at the right location, while scenario 2 seems to prioritize the protection of the throughput. As can be noted, the usage of buffer and RLT reduction – scenario 2 – seems to protect the buffer at the expanse of more inventories, hence the increase of the IDD. In scenario 3 it is possible to note an improvement in the IDD along with an TDD increase. For scenario 4 – dynamic buffer management – the TDD is worse than in scenario 3, even though the IDD is improved. For scenarios 5 and 6, which combine forecasting models with the TOC solution it is possible to observe that the IDD is better than the previous scenarios. The difference between the two is the IDD, which is better in scenario 5, even though it is higher than the base model.

Continuing the analysis, the inventories are also assessed and presented in Table 17. From the aggregation of stocks, the "shops" – i.e. the mixing units – inventories are improved and stays the same throughout the following scenarios, while the total inventories seem to increase. This is expected as the TOC steps are sequentially implemented in the model. Once the aggregation of stocks is applied to the model, the requesting units – i.e. the shops – issue transfers orders only with the consumption or sales quantities (as an MTO, the consumption is known for at least two weeks). However, as the shops hold less inventory, the inventories at the CWH increase. The inventories increase gradually in scenarios 1, 2, and 3 and decrease from the application of the dynamic buffer management. When compared to the base model, only with the usage of the dynamic buffer management is that the total inventory is reduced. Scenarios 5 and 6 also increase the total inventories, but 6 presents the highest inventory levels among all scenarios.

Table 17 – Scenarios descriptive analysis for inventory

Scenario	Variable	Mean	Standard Deviation	Minimum	1st quartile	3rd quartile	Maximum	Sum	%mean difference
Base model	Total inventory	213.368	63.971	126.604	163.293	256.470	336.459	11.735.214	-
1	Total inventory	217.224	68.817	127.205	164.980	259.207	363.946	11.947.333	2%
2	Total inventory	296.254	82.970	141.040	220.726	374.013	416.298	16.293.975	39%
3	Total inventory	224.542	72.369	107.371	154.694	290.020	336.042	12.349.795	5%
4	Total inventory	174.957	76.445	43.175	99.443	239.441	291.031	9.622.627	-18%
5	Total inventory	321.240	117.248	141.040	229.433	445.723	514.792	17.668.210	51%
6	Total inventory	366.775	80.615	141.040	352.400	414.646	502.678	20.172.628	72%
Base model	CWH inventory	149.758	57.030	74.271	102.861	191.638	277.428	8.236.676	-
1	CWH inventory	196.298	72.264	77.843	145.881	244.575	343.751	10.796.394	31%
2	CWH inventory	275.328	89.217	77.843	204.318	357.495	390.613	15.143.035	84%
3	CWH inventory	203.616	75.656	77.843	130.436	277.056	306.975	11.198.855	36%
4	CWH inventory	154.031	77.332	24.203	79.248	227.183	263.256	8.471.687	3%
5	CWH inventory	300.314	122.200	77.843	210.750	425.528	493.033	16.517.270	101%
6	CWH inventory	345.849	88.343	77.843	330.339	391.224	476.366	19.021.688	131%
Base model	Shop inventory	63.610	16.285	33.308	52.916	75.399	104.346	3.498.538	-
1	Shop inventory	20.926	11.707	58	14.913	24.722	63.197	1.150.940	-67%
2	Shop inventory	20.926	11.707	58	14.913	24.722	63.197	1.150.940	-67%
3	Shop inventory	20.926	11.707	58	14.913	24.722	63.197	1.150.940	-67%
4	Shop inventory	20.926	11.707	58	14.913	24.722	63.197	1.150.940	-67%
5	Shop inventory	20.926	11.707	58	14.913	24.722	63.197	1.150.940	-67%
6	Shop inventory	20.926	11.707	58	14.913	24.722	63.197	1.150.940	-67%

Source: the author (2020).

In the model, the increase of the replenishment frequency is not used as a TOC step application. It is understood for the case situation that it is a necessary consequence or condition in order to implement all the other TOC steps. Thus, a descriptive analysis of the purchase frequency is also conducted in order to assess if the replenishment frequency – represented by the purchase frequency – is also impacted. This analysis is presented in

Table 18. From data presented in the table, it is possible to note that the purchase frequency increases greatly when compared to the base model. Since the TOC utilizes buffers and is always trying to replenish those it is logically accepted this increase of the purchase frequency. Since the model considers the batches premises of the suppliers, this increase should not be constraint. While the inventory aggregation does not change the frequency, as expected, scenario 5 has a slight increase though, all the other steps present a high increase in the purchase frequency.

Table 18 – Descriptive analysis for purchase frequency

Scenario	Mean	Standard Deviation	Minimum	1stquartile	3rdquartile	Maximum	Sum	%mean difference
Base	61,63	37,39	7	27	98	126	3.390	0%
1	61,6	37,39	7	27	98	126	3.390	0%
2	228,78	150,06	11	89	357	505	12.583	271%
3	203	146	6	63	329	476	11.166	229%
4	191	139	8	59	312	450	10.478	209%
5	75,81	42,06	13	37	120	140	4.170	23%
6	178	90	11	89	262	284	9.793	189%

Source: the author (2020).

Although the descriptive analyses presented are helpful to have an initial idea of the TOC implementation impacts, they do not present a sound and statistically valid answer. In order to so and to be able to compare the multiple scenarios presented, additional tests are necessary. First, in order to check if the scenarios differ among them a Kruskal-Wallis test is performed for all the interest variables. The Kruskal-Wallis non-parametric test is used as the variables are not normally distributed – as seen in the Shapiro-Wilk tests, presented in Table 15. All the seven scenarios are compared with a 5% significance level. The results of the test are presented in Table 19.

Table 19 – Kruskal-Wallis test for the interest variables

Variable	Chi square	Degrees of freedom	p-value
TDD	90,49	6	< 0,0001
IDD	126,90	6	< 0,0001
Total Inventory	133,62	6	< 0,0001
Purchase frequency	104,76	6	< 0,0001

Source: the author (2020).

Since the p-value for all variables is lower than the significance level, the null hypothesis that the variables have the same distribution functions is rejected. Thus, it can be inferred that at least one scenario differs from the others. In order to make this same comparison, but between each one of the scenarios presented, a multiple comparison test is utilized. Thus, the Hochberg multiple comparison test is conducted for all scenarios and for all the interest variables with a 5% significance level. The results of the test for the TDD are presented in

Table 20.

Table 20 – TDD multiple comparison test results

Scenario compared	Observed difference	Statistic	Adjusted p-value
Base - 1	32,66	1,75	0,4074
Base - 2	38,48	2,06	0,2820
Base - 3	-14,90	0,80	0,7559
Base - 4	-35,86	1,92	0,3353
Base - 5	121,96	6,52	-
Base - 6	98,71	5,28	-
1 - 2	5,82	0,31	0,7559
1 - 3	-47,56	2,54	0,0910
1 - 4	-68,53	3,66	0,0034
1 - 5	89,30	4,78	-
1 - 6	66,05	3,53	0,0051
2 - 3	-53,38	2,85	0,0409
2 - 4	-74,35	3,98	0,0011
2 - 5	83,48	4,46	0,0001
2 - 6	60,23	3,22	0,0139
3 - 4	-20,96	1,12	0,7559
3 - 5	136,86	7,32	-
3 - 6	113,61	6,08	-
4 - 5	157,83	8,44	-
4 - 6	134,57	7,20	-
5 - 6	-23,25	1,24	0,7559

Source: the author (2020).

From the p-values presented, it is possible to note that only scenarios 5 and 6 present a statistically significant TDD change when compared to the base model. This analysis also allows to verify the statistically significant changes between scenarios other than the base model. After the aggregation of stocks, scenarios 4, 5, and 6 present a change in the TDD when compared to scenario 1. Based on scenario 2, the application of steps 3 and 4 also present significant changes. Meaning that although both scenarios 1 and 2 do not significantly change the TDD they may serve as a base for the improvement of the IDD and inventory levels. Based on this, scenarios 5 and 6 present statistically significant changes in the results for TDD when compared to the TOC steps. The same is done for the IDD and is presented in Table 21.

Table 21 – IDD multiple comparison test results

Scenarios compared	**Observed difference**	**Statistic**	**Adjusted p-value**
Base - 1	84,91	4,85	0,0000
Base - 2	-26,24	1,50	0,5387
Base - 3	30,31	1,73	0,4206
Base - 4	88,45	5,05	0,0000
Base - 5	-3,95	0,23	0,8396
Base - 6	-111,64	6,38	-
1 - 2	-111,15	6,35	-
1 - 3	-54,60	3,12	0,0136
1 - 4	3,55	0,20	0,8396
1 - 5	-88,85	5,08	0,0000
1 - 6	-196,55	11,23	-
2 - 3	56,55	3,23	0,0107
2 - 4	114,69	6,55	-
2 - 5	22,29	1,27	0,6107
2 - 6	-85,40	4,88	0,0000
3 - 4	58,15	3,32	0,0088
3 - 5	-34,25	1,96	0,3063
3 - 6	-141,95	8,11	-
4 - 5	-92,40	5,28	0,0000
4 - 6	-200,09	11,43	-
5 - 6	-107,69	6,15	-

Source: the author (2020).

Regarding the IDD and comparing to the base model, only scenarios 1, 4, and 6 present statistically significant changes. When compared to the base model, scenarios 2, 3, and 5 seem to present similar distributions. Regarding the comparison between scenarios, the pairs of scenarios 1 and 4, 2 and 5, and 3 and 5 all seem to present similar results. Next, the analysis is conducted for the total inventory and presented in Table 22.

Table 22 – Total inventory multiple comparison test results

Scenarios compared	Observed difference	Statistic	Adjusted p-value
Base - 1	-4,25	0,25	0,8056
Base - 2	-95,62	5,54	-
Base – 3	-16,59	0,96	0,8056
Base – 4	30,79	1,78	0,3771
Base – 5	-108,44	6,28	-
Base – 6	-161,17	9,33	-
1 – 2	-91,36	5,29	0,0000
1 – 3	-12,34	0,71	0,8056
1 – 4	35,05	2,03	0,2589
1 – 5	-104,18	6,03	-
1 – 6	-156,92	9,09	-
2 – 3	79,03	4,58	0,0001
2 – 4	126,41	7,32	-
2 – 5	-12,82	0,74	0,8056
2 – 6	-65,55	3,80	0,0015
3 – 4	47,38	2,74	0,0446
3 – 5	-91,85	5,32	0,0000
3 – 6	-144,58	8,37	-
4 – 5	-139,23	8,06	-
4 – 6	-191,96	11,11	-
5 – 6	-52,74	3,05	0,0194

Source: the author (2020).

Regarding the total inventory level, scenarios 1, 3, and 4 did not presented a statistically significant difference when compared to the base model. Scenarios 2, 5 and 6 show significant increases in the inventory levels. When comparing the scenarios between themselves, the scenarios pairs 1 and 3, 1 and 4, and 2 and 5 did not present statistically significant differences, meaning that their inventory levels might be similar, while all other pair combinations are statistically different.

Table 23 – Purchase frequency multiple comparison test results

Scenarios compared	Observed difference	Statistic	Adjusted p-value
Base - 1			1,0000
Base - 2	-140,29	7,69	-
Base - 3	-119,16	6,53	-
Base - 4	-111,01	6,09	-
Base - 5	-24,54	1,35	1,0000
Base - 6	-122,81	6,73	-
1 - 2	-140,29	7,69	-
1 - 3	-119,16	6,53	-
1 - 4	-111,01	6,09	-
1 - 5	-24,54	1,35	1,0000
1 - 6	-122,81	6,73	-
2 - 3	21,13	1,16	1,0000
2 - 4	29,28	1,61	0,9829
2 - 5	115,75	6,35	-
2 - 6	17,48	0,96	1,0000
3 - 4	8,15	0,45	1,0000
3 - 5	94,63	5,19	0,0000
3 - 6	-3,65	0,20	1,0000
4 - 5	86,47	4,74	0,0000
4 - 6	-11,80	0,65	1,0000
5 - 6	-98,27	5,39	0,0000

Source: the author (2020).

Regarding the purchase frequency, scenarios 2 to 4 and scenario 6 present a statistically significant change when compared to the base model. Additionally, for the pairwise scenario comparison, the scenarios pairs 1 and 5, 2 and 3, 2 and 4, 2 and 6, 3 and 4, 3 and 6, and 4 and 6 all seem to have statistically similar results.

From the results, when compared to the base model, it can be concluded that any scenario has a statistically significant change on TDD, IDD, inventory, or transfer frequency. This analysis provides initial insights on the statistical significance of the application of the TOC steps, however, it yet does not provide the impacts regarding the interest variables at each step implementation. Therefore, in order to identify those impacts, the Causal Impact analysis is conducted and presented in the next section.

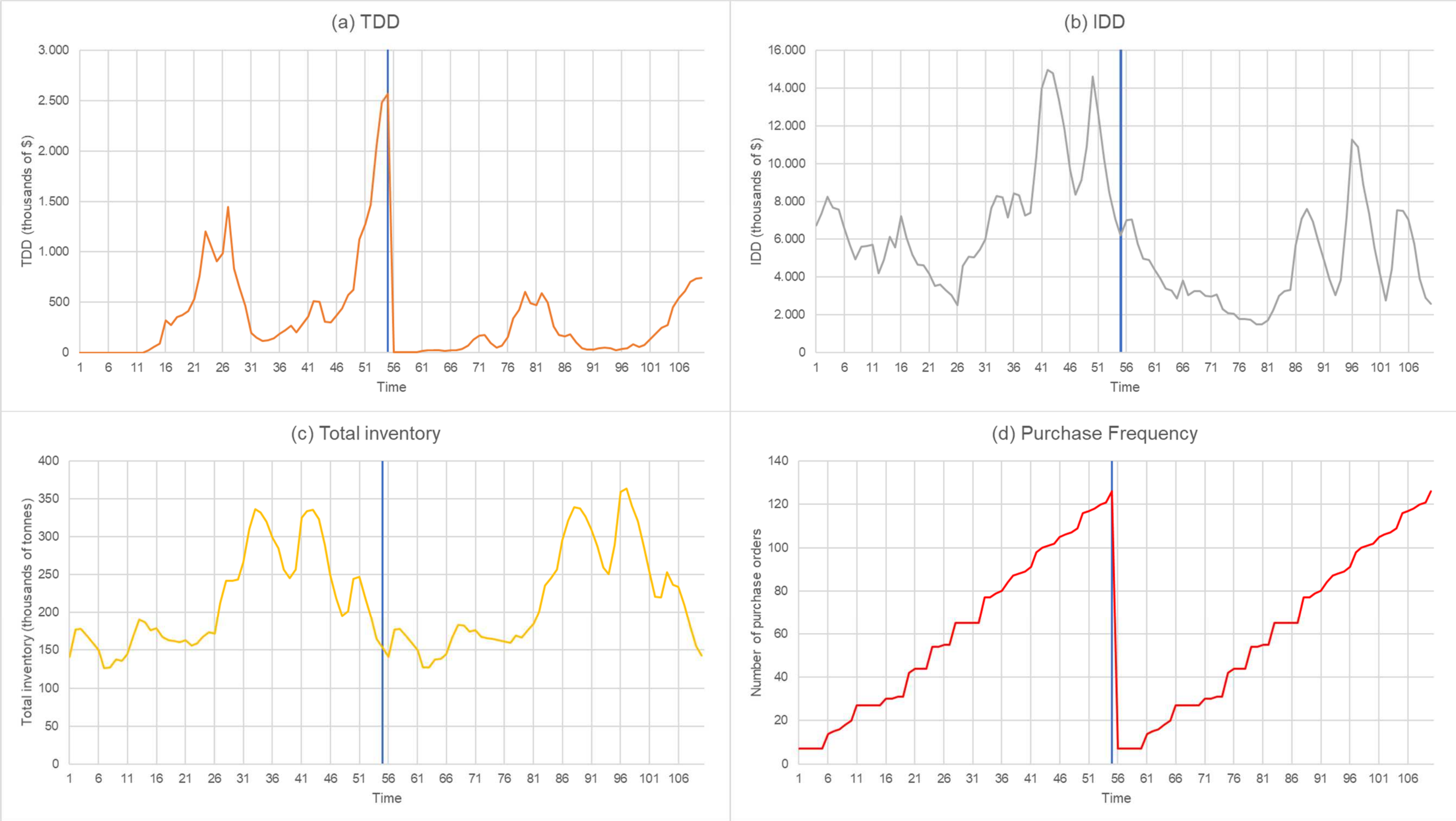
5.3 CAUSAL IMPACTS OF TOC STEPS APPLICATION

In order to better understand the impacts of the TOC steps application in the system, the causal impacts analysis is conducted. The causal impact estimates the causal effect of a designed intervention on a time series. In order to so, it is necessary to have a response time series and a control time series. From the control time series, the model tries to predict a counterfactual, i.e. how the response variable would behave if the intervention had not occurred. Also, it is important to know when the intervention takes place, delimiting the pre intervention and the post intervention period. The first analysis observes the impacts comparing the scenarios to the base model.

5.3.1 Impacts with Regards to the Base Model

The first scenario to be analyzed is the stock aggregation. Therefore, the interest variables averages through time are compared. Figure 36 presents the comparison between the base model and scenario 1. The figure presents the results for TDD in a), IDD in b), total inventory in c), and purchase frequency in d). The solid blue line represents the time where the intervention takes place in the system, which is at time 55. Thus, before the blue line are the results of the base model – from time 1 to 55 – and after the line are the results found in the respective scenario – from time 56 to 110. From the figure, it is possible to note the positive impact in both TDD and IDD from the application of the inventory aggregation. The total inventory no noticeable changes, and the purchase frequency stays the same, as expected.

Figure 36 – Base model and scenario 1 distributions comparison

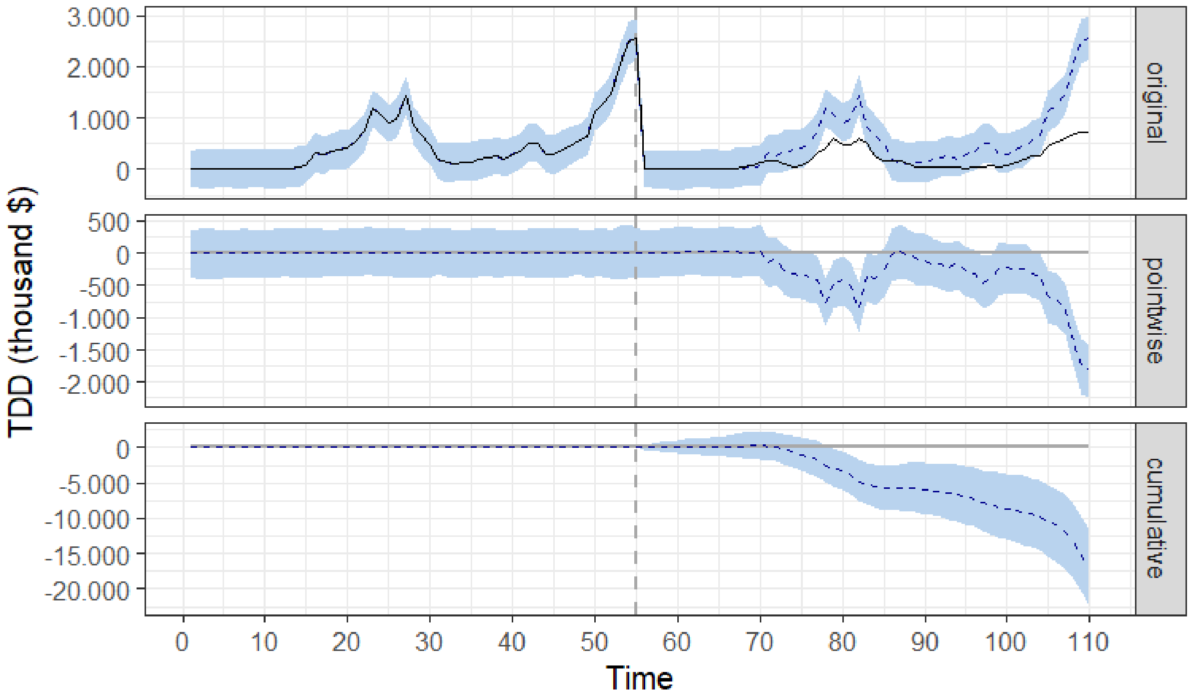


Source: the author (2020).

The distributions presented above are used in the causal impact analysis. The causal impact model compares a control variable and a response variable, identifying the impacts caused by an intervention in the response variable and checking if that intervention is statistically significant or not. In order to do so, the base model observations are used in both the response variable and the control variable. In order to compare the different scenarios, the time series is doubled, forming a two-year time series. In the case the first year comprise weeks 1 to 55, while the second year refers to week 56 to 110. As the model and the simulations created have only 55 weeks, the time series must be replicated or complemented. For the control variables, the two years are the same, representing a scenario where there is not intervention or any other kind of disturbance, such as an increase in demand. Maintaining the same time series is important for the sake of comparison. Then, the control variable have one year that is equal to the control variable and the second year the actual observed time series for the respective scenario.

The TDD, IDD, total inventory and purchase frequency causal impacts are performed in R, all the analyses use 5% level of significance. The period before the intervention is always from time 1 to 55 and the post-intervention period is defined from 56 to 110. The causal impact plot function provides three different plots. The original plot depicts the result variable – denoted by a black solid line – compared to a predicted counterfactual predicted based on the control time series. The pointwise chart presents the differences between the observed data and the counterfactual, which results in the cumulative plot, showing the cumulative effect of the intervention. In the following plot, the control variable is the base model TDD results and the result variable is the TDD observed in scenario 1, the resulting plot is presented in Figure 37.

Figure 37 – TDD causal impact plot between the base model and scenario 1



Source: the author (2020).

It is possible to note that the effects start to differ from the base model from time 70 onwards, so at least 15 weeks after the intervention to demonstrate a slight increase. From time 75 onwards the cumulative effects become more apparent, so it would take approximately 20 weeks for one to see the apparent results the application of TOC's first step. Additionally, a report on the causal impact analyses is also created. The report is presented in Table 24. The table shows the average and cumulative values with and without the intervention, as well as their confidence bounds, standard deviations, the absolute effects in percentage, and the p-value.

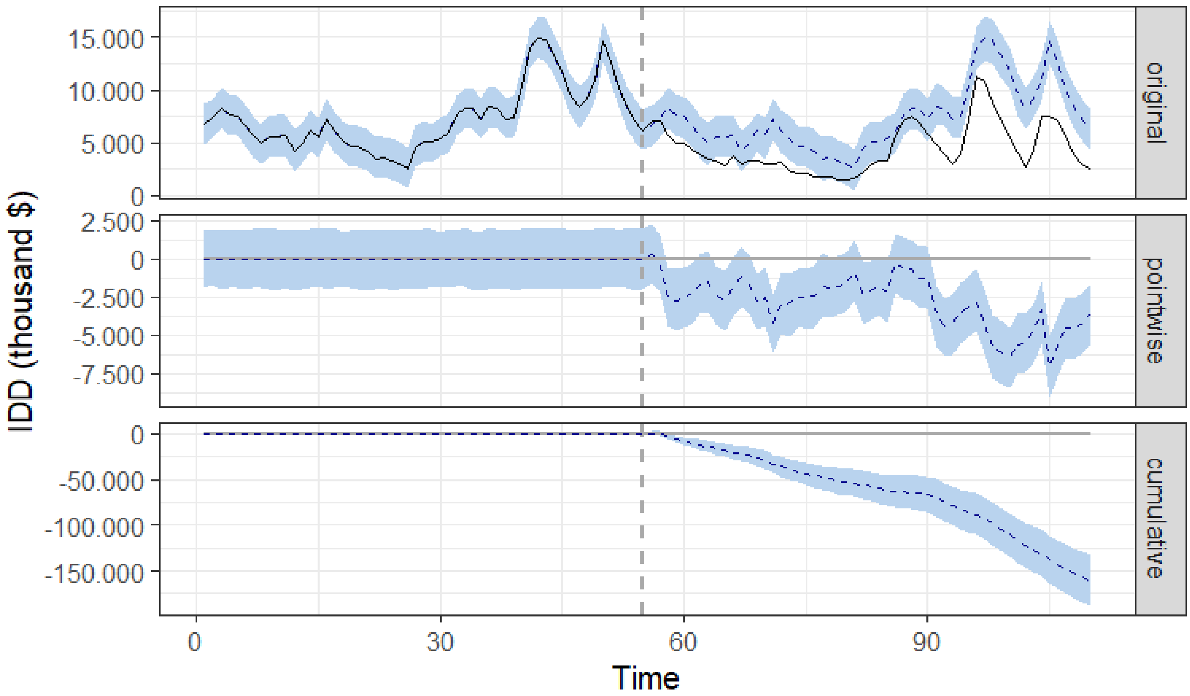
Table 24 – Causal impact results for TDD in scenario 1

Results	Average	Cumulative
Actual (with intervention)	193.068	10.618.725
Prediction (without intervention)	500.966	27.553.153
Prediction lower bound	400.205	22.011.262
Prediction upper bound	602.032	33.111.740
Prediction s.d.	51.956	2.857.605
Absolute effect	-307.899	-16.934.428
Absolute effect lower bound	-408.964	-22.493.016
Absolute effect upper bound	-207.137	-11.392.538
Absolute effect s.d.	51.956	2.857.605
Relative effect	-61%	-61%
Relative effect lower bound	-82%	-82%
Relative effect upper bound	-41%	-41%
Relative effect s.d.	10%	10%
p-value	0,0010	0,0010

Source: the author (2020)

From the results, it is possible to observe that the cumulative prediction without intervention is 27,55 M$, with the confidence intervals between 22,01 M$ and 33,11 M$. Also, there is a reduction of -61% in the TDD, with the confidence intervals between -82% and -41%. This means that the decrease in the TDD after the intervention period is statistically significant, contradicting the Hochberg's test. Corroborating to the result found, the p-value of 0,0010 is smaller than the 0,05 significance level, meaning that the probability of obtaining the TDD causal effect by chance is very small. Thus, the causal effect can be considered statistically significant. The same analysis conducted for the IDD and presented in Figure 38 and Table 25.

Figure 38 - Causal impact plot for IDD in scenario 1



Source: the author (2020).

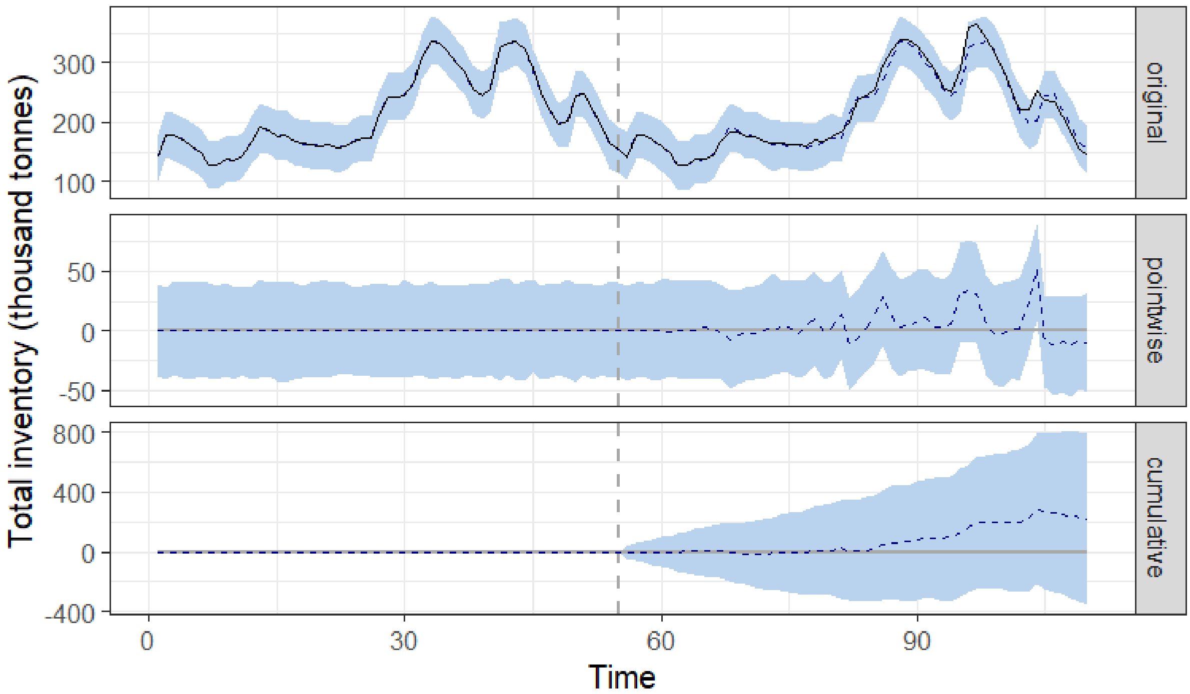
Table 25 - Causal Impact results for IDD in scenario 1

Results	Average	Cumulative
Actual (with intervention)	4.479.555	246.375.550
Prediction (without intervention)	7.382.317	406.027.441
Prediction lower bound	6.847.199	376.595.933
Prediction upper bound	7.920.827	435.645.475
Prediction s.d.	264.596	14.552.790
Absolute effect	-2.902.762	-159.651.892
Absolute effect lower bound	-3.441.271	-189.269.925
Absolute effect upper bound	-2.367.643	-130.220.383
Absolute effect s.d.	264.596	14.552.790
Relative effect	-39%	-39%
Relative effect lower bound	-47%	-47%
Relative effect upper bound	-32%	-32%
Relative effect s.d.	4%	4%
p-value	0,0010	0,0010

Source: the author (2020).

Different from the TDD, the IDD impacts can be observed earlier. The effects start to take place right after the intervention, as a result of the units requiring only what is to be consumed. Improvements can be noted from week 60 onwards, so approximately 5 weeks after the intervention. Once again, it is possible to observe a reduction in the IDD, this time a -39% difference, with confidence intervals between -47% and -32%. The reduction effect during the intervention period is therefore statistically significant. The p-value supports the statistical significance as it is below the significance level of 0,05, thus the causal effect can be considered statistically significant for the IDD in scenario 1. The same logic is applied for total inventory, presented in Figure 1 and Table 26.

Figure 39 – Causal impact plot for inventory in scenario 1



Source: the author (2020).

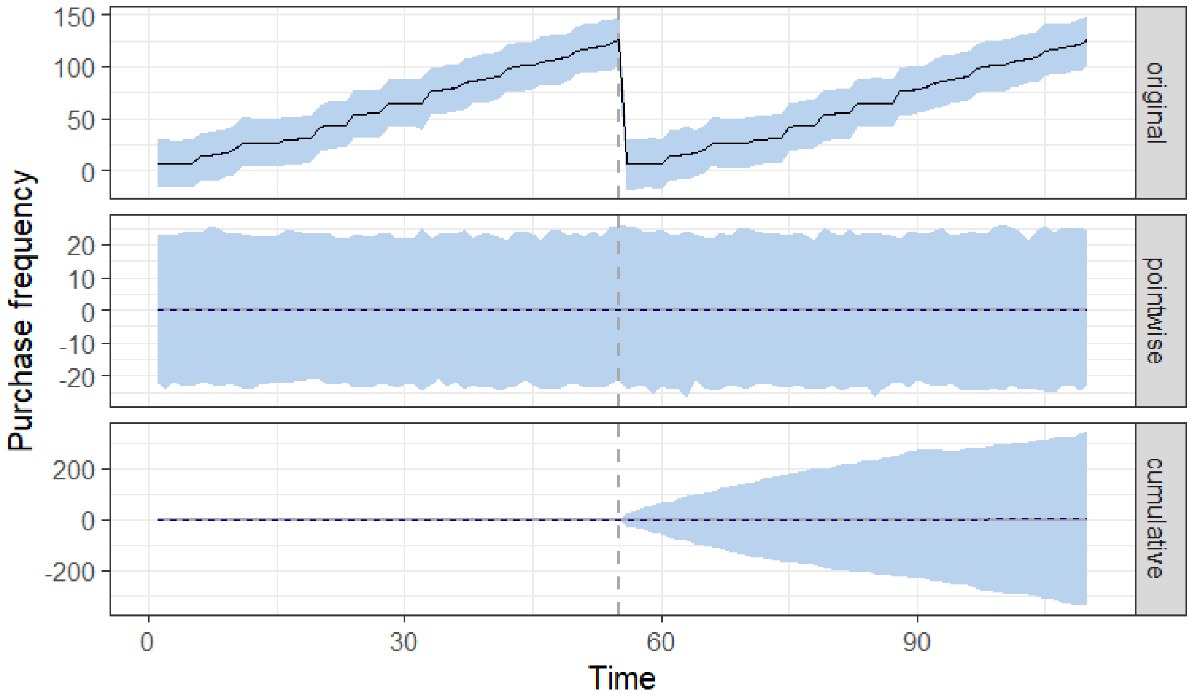
Table 26 – Causal impact results for inventory in scenario 1

Results	Average	Cumulative
Actual (with intervention)	217.224	11.947.333
Prediction (without intervention)	213.287	11.730.766
Prediction lower bound	202.610	11.143.571
Prediction upper bound	224.003	12.320.145
Prediction s.d.	5.611	308.616
Absolute effect	3.938	216.567
Absolute effect lower bound	-6.778	-372.811
Absolute effect upper bound	14.614	803.762
Absolute effect s.d.	5.611	308.616
Relative effect	2%	2%
Relative effect lower bound	-3%	-3%
Relative effect upper bound	7%	7%
Relative effect s.d.	3%	3%
p-value	0,2428	0,2428

Source: the author (2020).

Observing the distributions in Figure 36 and the causal impact plots for inventories, it is possible to note that they are similar, meaning that the causal impact model is able to replicate the distributions properly. The impacts on inventory also take longer to be observed, as the inventory levels only increase during the high season period, starting between weeks 85 to 90. So, the effects on inventory, although minor, would be perceived almost 30 weeks after the implementation. Also, the p-value denotes that scenario 1 has similar levels of inventory when compared to the base model. The results presented in the table support this hypothesis, demonstrating that changes in inventory levels are non-significant – p-value not smaller than the significance level. Finally, the same analyses are conducted for the purchase frequency and are presented in Figure 40 and Table 27.

Figure 40 – Purchase frequency causal plot for scenario 1



Source: the author (2020).

Table 27 – Purchase frequency causal impact results in scenario 1

Results	Average	Cumulative
Actual (with intervention)	78	3.137
Prediction (without intervention)	76	3.051
Prediction lower bound	64	2.561
Prediction upper bound	90	3.599
Prediction s.d.	7	262
Absolute effect	2	86
Absolute effect lower bound	-12	-462
Absolute effect upper bound	14	576
Absolute effect s.d.	7	262
Relative effect	3%	3%
Relative effect lower bound	-15%	-15%
Relative effect upper bound	19%	19%
Relative effect s.d.	9%	9%
p-value	0,3609	0,3609

Source: the author (2020).

As expected, it is possible to observe that the purchase frequency is not significant, or no causal impact can be inferred in the frequency in scenario 2 when compared to the base model. In fact, from the distributions of the observed results it is possible to see that the purchase frequency is the same for both scenarios. Therefore, the non-significance result fits the observations.

The same analysis is conducted for all the other scenarios, always comparing the four variables at each scenario with the base model results. The complete causal impact plots can be found in Appendix K. A summary of the causal impact results is presented in Table 28, demonstrating the causal impact, the relative impact and its confidence bounds, as well as the significance tests from Hochberg's test and the causal impact. The complete results can be consulted in Appendix L.

Table 28 – Causal impact results

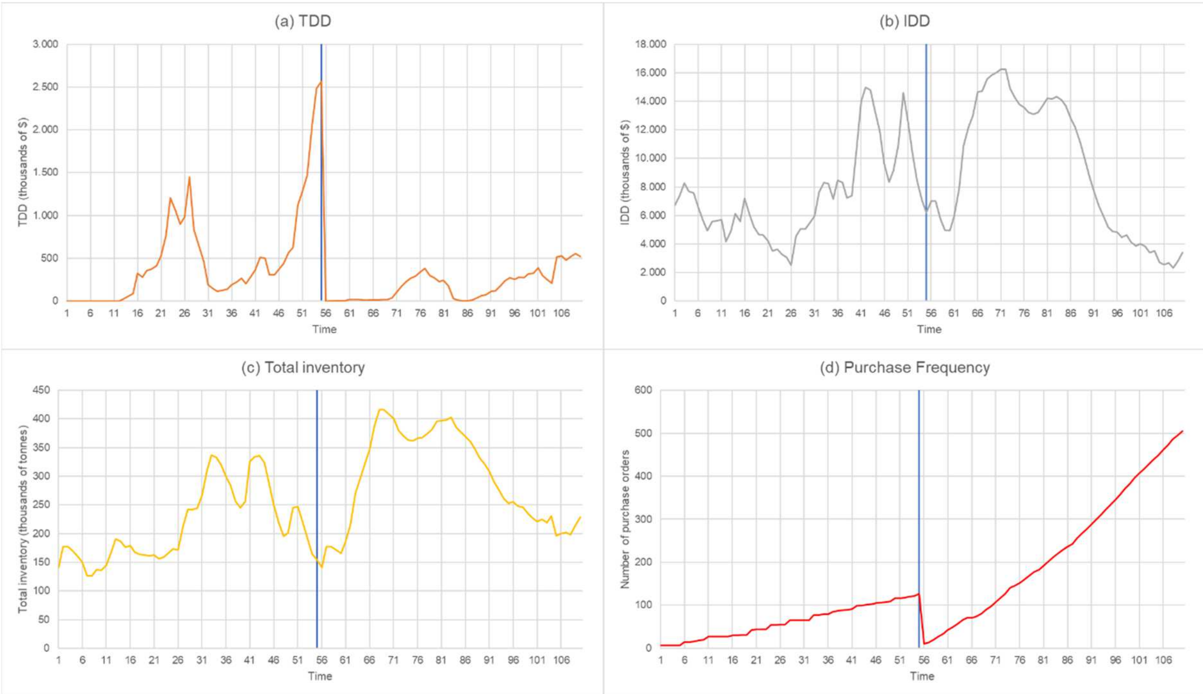
Scenarios	Variable	Hochberg test significance	Actual (with intervention)	Prediction (w/o int.)	Absolute effect	Relative effect	Rel. effect lower	Rel. effect upper	Causal significance
1 – base	TDD	Non-significant	10.618.725	27.553.153	-16.934.428	-61%	-82%	-41%	Significant
1 – base	IDD	Significant	246.375.550	406.027.441	-159.651.892	-39%	-47%	-32%	Significant
1 – base	Total inventory	Non-significant	11.947.333	11.730.766	216.567	2%	-3%	7%	Non-significant
1 – base	Purchase freq.	Non-significant	3.390	3.388	2	0%	-10%	10%	Non-significant
2 – base	TDD	Non-significant	10.025.595	27.553.153	-17.527.557	-64%	-83%	-43%	Significant
2 – base	IDD	Non-significant	507.496.726	406.027.441	101.469.285	25%	18%	32%	Significant
2 – base	Total inventory	Significant	16.293.975	11.730.766	4.563.209	39%	34%	44%	Significant
2 – base	Purchase freq.	Significant	12.583	3.388	9.195	271%	262%	282%	Significant
3 – base	TDD	Non-significant	31.621.247	27.553.153	4.068.094	15%	-5%	35%	Non-significant
3 – base	IDD	Non-significant	349.907.088	406.027.441	-56.120.353	-14%	-21%	-6%	Significant
3 – base	Total inventory	Non-significant	12.349.795	11.730.766	619.029	5%	0%	11%	Significant
3 – base	Purchase freq.	Significant	11.166	3.388	7.778	230%	219%	240%	Significant
4 – base	TDD	Non-significant	49.583.943	27.553.153	22.030.790	80%	61%	100%	Significant
4 – base	IDD	Significant	225.752.325	406.027.441	-180.275.116	-44%	-51%	-37%	Significant
4 – base	Total inventory	Non-significant	9.622.627	11.730.766	-2.108.139	-18%	-23%	-13%	Significant
4 – base	Purchase freq.	Significant	10.478	3.388	7.090	209%	199%	220%	Significant
5 – base	TDD	Significant	2.235.824	27.553.153	-25.317.329	-92%	-113%	-72%	Significant
5 – base	IDD	Non-significant	481.128.918	406.027.441	75.101.476	18%	12%	25%	Significant
5 – base	Total inventory	Significant	17.668.210	11.730.766	5.937.444	51%	46%	55%	Significant
5 – base	Purchase freq.	Non-significant	4.170	3.388	782	23%	13%	33%	Significant
6 – base	TDD	Significant	3.721.721	27.553.153	-23.831.432	-86%	-105%	-65%	Significant
6 – base	IDD	Significant	733.238.213	406.027.441	327.210.771	81%	74%	87%	Significant
6 – base	Total inventory	Significant	20.172.628	11.730.766	8.441.862	72%	67%	77%	Significant
6 – base	Purchase freq.	Significant	9.793	3.388	6.405	189%	179%	200%	Significant

Source: the author (2020).

From the results presented it is possible to observe that the causal significance diverges at some points from the Hochberg's test. According to the causal impact analysis, only total inventory levels and the purchase frequency in scenario 2 and the TDD in scenario 4 are not significant changes caused by the TOC application. The Hochberg's test finds various situations where the differences are not significantly different. However, the causal impact demonstrates significant effects in many of those situations. This difference is due to Hochberg's test methodology that unlike the causal impact analysis, takes all scenarios into consideration and considers the total variation between those. Thus, Hochberg's test tends to identify the ones that show greater difference between the "scenario pool", as can be noted, for instance, in the TDD that is only significant in scenarios 5 and 6. In contrast to that, the causal impact analysis compares pairs of time series at each time and, therefore, tends to be more sensitive to smaller differences.

The aggregation of inventories at the highest point of the supply chain presents an improvement of the TDD and IDD, with no significant impacts in the inventory levels and the no changes in the purchase frequency. From those results imply that the loses of throughput can be related to the late delivery on the 'shops', as a simple re-arrangement of inventory positions bring a huge benefit in the throughput. Proof of that is the improvement in the inventory-dollar-days with no significant impact, which only means that the inventory is better positioned instead of increase. Moving with the analysis, demonstrates the distributions found in scenario 2.

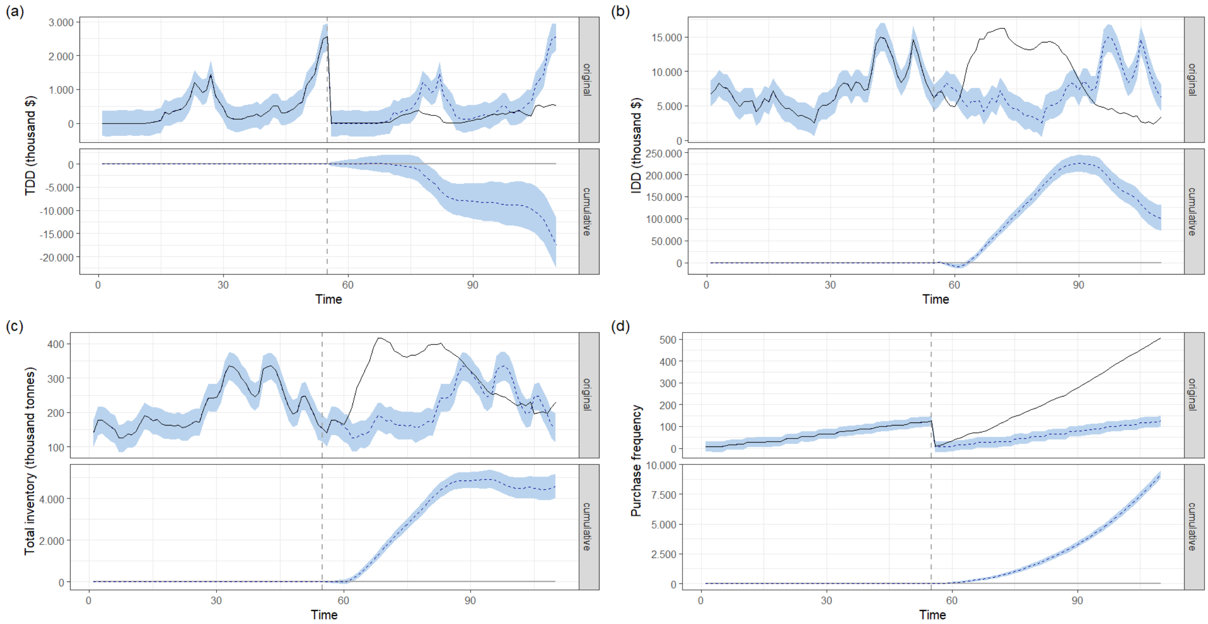
Figure 41 - Base model and scenario 2 distributions comparison



Source: the author (2020).

In scenario 2, with the reduction of the replenishment lead time and the creation of buffers the TDD also improves, but both the IDD and total inventory levels increase. However, the improvement in the TDD is greater than those increases in inventory and IDD. Still, although the average inventory increases, it is important to note that this is not the behavior for the whole time series. The causal impact plots are presented in Figure 42. As can be seen in Figure 41 and Figure 42 (c), the inventory level peak is around time 66 and 86 – or 13 to 27 in the original time series –, which starts decreasing from that point. The effects of the seasonality in the throughput are diminished in this scenario as depicted in part (a). Also, a small amount of improvement in the TDD is noted in scenario 2 in comparison to 1. In comparison to the base model, more inventory is kept during the normal season, and less inventory is held during the high season. However, the cumulative effect for the time period is of 39%. From the plots it is also possible to note that time it takes to observe the facts is similar to the ones found in scenario 1 for the TDD and the IDD. Regarding inventory levels and the purchase frequency, it is possible to note the increase right after the intervention, approximately at time 60, i.e. about 5 weeks after the intervention.

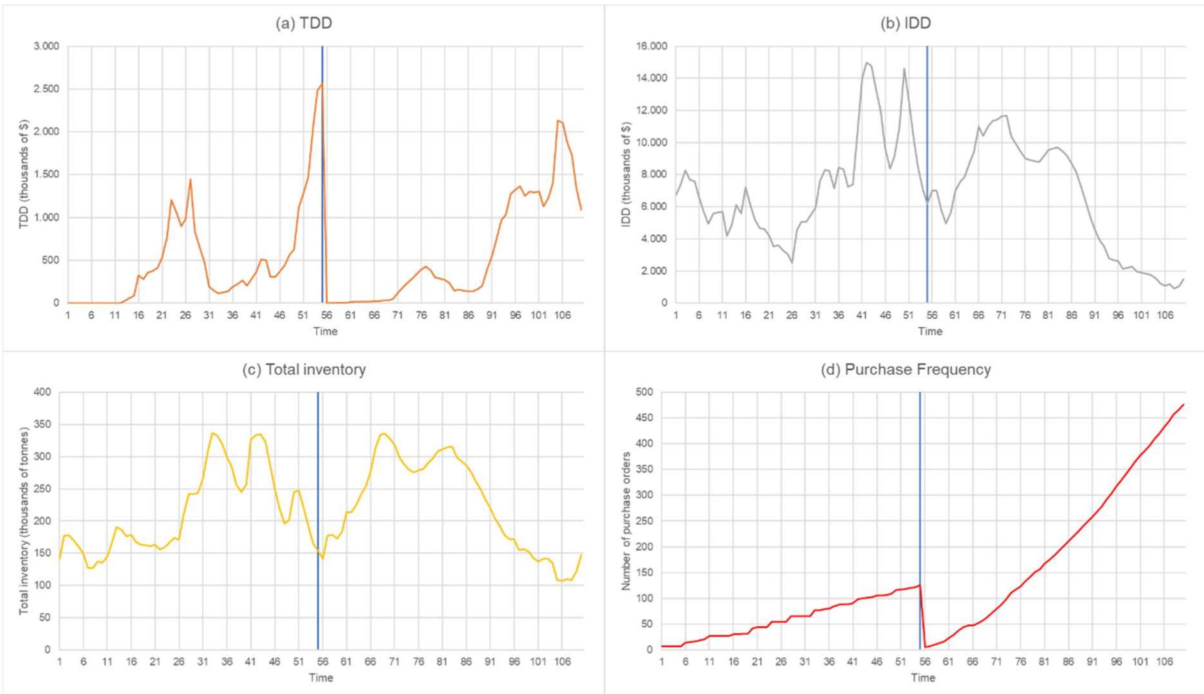
Figure 42 – Causal impacts plots for scenario 2



Source: the author (2020).

Scenario 3 implements the utilization of the buffer penetration concept. The distributions for the TDD, IDD, total inventory, and purchase frequency are presented in Figure 43.

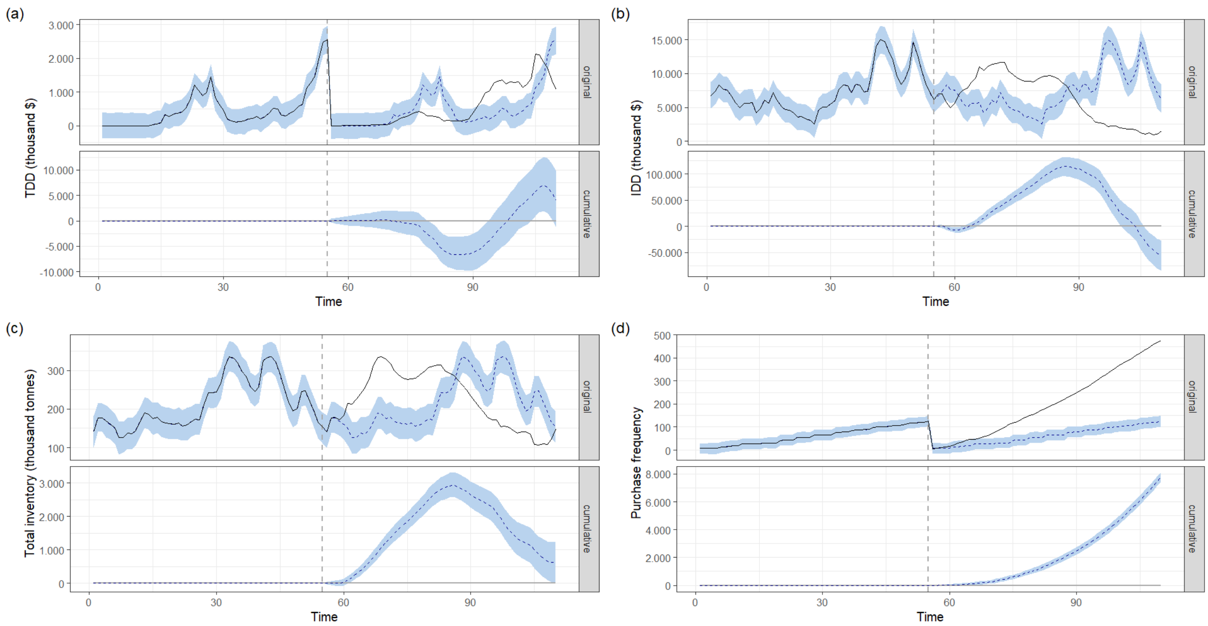
Figure 43 – Base model and scenario 3 distributions comparison



Source: the author (2020).

The causal plots for this comparison are presented in Figure 44. Part (a) demonstrates TDD behavior for this scenario. Following the cumulative effect, the TDD is improved during the normal season, but decreases significantly during the high season. The mean result for the TDD increase, however, is not statistically significant. Since in this scenario the replenishment of the buffer is solely based on the buffer sizes determined in scenario 2, the inventory kept is not enough to protect the throughput. Parts (b) and (c) demonstrate the decrease in inventory levels when the time consumption rises, which although improve both IDD and inventory may compromise the TDD.

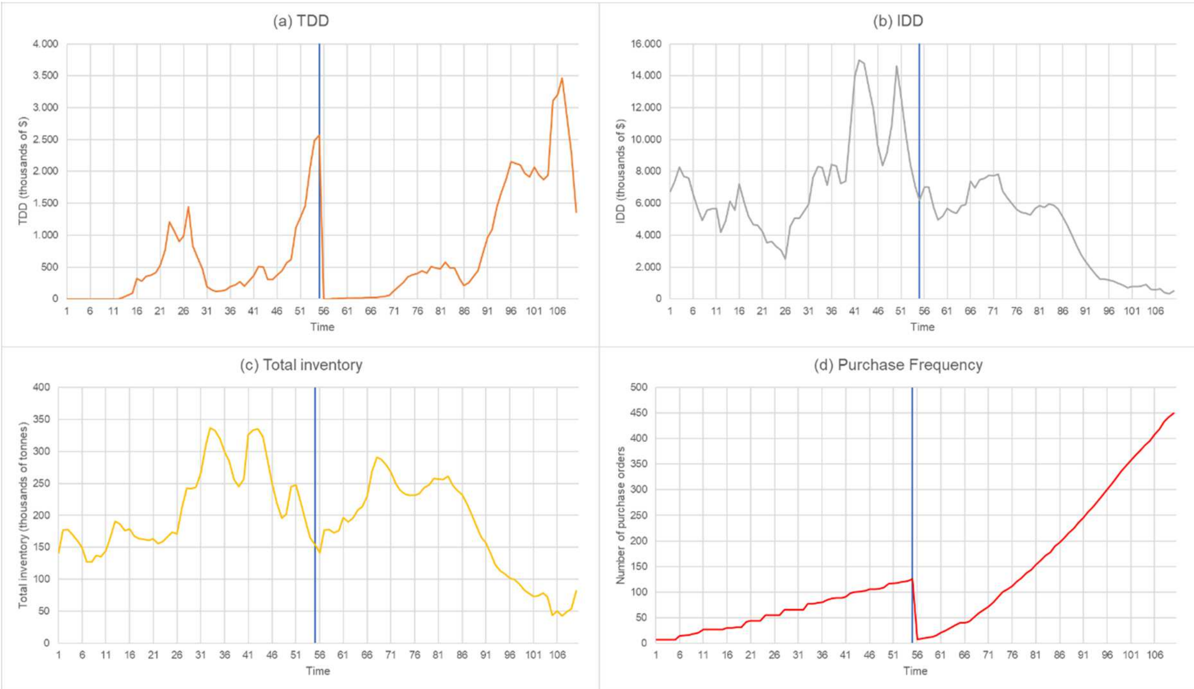
Figure 44 – Causal impacts plots for scenario 3



Source: the author (2020).

Scenario 4, the last scenario where the TOC solution is purely applied in the system, demonstrates to be similar to the previous step. Its distributions are presented in Figure 45.

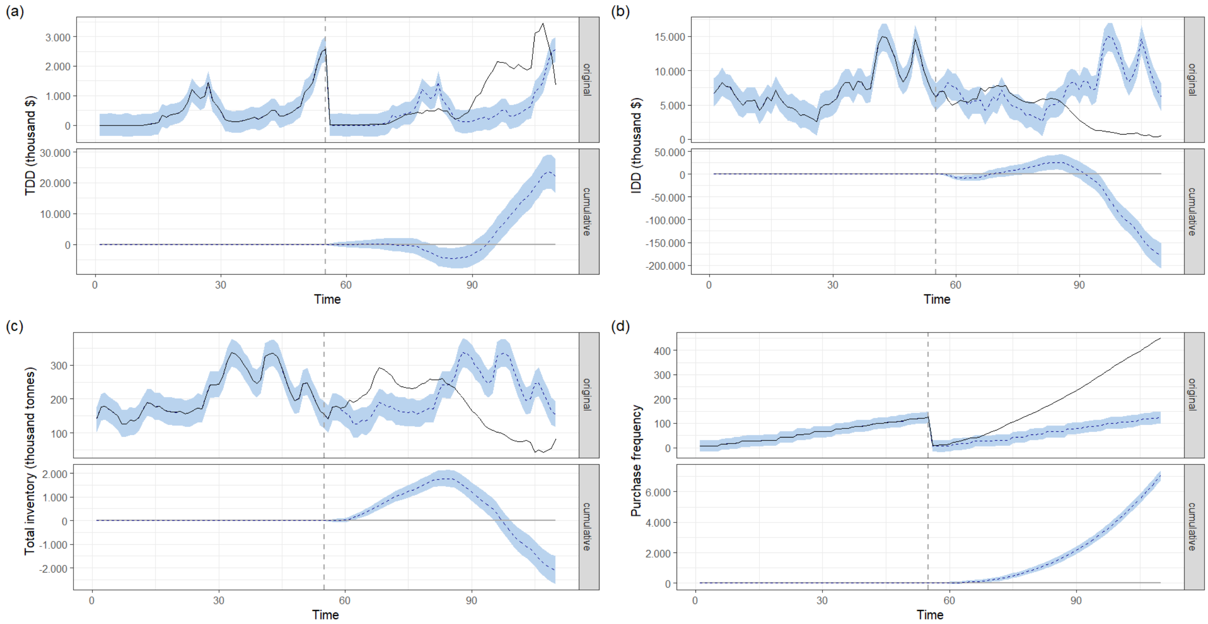
Figure 45 – Base model and scenario 4 distributions comparison



Source: the author (2020).

Both the inventory-dollar-days and the inventory levels improve, and the IDD is even better than scenario in 1. However, as in scenario 3, the TDD is impacted. Part (a) of Figure 46 demonstrates the problems with seasonality. As can be noted, the cumulative TDD in 'under control' and even better than the base scenario until the high demand point. From that point, the losses increase only to start decreasing at the end of the period. The effects on the TDD are observed approximately at time 70 which decreases up to around time 90. From that time onwards, the TDD is impacted negatively and the cumulative effect starts increasing. The other variables are impacted before that, following the pattern from previous scenarios, being able to observe their impacts around time 60.

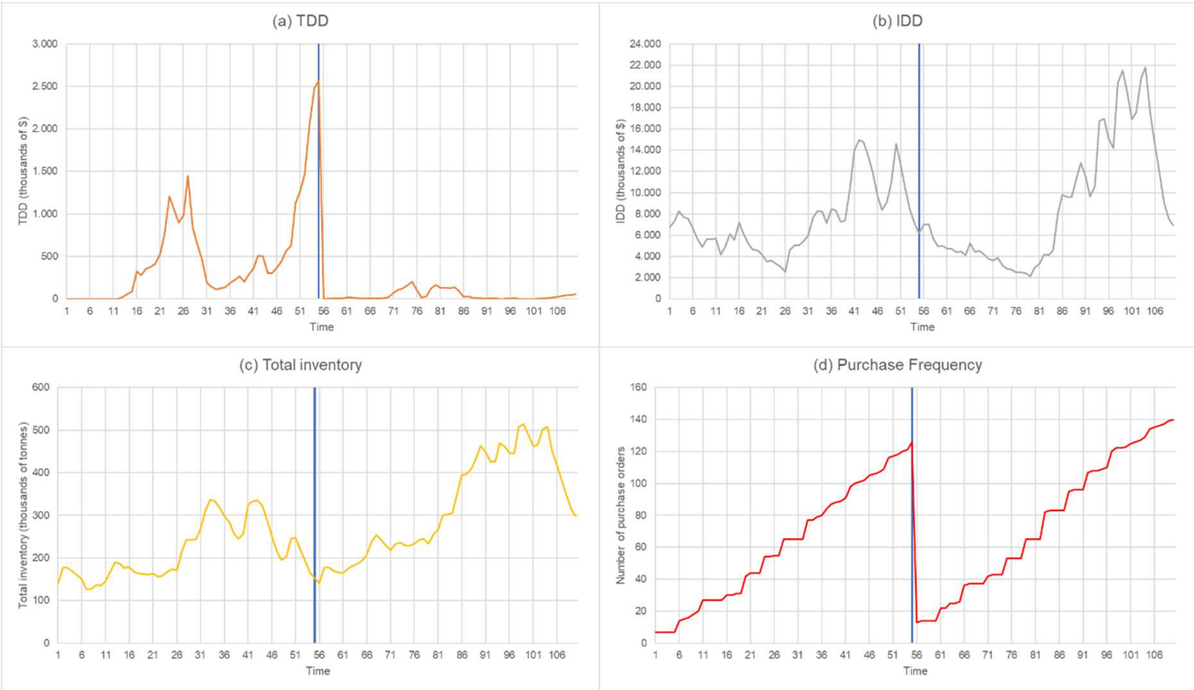
Figure 46 – Causal impacts plots for scenario 4



Source: the author (2020).

From this point, it is possible to say that scenarios 1 and 2 present the best results for the case. In scenario 1, the throughput and the IDD increase with no major impact on the inventory levels, meaning that the shops are better protect from lost sales and their inventories are better positioned. In scenario 2, the throughput is even better than in scenario 1, but the inventory levels increase, which consequently increase the IDD. This is caused by the increase in inventory levels by the utilization of buffers, as the traditional TOC buffers are conservative and possess safety measures to be less dependent on the forecasts and secure the throughput. Thus, in order to find a better model to deal with the system's seasonality, two other scenarios are tested. Thus, Figure 47 presents the distributions for scenario 5.

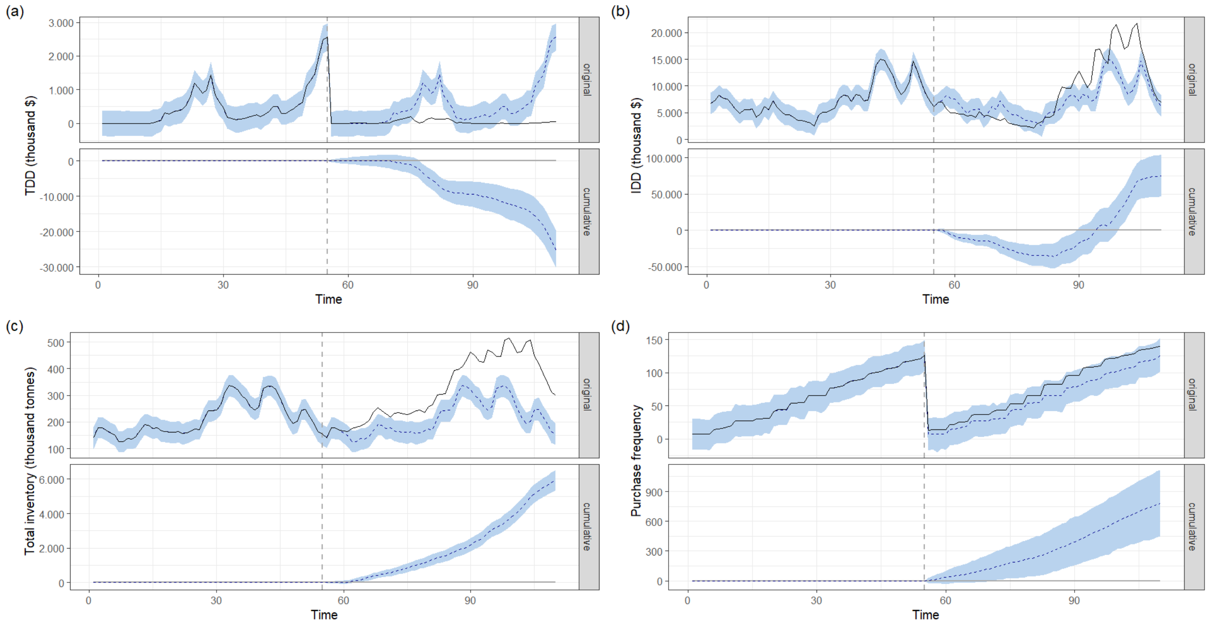
Figure 47 – Base model and scenario 5 distributions comparison



Source: the author (2020).

Scenario 5, which uses forecast-based buffers, present the highest impact in the TDD. However, the IDD levels and the total inventory increase in comparison to the base model. It presents a TDD improvement of 92%, along with a mean increase on inventory of 51% and an IDD increase of 18%. The inventory increase for this scenario is greater than any increase found in the previous scenarios. However, the high impact on the TDD might compensate the increases of inventory. It also important to note that the inventory levels are not much higher than the base model for a significant part of the time. As can be seen in part (c) of Figure 48 the inventory levels increase specially during the high season period and start decreasing once this period has passed.

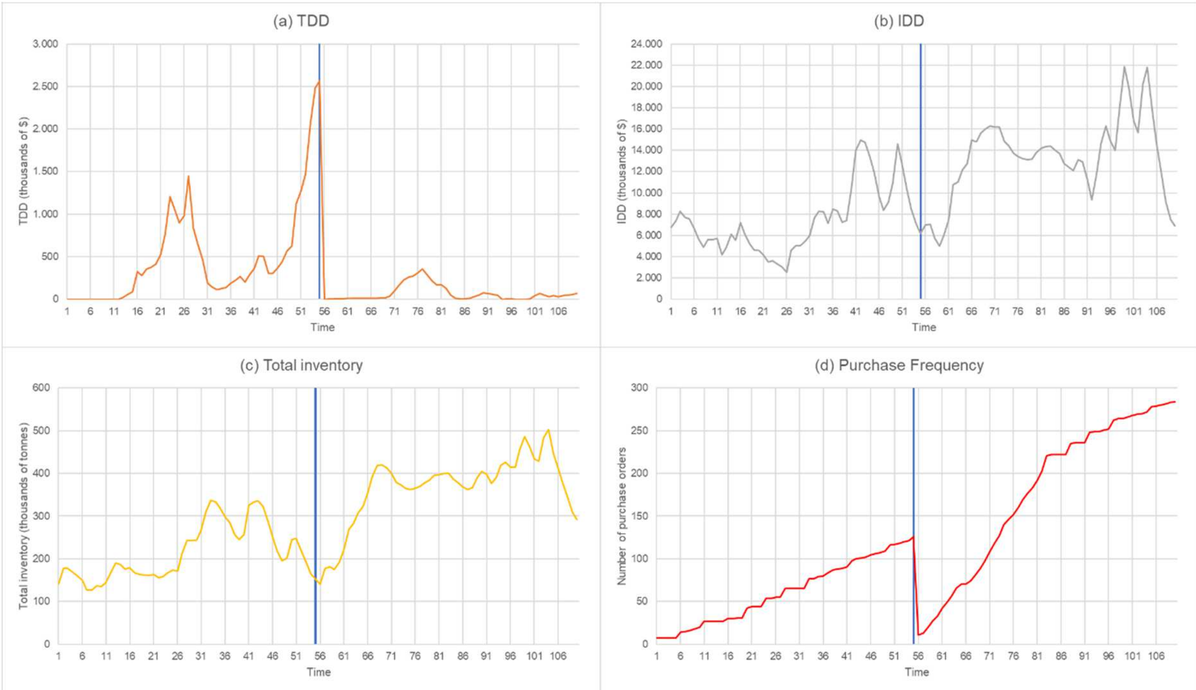
Figure 48 - Causal impacts plots for scenario 5



Source: the author (2020).

Scenario 6 combines the utilization of the forecast-based buffers with the traditional TOC buffers. Forecast-based buffers are used during the high-season period, while the TOC buffers are used during the normal season. Scenario 6 present the second best TDD value, but at the same time has the highest inventory levels. Figure 49 presents the distributions for this scenario.

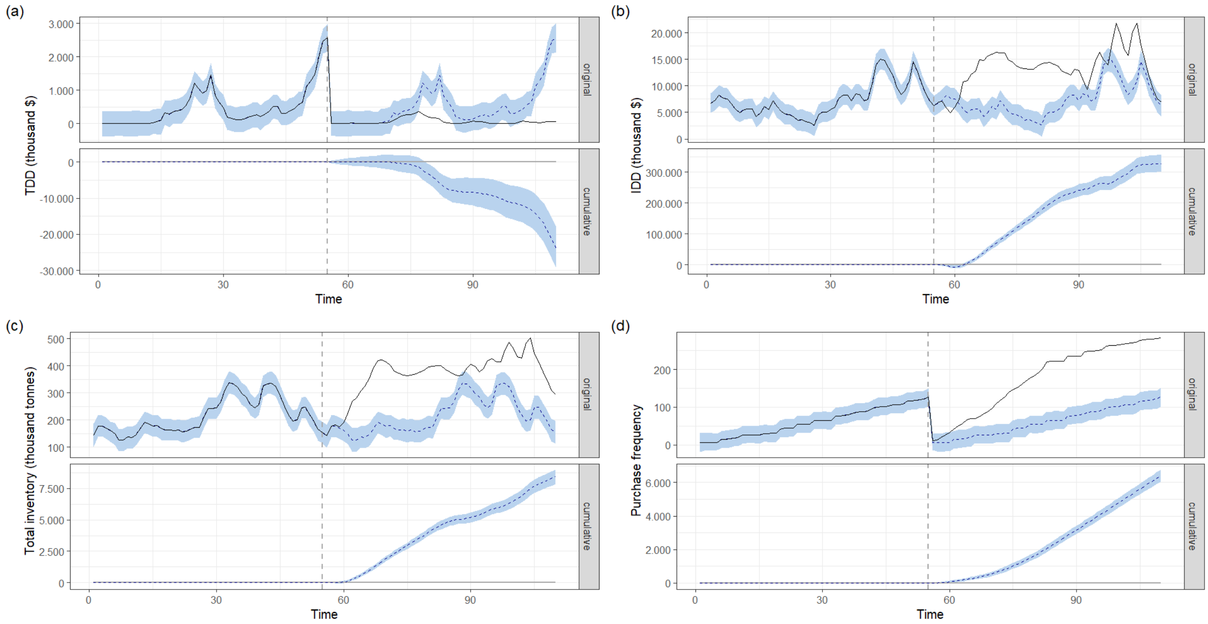
Figure 49 – Base model and scenario 6 distributions comparison



Source: the author (2020).

Figure 50 presents the causal impact plots for scenario 1. It can be noted that the TOC build up the stock before the high season and protects the throughput and during the high season. When the forecast-based buffers start acting there is not enough time to return the inventory levels and the IDD, which start decreasing only at the end of the period. Both scenarios 5 and 6 presents the same patterns found in previous model with regards to the time taken for effects to be noticed. The IDD starts improving around time 70, while all the other variables start increase from time 60 onwards.

Figure 50 – Causal impact plots for scenario 6



Source: the author (2020).

Regarding the purchase frequency, it can be noted from the plots and the results that it increases in any scenario when compared to the base model. Therefore, for the studied case it seems that the replenishment frequency increase is much more a consequence or requirement for the TOC application than a proper “intervention” in the system. In that sense, the replenishment frequency seems to be more than a constraint than a TOC solution step.

From this point, besides the already mentioned scenarios 2 and 3, scenario 6 present good results as well. With a significant impact of 92% in the throughput, the absolute increases of 51% in the inventory levels might be worth considering for application in the case. In addition to the comparison of the scenarios with the base model, a comparison among the other scenarios is also conducted, in order to measure the significance of the impacts of the TOC at each step.

5.3.2 Incremental Step Application Impacts Comparison

Besides comparing and measuring the effects of the TOC implementation in comparison to the base scenarios, a few comparisons among the other scenarios are also conducted. With this analysis it is possible, for instance, to assess if the TDD increase of 64% in scenario 2 is significant when compared to the 61% increase achieved during scenario 1. The aim is to assess each incremental step of the TOC application, thus the causal impacts between scenarios 1 and 2, 2 and 3, and 3 and 4 will be measured. Additionally, scenarios 5 and 6 are both compared to scenario 4, which represents the application of the last TOC step. A summary of the results from the analysis are presented in Table 29. The complete results can be found in Appendix L. Additionally, the causal plots can be consulted in Appendix K.

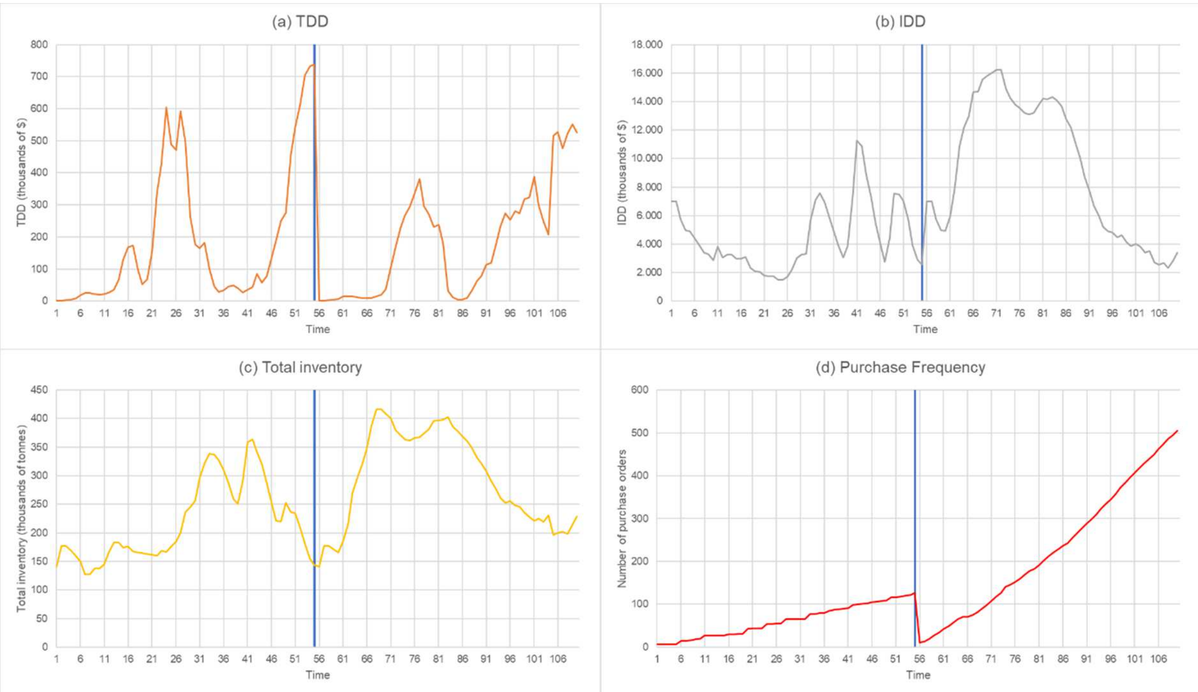
Table 29 – Incremental causal impact

Scenario	Variable	Hochberg test significance	Actual (with intervention)	Prediction (without intervention)	Absolute effect	Relative effect	Relative effect lower bound	Relative effect upper bound	Causal significance
2 - 1	TDD	Non-significant	10.025.595	10.603.993	-578.397	-5%	-23%	12%	Non-significant
2 - 1	IDD	Significant	507.496.726	246.353.877	261.142.849	106%	97%	115%	Significant
2 - 1	Total inventory	Significant	16.293.975	11.942.563	4.351.413	36%	31%	42%	Significant
2 - 1	Purchase frequency	Significant	12.583	3.388	9.195	271%	261%	282%	Significant
3 - 2	TDD	Significant	31.621.247	10.014.154	21.607.093	216%	200%	232%	Significant
3 - 2	IDD	Significant	349.907.088	507.176.113	-157.269.024	-31%	-39%	-22%	Significant
3 - 2	Total inventory	Significant	12.349.795	16.285.296	-3.935.501	-24%	-29%	-19%	Significant
3 - 2	Purchase frequency	Non-significant	11.166	12.573	-1.407	-11%	-22%	0%	Significant
4 - 3	TDD	Non-significant	49.583.943	31.586.330	17.997.613	57%	39%	75%	Significant
4 - 3	IDD	Significant	225.752.325	349.720.067	-123.967.742	-35%	-45%	-26%	Significant
4 - 3	Total inventory	Significant	9.622.627	12.343.612	-2.720.985	-22%	-27%	-16%	Significant
4 - 3	Purchase frequency	Non-significant	10.478	11.157	-679	-6%	-19%	6%	Non-significant
5 - 4	TDD	Significant	2.235.823	49.529.483	-47.293.659	-95%	-113%	-77%	Significant
5 - 4	IDD	Significant	481.128.918	225.668.168	255.460.750	113%	103%	124%	Significant
5 - 4	Total inventory	Significant	17.668.210	9.617.471	8.050.739	84%	76%	91%	Significant
5 - 4	Purchase frequency	Significant	4.170	10.470	-6.300	-60%	-72%	-48%	Significant
6 - 4	TDD	Significant	3.721.721	49.529.483	-45.807.762	-92%	-111%	-72%	Significant
6 - 4	IDD	Significant	733.238.213	225.668.168	507.570.044	225%	214%	236%	Significant
6 - 4	Total inventory	Significant	20.172.628	9.617.471	10.555.157	110%	102%	117%	Significant
6 - 4	Purchase frequency	Non-significant	9.793	10.470	-677	-6%	-18%	6%	Non-significant

Source: the author (2020).

From the results presented it is possible to notice that there are no significant improvements in the TDD when scenarios 2 and 1 are compared. However, the increases in both inventories and IDD are statistically significant, meaning that there is no relevant improvement from implementing scenario 2 after scenario 1. An important point tough is to mention that the determination of buffer sizes, which is conducted in scenario 2, serves as a structure to both TOC steps 4 and 5, which are represented in scenarios 3 and 4. In order to replenish the buffers, the purchase frequency increases significantly as well. Figure 51 shows the comparison of the distributions for scenarios 1 and 2.

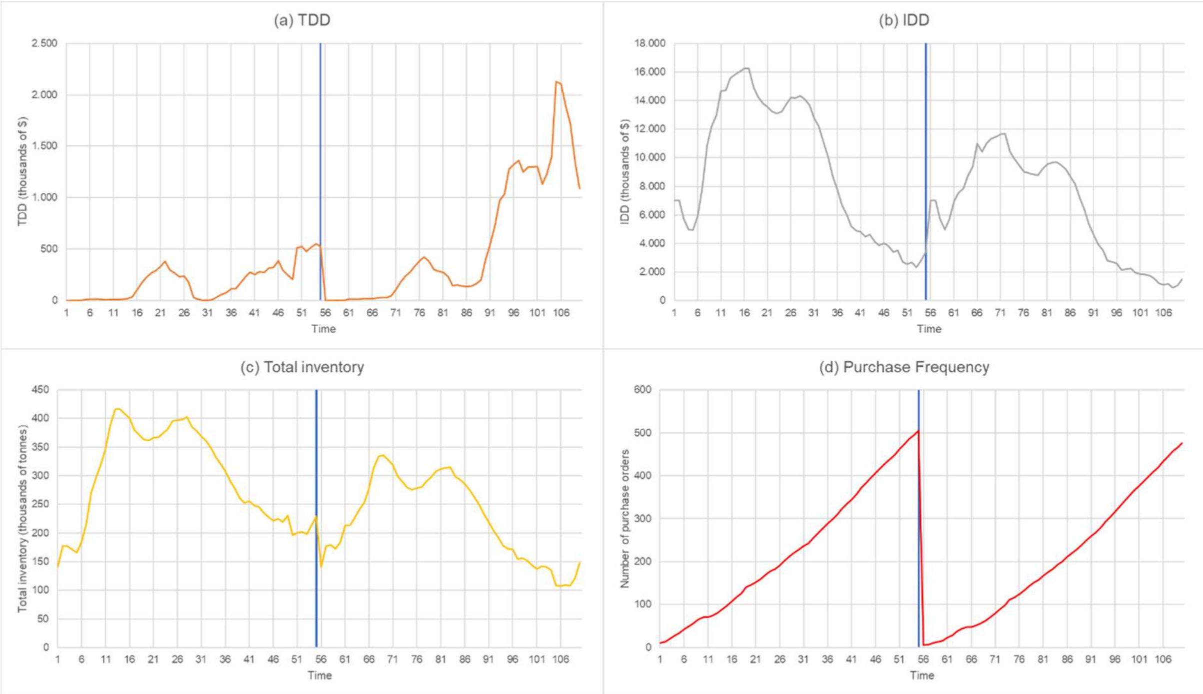
Figure 51 – Scenarios 1 and 2 distributions comparison



Source: the author (2020).

Next, scenarios 3 and 4 are compared to scenario 2 and 3, respectively. Figure 52 presents the distributions for scenarios 2 and 3 and Figure 53 does the same for scenarios 3 and 4. Following on the analyses conducted previously, the charts present the previous scenario distribution before the intervention point, while the scenario being analyzed is shown after the intervention time.

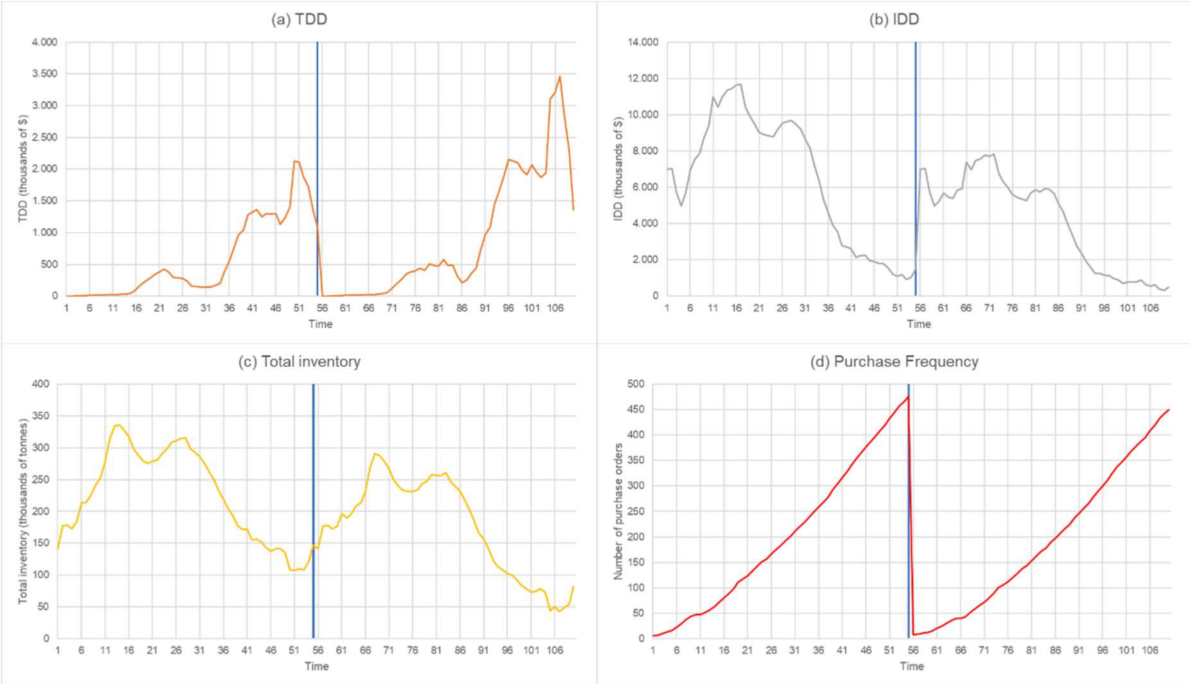
Figure 52 - Scenarios 2 and 3 distributions comparison



Source: the author (2020).

Both scenarios present improvements in the IDD and inventory levels but restrictive values for the throughput in relation to its previous scenario. In scenario 4, inventory and IDD are higher but TDD is considerably worse when compared to scenario 3, especially during the high season period. The purchase frequency remains the same as the previous step.

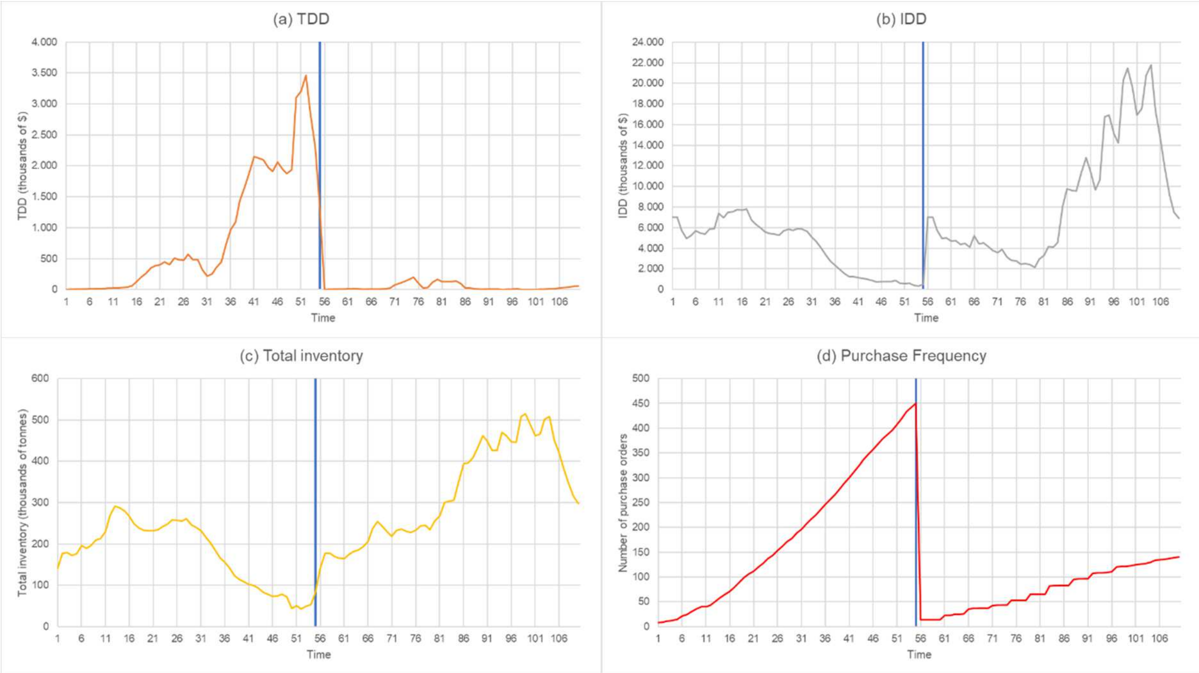
Figure 53 – Scenarios 3 and 4 distributions comparison



Source: the author (2020).

In the hybrid scenarios, improvements can be noted when compared to the traditional TOC steps. This indicates that the hybrid solutions, specially the one described in scenario 5, might be a better fit for the case. In scenario 5, inventory levels and IDD are lower when compared to scenario 4, however, the TDD presents 95% improvement. Both IDD and inventories start increasing especially at the high-season period, which can be observed at around time 80 and onwards.

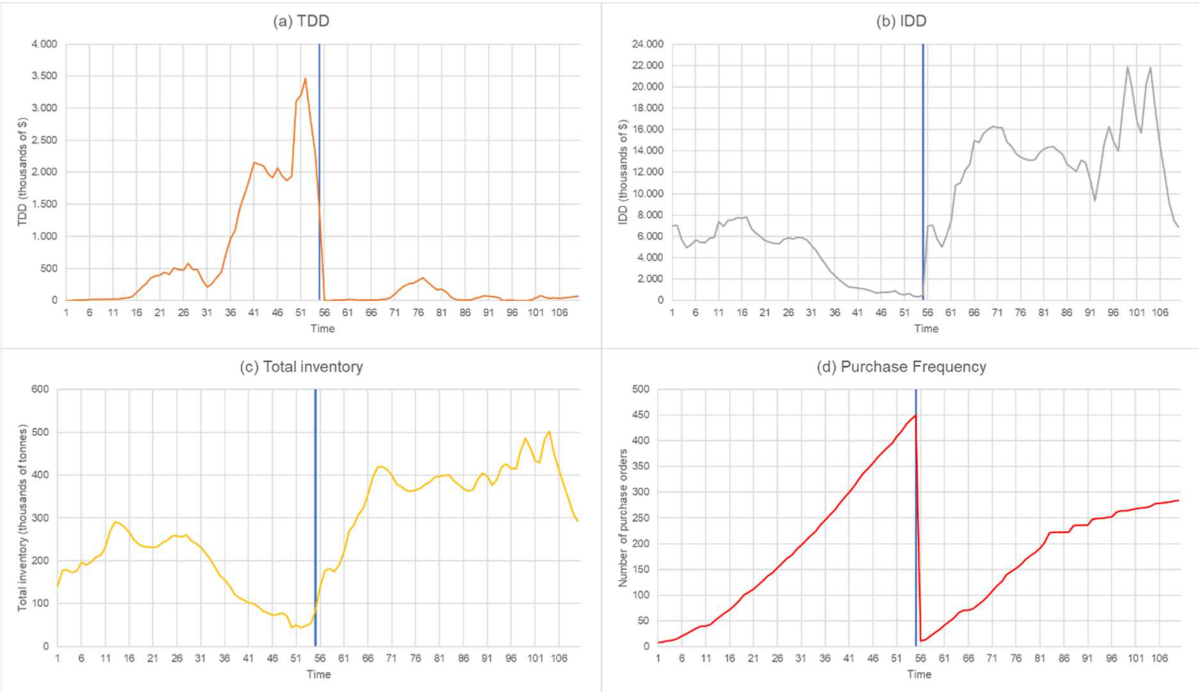
Figure 54 – Scenarios 4 and 5 distributions comparison



Source: the author (2020).

In scenario 6, the TDD decrease is significant, but the inventory levels more than double up in comparison to scenario 4. Both scenarios 5 and 6 required a lower purchase frequency in comparison to scenario 4.

Figure 55 - Scenarios 4 and 6 distributions comparison



Source: the author (2020).

Finally, Frame 10 presents a summary of the results from this and the previous section. It is important to note that both scenarios 5 and 6 have scenario 4 as their “previous” scenario.

Frame 10 – Comparison of the results

Scenario	Compared to scenario 1			Compared to previous scenario		
	TDD	IDD	Inventory	TDD	IDD	Inventory
1	↑	↑	↑	-	-	-
2	↑	↓	↓	X	↓	↓
3	X	↑	↓	↓	↑	↑
4	↓	↑	↑	↓	↑	↑
5	↑	↓	↓	↑	↓	↓
6	↑	↓	↓	↑	↓	↓

↑: improves
↓: worsens
X: not statistically significant

Source: the author (2020).

In summary, it can be noted that the TOC steps always try to prioritize the throughput, but the impacts of seasonality impacts the solution, especially the ones that use buffers. With inventory aggregation throughput, IDD, and inventory levels are improved. In step 3, with the utilization of buffers and the decrease of the replenishment type the TDD improves when compared to the base model. Although the improvement in TDD from step 2 to 3 is not significant, the buffer utilization serves as a base to construct the other TOC steps as well as the hybrid scenarios. In scenario 4 improves the IDD with no significant impacts on the throughput and a small increase in the inventory levels. It serves as a base for scenario 5, which improves the inventory levels and IDD, but penalizes the throughput significantly. Thus, by observing the causal impact plots, the TOC solution demonstrates problems with high increases in demand. However, two other proposals are created in order to deal with those problems.

Then in scenario 6, which utilizes TOC buffers levels based on the forecast and not solely in demand, the throughput reaches its better level, but the IDD and inventory levels increase. In fact, scenario 6 presents 92% improvement in the TDD, with 18% increase on the IDD and 51% increase in the inventory levels when compared to the base scenario. Thus, the relative impact on the TDD surpasses all the increments the in IDD and the inventory levels. Finally, regarding the replenishment frequency, except for scenario 2, all the other scenarios significantly increase it. Thus, it means that the replenishment frequency is more a requirement of the solution than an implementation step.

6 DISCUSSION OF THE RESULTS

This section aims to discuss the contributions of this research to the empirical and academical aspects. Regarding the empirical impacts, a discussion of the impacts to real case is conducted, clarifying the impacts for the company and its managers. In the academic aspect, contributions aim to expand the Theory of Constraints literature within the supply chain management context.

6.1 EMPIRICAL CONTRIBUTIONS WITHIN THE COMPANY CONTEXT

With long lead times, delays in replenishment, lost sales, and fierce competition the studied case presented a huge opportunity for supply chain performance improvement. As a big multinational company and with many foreign suppliers composing its supply chain, those operational improvements can take time and often are costly and risky. In that sense, simulation and modeling presents itself as a good tool for more assertive, cheaper and safer decisions with regards to supply chain redesign. Regarding the improvements necessary to elevate supply chain operations the Theory of Constraints can offer a good guideline of practices and management principles.

As detailed in the analysis of the results, better levels of throughput can and must be achieved, directly and positively impacting the 30 million dollars of estimated sales margin losses. At first, the implementation of the aggregated inventories at the highest level of supply chain demonstrates an excellent increase in the throughput with no statistically significant increases in the inventory levels. On the contrary, what is perceived is a huge reduction of the inventories at the shop, in other words the requesting units. If the throughput and the sales margin losses estimated by the company could be related and directly connected, one could say that the 61% TDD impact of the aggregation could represent a 18,3 million dollars improvement. However, the connection between the throughput and sales margin loss is not part of the scope of this research. Besides the high impact on the sales, a 61% decrease of inventory in the 3 smaller plants is attractive as well for the business.

The utilization of buffers can also contribute to improve the results of the company's supply chain. The application of forecast-based buffers also show that better results can be achieved through the application of TOC concepts, achieving up to 92% improvement in the TDD. Drawing once again from the sales margin analogy, the improvements found in this scenario would result in a 27,6 million dollars benefit, directly impacting EBITDA. The sales margin loss would reduce to as low as 2,4 million dollars. However, in order to achieve this impact an increase of inventories would be necessary. Then, two valuable options derive from this research as suggestions of impactful improvements for the company. One with significant impacts on the throughput and no increase in the total inventory levels – but a significant decrease at the lowest points of the supply chain – and other that maximizes the throughput and, consequently, increases the inventories at the SC. A thoughtful comparison was presented in this research, which can support manager's decision for whichever path is chosen, be it the maximum prioritization of the throughput, or a middle-term solution that won't impact the overall inventory level.

It is also important to mention that all TOC steps presented a significant impact in at least one of the key variables. But it also presented some of the theory's flaws, especially when dealing with abrupt changes in demand. However, the solutions presented in scenarios 6 and 7 demonstrate that the theory can be adapted and refined to suit best the needs of the supply chains. Also, some limitations of the model have to be considered, as the model do not aim to assess other supply chain related impacts, such as logistics costs, manufacturing level components, production capacity, storage limitations, etc.

Additionally, the model simulates only one part of the complete supply chain of the organization. As previously stated, the state represents almost 30% of the total supply chain. In that sense, other 70% remains as opportunities for the benefits here described. Thus, the state could, for instance, serve as a pilot for the TOC implementation in the company's supply chain and be extended to the states as well. Not only that, but the improvements and practices herein could be extended to the international levels as well. In that sense, as Brazil represents 30% of the global revenues of the company, there would be still other 70% in operations of other countries that could benefits from the practices discussed. Demonstrating, huge opportunities for improvement.

One final contribution regards the company's data. The data structure of one of the core and most important activities of the company is still very poorly managed. Lots of manual work in conduct by both managers and analysts in order to have the raw-material purchase requisitions and calculate the replenishment quantities. With a yearly raw material spend that surpasses a billion dollars it is concerning to know that there is no investment in software to support supply chain and planning decisions. Additionally, it is odd that the company does not control the data of its own sales order. As researched with the specialists there is no accurate and reliable method to have historical data on sales delays and losses, for instance. This, however, is being studied by the company in the implementation of a shared services center that will support sales operations with improved data and track records. For the supply, planning and replenishment tough, no initiative of such kind is planned. Thus, methods to improve data analytics and technology for supply chain operations should be of the highest importance.

6.2 ACADEMIC CONTRIBUTIONS

The research provides an empirical research of the Theory of Constraints within the supply chain context. The causal impact analysis allows for a better understanding of the TOC steps impacts and goals. It also demonstrates some problems especially with regards to the buffer management proposals. It was noted that the buffers performance are negatively impacted when sudden abrupt changes in demand occur, just as claimed by Schragenheim (2010). The suggestion of turning TOC buffers ‘on’ and ‘off’ according to those expected changes was also tested. The solution – presented in scenario 7 – affected positively the system’s throughput, but negatively impacted the inventories and the IDD. Suggesting that Schragenheim’s (2010) proposition might not be effective as expected. Nevertheless, drawing from the TOC replenishment solution, a middle term approach is proposed in the research and the positive effects of its application are demonstrated.

In a general sense, the research also aims to shed light into each one of the TOC steps solutions that are directly linked to supply chain management. Other than providing the causal impacts of the TOC implementation in a empirical supply chain, some general findings regarding the objectives of each TOC solution step. It is important to note though, that those findings might not apply to all cases, but might be helpful in other similar cases, such as MTO global supply chains with seasonal demand patterns. A summary of these findings is presented in Frame 11.

Frame 11 – TOC solution findings

TOC step	Findings	Affects positively	Affects negatively
Inventory aggregation	Aims to strategically position the inventories in the SC, avoiding throughput losses in the shops, while keeping the same inventory levels in the whole SC.	Throughput, inventory-dollar-days and shop's inventories	-
Buffer size and RLT	Protects the throughput in the SC, but increase safety measures to do so, i.e. inventories	Throughput	Inventory-dollar-days and total SC inventories levels
Replenish. frequency	Serves as a constraint or enabler for the other steps implementation	-	-
Buffer penetration	Drawing from buffer determination, tries to maintain the achieved throughput level, correct inventory positions while setting up a more constant pace for replenishment	Inventory-dollar-days	Throughput and total SC inventory levels
Dynamic buffer management	Adjust TOC buffers in other to decrease the inventory levels and find its optimal point	Inventory-dollar-days and total SC inventory levels	Throughput

Source: the author (2020).

Some key improvements are worth mentioning. The 92% improvement in the throughput derived from scenario 5 is relevant, even though there are increases in the inventory levels. Also, the 62% improvement in the TDD from the aggregation of stocks with no significant increase in the total inventory levels, but a 67% decrease in the mixing units' inventory is also quite relevant. The IDD, improves to almost 40% in the stock aggregation, meaning that the inventories are better positioned throughout the supply chain. In addition to that, not only those effects and their impacts were calculated, but also the time it takes for one to see those results. From the results and the causal impact analysis it was possible to note that the throughput takes more time to be noted in the system after the implementation of the suggested steps when compared to the IDD and inventory levels. From the observed results, the TDD took up to 20 weeks to have an observable increase or decrease. For the IDD and inventories though, those impacts could be observed in approximately 5 weeks. This is not only relevant to the academic context, but for managers as well, as this can provide a good perception for when the benefits of the application of the theory can take place after they are implemented.

An important point worth mentioning is regarding the increase of the replenishment frequency, which can go up as 271% when the buffers are being used. From the results and findings of this research, it seems that the replenishment frequency acts more as a consequence, an enabler, or a constraint to the theory's implementation than a proper step to achieve determined benefits. It seems unlikely that without the constant replenishment of the buffers, initiatives such as buffer penetration and dynamic buffer management could occur. In that sense, it seems to function like a reality check or a pre-requisite to move into those other initiatives.

Having concluded the discussions regarding the academic contributions of this research, the next section presents the conclusion. Thus, a summary of the whole research is demonstrated, pointing out its major contributions as well as future venues of study.

7 CONCLUSION

Through this section, the research objectives are explored again and the findings in relation to those are discussed. Additionally, some potential studies to continue the research are suggested, as well as the limitations of the research and the proposed model.

In the introduction, a contextualization of the current supply chain problems is presented, while defining the research's aim. The complexity of the global supply chains and the fierce competition still pose as significant challenges to supply chain management. Thus, supply chain redesign is a constant theme of discussion regarding the operational improvement that can be achieved from it. The Theory of Constraints presents itself as a solution for many of the problems faced by those supply chains. Although not fully explored and somehow yet limited both academically and empirically, the TOC proposes guidelines for supply chain management, especially from the solution outlined and detailed by Schragenheim (2010). Deriving from the theory's inherent simplicity, the TOC supply chain solution aims to rely less on forecasts, while being able to increase sales and reduce inventory levels. Although a sound theory, not many studies detail the improvements achieved in supply chain by the application of TOC supply chain solution. Therefore, observing this gap within the literature this research proposes to asses each one of those steps and evaluate its impacts.

In order to do so, a simulation study is proposed, based on an empirical case. The case under study is the supply chain of an international company with operations in Brazil. The company is active in more than 160 countries and is the segment market leader in Brazil. Possessing 5 production units, 24 mixing units, the case of study focus on the Rio Grande do Sul state – the most representative state for the company in the country –, comprising of one production unit and three mixing units. Then, a system dynamics model is proposed, by simulating the actual scenario of the company and other scenarios that simulate the application of the TOC solution step by step. By this procedural application of the steps an detailed understanding of its impacts and effects are expected to be achieved.

Also, in order to sustain and create the knowledge background, a systematic literature review was conducted. Within the SLR, 46 studies were analyzed completely in order to create the basic theory's foundation. Within this, a descriptive analysis of the literature is presented, as well a content analysis exploring the TOC's supply chain solution and its performance measures.

Then the work methodology is streamlined. The data collection is conducted on the field by the researcher with the support of relevant specialists, access to the company's database and its ERP system. In the data analysis, multivariate statistics are used in order to test the significance of the results. Additionally, the causal impact technique is utilized to measure TOC's impact in the supply chain. The causal impact provides good visuals resources to assess those impacts, as well as meaningful data to support the negative and positive effects of the interventions on the system.

In the model construction, the base model is the initial step. After its verification and validation, the model seems to be a good representation of the real-world scenario and can be modified to assess the impacts of the TOC. Therefore, the creation of a good simulation model is defined as a specific objective. With the validated model, it is possible to simulate the TOC steps in the model. Also, TOC's performance measures are modelled in order to have the evaluation of its implementation. The model is detailed in the model construction section, as well as each one of its modules. After that the simulations are conducted and presented in the analysis of the results section.

The TOC steps are modeled, simulated and measured in comparison to the base scenarios as well as with each previous step. From the causal impact analysis, it is possible to note improvements in the system's throughput of up to 92% and up to 62% decrease in inventories, depending on the scenario. The inventories at the shop decrease up to 67% and the throughput results improve at the same time. Additionally, two other scenarios are proposed in order to deal with the inherent seasonality found in the system.

Although positive impacts are found, some negative effects are also discovered and discussed. The difficulties to deal with high seasons of demand presented by the buffer are analyzed and the TOC SC suggestion to deal with those is also tested. However, as explained, the results are satisfactory and other scenarios tend to present better results. Nevertheless, some insightful considerations, contributions and options are made to the company that might help improve supply chain operations. Regarding the academic aspect, a detailed empirical research is presented, and each TOC step solution is detailed, as well as the outcomes and effects from that implementation.

Also, some limitations of the model must be considered. Since there is no actual data for sales orders delays or missing sales due to those delays, the model uses the raw-material consumption to calculate throughput losses. However, as a MTO company, the raw material consumption can be defined as a good proxy for delayed or lost sales orders. Also, the model does not consider logistics costs, other external supply chain related issues, or the manufacturing level of operations. Thus, the last step of the TOC solution, the virtual buffers and its prioritization, cannot be assessed.

For future venues of study, many scenarios can be suggested. Within the company context, the of TOC's application could be expanded to the whole country. Also, the practical implementation of a pilot could be accompanied by a researcher to test the results derived from this research. As an international company and supply chain another subject that is rarely explored in the TOC context is the intercompany trades and the complex dynamics involving the transfer prices. From the academic perspective, the study could be replied in other similar scenarios – MTO, high level of international suppliers, etc. – to refute or corroborate with the results derived from this study. Moreover, any other empirical applications of TOC with quantitative measures of its impacts are welcome and could be used for comparison and improvement of the theory.

Overall, this research has presented some insightful concepts for the academic and empirical contexts. It provided sound actions to improve the case's supply chain operations levels and options to support mangers decisions. In the academic context, it explored a not yet fully scrutinized theme, that can be improved to gather more adepts in the industry and more academic relevance.

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APPENDIX A – RESEARCH PROTOCOL

Frame 12 – Systematic review protocol

<table>
<tr><td colspan="4">Framework Conceitual: o redesenho das cadeias de suprimentos é realizado visando redução de custos, redução de inventários e melhoria da performance. A TOC, por sua, vez propõe uma solução centrada no aumento do ganho da cadeia como um todo, através de um redesenho com base nas suas políticas.</td></tr>
<tr><td>Contexto:</td><td colspan="3">A pesquisa focará nas políticas propostas pela solução de distribuição da TOC.</td></tr>
<tr><td>Horizonte:</td><td colspan="3">Não haverá limitação quanto ao horizonte, utilizando-se todos os estudos encontrados, independente do período.</td></tr>
<tr><td>Correntes Teóricas:</td><td colspan="3">Gestão da Cadeia de Suprimentos
Teoria das Restrições
Dinâmica de Sistemas
Redesenho da Cadeia de Suprimentos
Solução da TOC para a Distribuição/Cadeia
Simulação e modelagem</td></tr>
<tr><td>Idiomas:</td><td colspan="3">Inglês</td></tr>
<tr><td colspan="4">Questão de Revisão: como são as propostas de redesenho das cadeias de suprimentos, quais os impactos que elas geram e como é a proposta da TOC neste sentido?</td></tr>
<tr><td>Estratégia de Revisão</td><td colspan="2">(X) Agregativa</td><td>( ) Configurativa</td></tr>
<tr><td rowspan="2">Critérios de Busca</td><td colspan="2">Critérios de Inclusão</td><td>Critérios de Exclusão</td></tr>
<tr><td colspan="2">Simulação para redesenho da cadeia;
TOC na cadeia;
Impactos de redesenho da cadeia</td><td>Estudos de áreas da saúde e hospitais
Relações públicas e/ou políticas
Sustentabilidade</td></tr>
<tr><td>Termos de Busca:</td><td colspan="3">Conforme Tabela 1</td></tr>
<tr><td colspan="4">Fontes de Busca:</td></tr>
<tr><td>Bases de Dados:</td><td>EBSCO</td><td>Scopus</td><td>ProQuest</td></tr>
</table>

Source: The author (2020).

APPENDIX B – THESAURUS OF TERMS

presents the terms that were translated to a new term in order to aggregate the terms to create the network in VOSviewer. Due to the long list, terms that do not appear in the frame were ignored as they were not considered to be relevant.

Frame 13 - Thesaurus of terms

Label	Replace By
account	account
accuracy	accuracy
actual demand	demand
actual market condition	market
advanced planning problem	planning
agent	simulation
agent negotiation	simulation
aggregate inventory buffer	buffer management
algorithm	optimization algorithm
appropriate dpbm strategy	buffer management
appropriate information	information
appropriate model	simulation
average inventory	inventory management
baseline computer simulation	simulation
bottleneck	constraint
bottleneck management strategy	constraint
bottleneck problem	constraint
buffer	buffer management
buffer level	buffer management
buffer management	buffer management
buffer management approach	buffer management
buffer management parameter	buffer management
buffer size	buffer management
buffer size determination	buffer management
buffering	buffer management
bullwhip effect	bullwhip effect
capacity	capacity
capacity augmentation	capacity
capacity constraint	constraint
cec	inventory management
cec policy	inventory management
central warehouse	central warehouse
centralized system	system
chain	supply chain management
chain collaboration	supply chain management
chain management	supply chain management

Label	Replace By
chain member	supply chain node
chain profitability	performance measure
chain replenishment system	TOC-SCRS
classical dpbm	buffer management
cohesive performance measurement system	performance measure
collaborative performance metric	performance measure
collaborative replenishment policy	supply chain management
company	supply chain node
competitive planning	planning
competitive world cost	costs
complexity	complexity
computational result	simulation
conceptual model	simulation
conflict	conflict
conflict problem	conflict
constraint	constraint
constraint activity	constraint
constraint perspective	constraint
constraint supply chain replenishment system	TOC-SCRS
constraints	constraint
constraints approach	theory of constraints
constraints buffer management	buffer management
constraints contribution	constraint
constraints drum buffer rope	drum-buffer-rope
constraints logic	theory of constraints
constraints managementrecent advance	theory of constraints
constraints methodology	theory of constraints
constraints perspective	theory of constraints
constraints replenishment	TOC-SCRS
constraints replenishment solution	TOC-SCRS
constraints supply chain replenishment system	TOC-SCRS
constraints technique	theory of constraints
consumer	customer
consumer goods company	FMCG
consumer need	demand
consumer supply	customer
continuous improvement path	theory of constraints
cost	costs
cost location candidate	costs
current distribution management	distribution
customer	customer
customer demand	demand
customer service level	service level
cut cost	costs
dbr	drum-buffer-rope

Label	Replace By
dbr scheduling method	drum-buffer-rope
dbr system	drum-buffer-rope
decision maker	decision making
decision making	decision making
decision process	decision making
decision systems	decision making
decision tree	decision making
demand	demand
demand change	demand
demand forecast	forecast
demand process	demand
demand pull approach	TOC-SCRS
demand pull replenishment	TOC-SCRS
demand pull replenishment strategy	TOC-SCRS
demandpull approach	TOC-SCRS
dilemma	conflict
discrete events simulation	simulation
discrete simulation	simulation
distribution	distribution
distribution logistic	TOC-SCRS
distribution resource planning	planning
distribution resource planning logic	planning
distribution supply chain	distribution
distribution system	distribution
dollar day	performance measure
dpbm	buffer management
dpbm strategy	buffer management
dpbm strategy application	buffer management
drp	drum-buffer-rope
drum buffer rope	drum-buffer-rope
drum buffer rope theory	drum-buffer-rope
drumbufferrope	drum-buffer-rope
dynamic bottleneck	constraint
dynamic demand problem	demand
dynamic inventory target level management	buffer management
echelon	supply chain echelon
economic analysis	economy
economic principle	economy
economic term	economy
effective inventory replenishment method	inventory management
effective supply chain management	supply chain management
effective toc	theory of constraints
effective toc scrs	TOC-SCRS
elongated replenishment frequency	replenishment frequency
emulation tool	simulation

Label	Replace By
enhanced simulation model	simulation
enhanced simulation replenishment model	simulation
enhancement model	simulation
environment	environment
equity function	economy
equivalent throughput	performance measure
excellent delivery performance	service level
excellent service	service level
fast moving consumer goods	FMCG
fast response	service level
financial advantage	finance
financial basis	finance
financial goal	finance
finished good	product
firm	supply chain node
flow shop mixed line production planning	planning
fmcg	FMCG
fmcg profit model	FMCG
fmcg supply chain fuzzy comprehensive evaluation model	FMCG
fmcg supply chain performance management field	FMCG
forecast accuracy	forecast
generic buffer management procedure	buffer management
genetic algorithm	optimization algorithm
genetic algorithm approach	optimization algorithm
global optimisation	optimization algorithm
global supply chain	supply chain management
goldratts theory	theory of constraints
good production planning	planning
goods inventory	inventory management
goods inventory level	inventory management
high customer delivery performance	service level
high customer service level	service level
high service level	service level
higher frequency	replenishment frequency
higher rf	replenishment frequency
improving supply chain performance	supply chain management
independent firm	supply chain node
information	information
information management	information
integrate market demand	demand
integrated master production schedule	planning
internal supply chain	supply chain node
international supply chain	supply chain management
inventory	inventory management
inventory buffer	buffer management

Label	Replace By
inventory control	inventory management
inventory control policy	inventory management
inventory control problem	inventory management
inventory dollar day	performance measure
inventory level	inventory management
inventory management	inventory management
inventory management effectiveness	inventory management
inventory quantity	inventory management
inventory replenishment	inventory management
inventory replenishment strategy	inventory management
inventory shortage occurrence	inventory management
inventory shortage problem	inventory management
inventory system	inventory management
jit	just-in-time
lead time	lead time
lead time reduction	lead time
lead times reduction	lead time
level replenishment frequency model	replenishment frequency
limited capacity	constraint
limited factory capacity	constraint
local measure	performance measure
local optimisation	performance measure
local toc measure	performance measure
logistics distribution	distribution
long lead time	lead time
long period	lead time
low cost	costs
low inventory	inventory management
lower frequency	replenishment frequency
lower inventory	inventory management
lower rf	replenishment frequency
lumpy demand	demand
manufacturing firm	supply chain node
manufacturing process planning problem	planning
manufacturing scheduling system	planning
manufacturing supply chain environment	supply chain management
market	market
market competitiveness	market
market demand	demand
market demand condition	demand
market demand forecast	forecast
market dominance	market
market dynamic	market
market economic	economy
market forecast information	forecast

Label	Replace By
market price system	market
market requirement	market
marketing	market
material inventory	inventory management
material replenishment	replenishment frequency
model	simulation
modeling	simulation
modelisation	simulation
modelling dynamic bottleneck	simulation
mrp	MRP
multi agent system	simulation
multi criteria decision method	optimization algorithm
multi objective optimisation algorithm	optimization algorithm
multilayer perceptron	optimization algorithm
network	system
neural network	optimization algorithm
new distribution center	central warehouse
new distribution centre	central warehouse
new distribution centre location	central warehouse
new global performance measure	performance measure
novel generic buffer management procedure	buffer management
nsga ii	optimization algorithm
nspso	optimization algorithm
operational planning	planning
optimal amount	optimization algorithm
optimization	optimization algorithm
optimization approach	optimization algorithm
optimization stage	optimization algorithm
organization	supply chain node
outbound	distribution
outbound logistic	distribution
overhaul lead time	lead time
overhaul lead time reduction plan	lead time
pareto optimal resource allocation	optimization algorithm
pareto optimal solution	optimization algorithm
pareto particle swarm optimization	optimization algorithm
particle swarm optimisation algorithm	optimization algorithm
particle swarm optimization	optimization algorithm
particle swarm optimization method	optimization algorithm
peak	demand
performance	performance measure
performance measure	performance measure
performance measurement system	performance measure
plant	supply chain node
process planning	planning

Label	Replace By
producer	supply chain node
product	product
product demand characteristic	demand
product distribution	distribution
product group	product
production need	demand
production network	system
production planning	planning
production scheduling	planning
pso	optimization algorithm
public transportation schedule	planning
purchase order	planning
push	inventory management
quick response	lead time
random demand	demand
re scheduling	planning
re scheduling problem	planning
real demand	demand
real demand data	demand
real supply chain	supply chain management
reliable replenishment time	lead time
replenishment	replenishment frequency
replenishment frequency	replenishment frequency
replenishment frequency model	replenishment frequency
replenishment lead time	lead time
replenishment management	TOC-SCRS
replenishment method	replenishment frequency
replenishment policy	TOC-SCRS
replenishment quantity	buffer management
replenishment strategy	TOC-SCRS
rescheduling problem	planning
resource planning	MRP
retail level transhipment	retailer
retail sector	retailer
retail shop	retailer
retailer	retailer
rf conversion period	replenishment frequency
rf determination model	replenishment frequency
right inventory	inventory management
right place	inventory management
right product	inventory management
right production target	inventory management
right time	inventory management
rrt	replenishment frequency
sale	sales

Label	Replace By
sales forecast	forecast
sales increase	sales
satisfying end customer need	service level
scm	supply chain management
scorecard	performance measure
sf optimization model	optimization algorithm
sf optimization scheme	optimization algorithm
ship schedule	planning
simple replenishment policy	TOC-SCRS
simulated scenario	simulation
simulation	simulation
simulation experiment	simulation
simulation model	simulation
simulation model design	simulation
simulation models reduction	simulation
simulation result	simulation
simulation software	simulation
simulation study	simulation
simulation task	simulation
specific buffer size	buffer management
stock	inventory management
stock out	inventory management
strategic decision	decision making
strategic planning	planning
supplier	supply chain node
supplier response time	lead time
supply chain	supply chain management
supply chain collaboration	supply chain management
supply chain coordination	supply chain management
supply chain design	supply chain management
supply chain design decision	supply chain management
supply chain environment	supply chain management
supply chain inventory	inventory management
supply chain management	supply chain management
supply chain management system	supply chain management
supply chain model	simulation
supply chain network	system
supply chain operations reference model	simulation
supply chain performance	performance measure
supply chain performance improvement	performance measure
supply chain profit model	simulation
supply chain replenishment system	TOC-SCRS
supply chain system	system
synchronization	drum-buffer-rope
synchronized supply chain	supply chain management

Label	Replace By
system	system
system emulation model	simulation
system financial performance	performance measure
system performance	performance measure
systemic approach	system
systemic behaviour	system
systemic structure	system
target inventory level	inventory management
tdd idd measure	performance measure
tdds idds	performance measure
throughput	performance measure
time buffer	buffer management
toc	theory of constraints
toc buffer management framework	buffer management
toc concept	theory of constraints
toc financial performance	performance measure
toc methodology	theory of constraints
toc operation mode	theory of constraints
toc philosophy	theory of constraints
toc practice	theory of constraints
toc principle	theory of constraints
toc scrs	TOC-SCRS
toc supply chain replenishment system	TOC-SCRS
toc supply chain solution	TOC-SCRS
toc systemic approach	theory of constraints
total cost	costs
total supply chain	supply chain management
total system inventory	inventory management
traditional demand	demand
traditional inventory strategy	inventory management
traditional manufacturing operation	supply chain node
transportation	distribution
transportation cost	costs
use simulation approach	simulation
world class global supply chain management	supply chain management

Source: The author (2020).

APPENDIX C – MODEL TIME UNITS TABLE

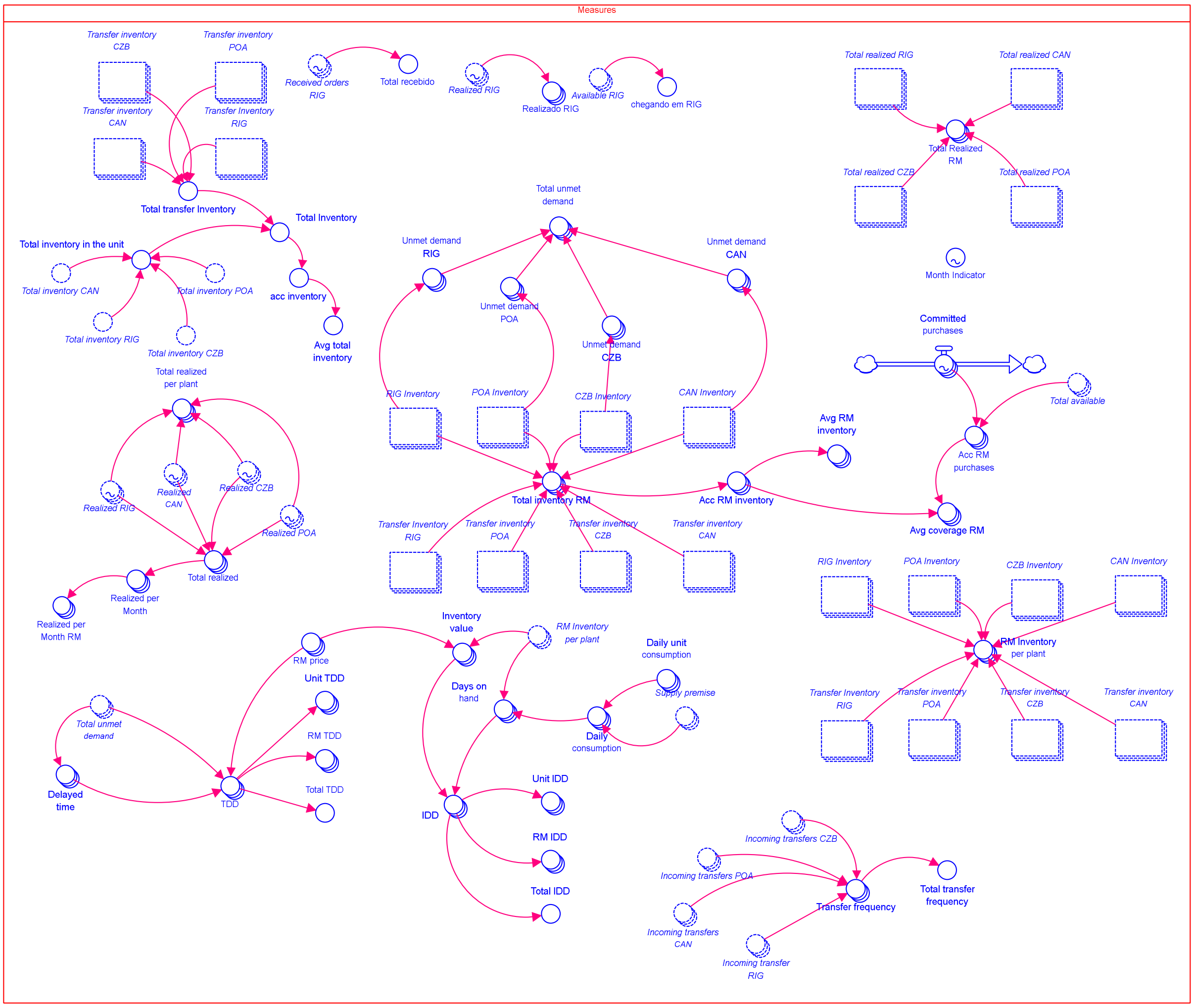
Table 30 – Months and model time units

Month	Time unit	Month	Time unit
01/11/2018	1	01/05/2019	28
	2		29
	3		30
	4		31
	5		32
01/12/2018	6	01/06/2019	33
	7		34
	8		35
	9		36
	10	01/07/2019	37
01/01/2019	11		38
	12		39
	13		40
	14		41
	15	01/08/2019	42
01/02/2019	16		43
	17		44
	18		45
	19	01/09/2019	46
01/03/2019	20		47
	21		48
	22		49
	23	01/10/2019	50
01/04/2019	24		51
	25		52
	26		53
	27		54
			55

Source: the author (2020).

APPENDIX D – METRICS MODULE

Figure 56 – Metrics module



Source: the author (2020).

APPENDIX E – FORECAST CALENDAR REPRESENTATION

The table below provides the time left in weeks for a raw material to be available at the specific forecast month.

Table 31 – Schematic for time units and their relation with the forecast month

	Forecast Month																			
Time	**1811**	**1812**	**1901**	**1902**	**1903**	**1904**	**1905**	**1906**	**1907**	**1908**	**1909**	**1910**	**1911**	**1912**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**
1	0	1	6	11	15	19	23	28	32	37	41	45	54	62	70	78	86	94	102	110
2	0	1	6	11	15	19	23	28	32	37	41	45	54	62	70	78	86	94	102	110
3	0	1	6	11	15	19	23	28	32	37	41	45	54	62	70	78	86	94	102	110
4	0	1	6	11	15	19	23	28	32	37	41	45	54	62	70	78	86	94	102	110
5	0	1	6	11	15	19	23	28	32	37	41	45	54	62	70	78	86	94	102	110
6	0	0	1	6	10	14	18	23	27	32	36	40	49	57	65	73	81	89	97	105
7	0	0	1	6	10	14	18	23	27	32	36	40	49	57	65	73	81	89	97	105
8	0	0	1	6	10	14	18	23	27	32	36	40	49	57	65	73	81	89	97	105
9	0	0	1	6	10	14	18	23	27	32	36	40	49	57	65	73	81	89	97	105
10	0	0	1	6	10	14	18	23	27	32	36	40	49	57	65	73	81	89	97	105
11	0	0	0	1	5	9	13	18	22	27	31	35	44	52	60	68	76	84	92	100
12	0	0	0	1	5	9	13	18	22	27	31	35	44	52	60	68	76	84	92	100
13	0	0	0	1	5	9	13	18	22	27	31	35	44	52	60	68	76	84	92	100
14	0	0	0	1	5	9	13	18	22	27	31	35	44	52	60	68	76	84	92	100
15	0	0	0	1	5	9	13	18	22	27	31	35	44	52	60	68	76	84	92	100
16	0	0	0	0	1	5	9	14	18	23	27	31	40	48	56	64	72	80	88	96
17	0	0	0	0	1	5	9	14	18	23	27	31	40	48	56	64	72	80	88	96
18	0	0	0	0	1	5	9	14	18	23	27	31	40	48	56	64	72	80	88	96
19	0	0	0	0	1	5	9	14	18	23	27	31	40	48	56	64	72	80	88	96
20	0	0	0	0	0	1	5	10	14	19	23	27	36	44	52	60	68	76	84	92
21	0	0	0	0	0	1	5	10	14	19	23	27	36	44	52	60	68	76	84	92
22	0	0	0	0	0	1	5	10	14	19	23	27	36	44	52	60	68	76	84	92

Time	Forecast Month 1811	1812	1901	1902	1903	1904	1905	1906	1907	1908	1909	1910	1911	1912	2001	2002	2003	2004	2005	2006
23	0	0	0	0	0	1	5	10	14	19	23	27	36	44	52	60	68	76	84	92
24	0	0	0	0	0	0	1	6	10	15	19	23	32	40	48	56	64	72	80	88
25	0	0	0	0	0	0	1	6	10	15	19	23	32	40	48	56	64	72	80	88
26	0	0	0	0	0	0	1	6	10	15	19	23	32	40	48	56	64	72	80	88
27	0	0	0	0	0	0	1	6	10	15	19	23	32	40	48	56	64	72	80	88
28	0	0	0	0	0	0	0	1	5	10	14	18	27	35	43	51	59	67	75	83
29	0	0	0	0	0	0	0	1	5	10	14	18	27	35	43	51	59	67	75	83
30	0	0	0	0	0	0	0	1	5	10	14	18	27	35	43	51	59	67	75	83
31	0	0	0	0	0	0	0	1	5	10	14	18	27	35	43	51	59	67	75	83
32	0	0	0	0	0	0	0	1	5	10	14	18	27	35	43	51	59	67	75	83
33	0	0	0	0	0	0	0	0	1	6	10	14	23	31	39	47	55	63	71	79
34	0	0	0	0	0	0	0	0	1	6	10	14	23	31	39	47	55	63	71	79
35	0	0	0	0	0	0	0	0	1	6	10	14	23	31	39	47	55	63	71	79
36	0	0	0	0	0	0	0	0	1	6	10	14	23	31	39	47	55	63	71	79
37	0	0	0	0	0	0	0	0	0	1	5	9	18	26	34	42	50	58	66	74
38	0	0	0	0	0	0	0	0	0	1	5	9	18	26	34	42	50	58	66	74
39	0	0	0	0	0	0	0	0	0	1	5	9	18	26	34	42	50	58	66	74
40	0	0	0	0	0	0	0	0	0	1	5	9	18	26	34	42	50	58	66	74
41	0	0	0	0	0	0	0	0	0	1	5	9	18	26	34	42	50	58	66	74
42	0	0	0	0	0	0	0	0	0	0	1	5	14	22	30	38	46	54	62	70
43	0	0	0	0	0	0	0	0	0	0	1	5	14	22	30	38	46	54	62	70
44	0	0	0	0	0	0	0	0	0	0	1	5	14	22	30	38	46	54	62	70
45	0	0	0	0	0	0	0	0	0	0	1	5	14	22	30	38	46	54	62	70
46	0	0	0	0	0	0	0	0	0	0	0	1	10	18	26	34	42	50	58	66
47	0	0	0	0	0	0	0	0	0	0	0	1	10	18	26	34	42	50	58	66
48	0	0	0	0	0	0	0	0	0	0	0	1	10	18	26	34	42	50	58	66
49	0	0	0	0	0	0	0	0	0	0	0	1	10	18	26	34	42	50	58	66
50	0	0	0	0	0	0	0	0	0	0	0	0	4	12	20	28	36	44	52	60
51	0	0	0	0	0	0	0	0	0	0	0	0	4	12	20	28	36	44	52	60

	Forecast Month																			
Time	**1811**	**1812**	**1901**	**1902**	**1903**	**1904**	**1905**	**1906**	**1907**	**1908**	**1909**	**1910**	**1911**	**1912**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**
52	0	0	0	0	0	0	0	0	0	0	0	0	4	12	20	28	36	44	52	60
53	0	0	0	0	0	0	0	0	0	0	0	0	4	12	20	28	36	44	52	60
54	0	0	0	0	0	0	0	0	0	0	0	0	4	12	20	28	36	44	52	60
55	0	0	0	0	0	0	0	0	0	0	0	0	4	12	20	28	36	44	52	60

Source: the author (2020).

APPENDIX F – ORDER TIME PROBABILITY FUNCTION

Table 32 – Order probability distribution

Order time (weeks)	Observations	Probability	Probability range	
			From	To
0	308	28,7%	0,0%	28,7%
1	233	21,7%	28,7%	50,4%
2	276	25,7%	50,4%	76,1%
3	180	16,8%	76,1%	92,9%
4	53	4,9%	92,9%	97,9%
5	14	1,3%	97,9%	99,2%
6	5	0,5%	99,2%	99,6%
7	3	0,3%	99,6%	99,9%
9	1	0,1%	99,9%	100,0%

Source: the author (2020).

APPENDIX G – TRANSIT TIME PROBABILITY FUNCTION

Table 33 – Transit time probabilities

Raw Material	Transit Time (Weeks)	Observations	Probability	Probability range From	Probability range To
DAP GR	4	2	67%	0%	67%
	7	1	33%	67%	100%
KCL GR	3	28	33%	0%	33%
	4	48	57%	33%	90%
	5	8	10%	90%	100%
KRISTA K	5	1	9%	0%	9%
	6	8	73%	9%	82%
	7	2	18%	82%	100%
KRISTA MAG	5	1	33%	0%	33%
	6	1	33%	33%	67%
	8	1	33%	67%	100%
KRISTA MAP	7	2	67%	0%	67%
	8	1	33%	67%	100%
KRISTA MKP	11	3	100%	0%	100%
KRISTA SOP GR	4	3	100%	0%	100%
KRISTA SOP ST	4	4	100%	0%	100%
KRISTALON 06 12 36	5	8	100%	0%	100%
KRISTALON 13 40 13	5	3	100%	0%	100%
KRISTALON 15 05 30	5	2	100%	0%	100%
NAM	3	1	33%	0%	33%
	5	1	33%	33%	67%
	7	1	33%	67%	100%
NIP GR	6	3	100%	0%	100%
PG MIX 14 16 18	5	6	100%	0%	100%
SAM GR	4	2	13%	0%	13%
	6	2	13%	13%	27%
	7	9	60%	27%	87%
	8	1	7%	87%	93%
	9	1	7%	93%	100%
SAM STD	7	1	100%	0%	100%
SSP GR	1	3	21%	0%	21%
	3	8	57%	21%	79%
	4	2	14%	79%	93%
	6	1	7%	93%	100%
TSP GR	2	4	24%	0%	24%
	3	7	41%	24%	65%
	4	3	18%	65%	82%
	5	2	12%	82%	94%
	6	1	6%	94%	100%
UREIA ADBLUE	3	1	5%	0%	5%
	5	1	5%	5%	10%
	6	5	24%	10%	33%

Raw Material	Transit Time (Weeks)	Observations	Probability	Probability range	
				From	To
UREIA ADBLUE	7	8	38%	33%	71%
	8	6	29%	71%	100%
UREIA GR	0	3	6%	0%	6%
	2	5	10%	6%	16%
	3	5	10%	16%	26%
	4	11	22%	26%	48%
	5	22	44%	48%	92%
	6	2	4%	92%	96%
	7	2	4%	96%	100%
YBELA AXAN	3	11	48%	0%	48%
	4	8	35%	48%	83%
	5	2	9%	83%	91%
	7	2	9%	91%	100%
YLIVA NITRABOR	3	4	44%	0%	44%
	4	5	56%	44%	100%
YMILA 13 24 12	3	2	22%	0%	22%
	4	2	22%	22%	44%
	5	2	22%	44%	67%
	7	3	33%	67%	100%
YMILA 16 16 16	4	7	35%	0%	35%
	5	9	45%	35%	80%
	7	4	20%	80%	100%
YMILA 19 04 19	3	4	50%	0%	50%
	4	3	38%	50%	88%
	7	1	13%	88%	100%
YMILA 21 07 14	3	2	67%	0%	67%
	4	1	33%	67%	100%
YTERA CALCINIT	3	9	35%	0%	35%
	4	9	35%	35%	69%
	5	1	4%	69%	73%
	7	6	23%	73%	96%
	8	1	4%	96%	100%
YVERA 40	3	8	100%	0%	100%

Source: the author (2020).

APPENDIX H – SEAPORT PROCESSING PROBABILITY FUNCTION

Table 34 – Seaport processing probabilities

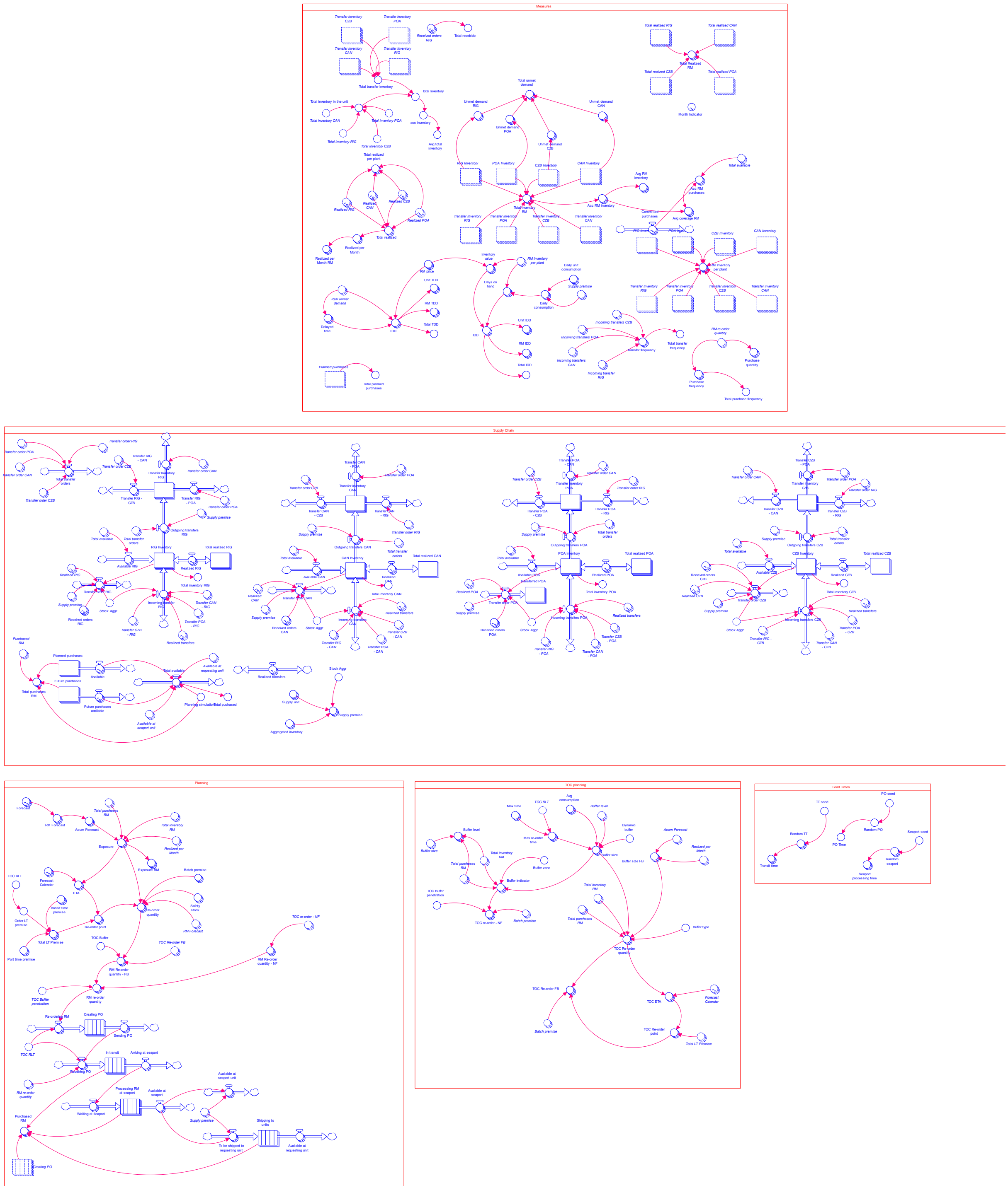
Raw Material	Processing time (weeks)	Observations	Probability	Probability range From	To
DAP GR	1	3	100%	0%	100%
KCL GR	0	2	2%	0%	2%
	1	39	46%	2%	49%
	2	38	45%	49%	94%
	3	5	6%	94%	100%
KRISTA K	0	3	27%	0%	27%
	1	1	9%	27%	36%
	2	4	36%	36%	73%
	3	2	18%	73%	91%
	4	1	9%	91%	100%
KRISTA MAG	1	2	67%	0%	67%
	2	1	33%	67%	100%
KRISTA MAP	2	3	100%	0%	100%
KRISTA MKP	1	2	67%	0%	67%
	2	1	33%	67%	100%
KRISTA SOP GR	1	1	33%	0%	33%
	3	2	67%	33%	100%
KRISTA SOP ST	0	1	25%	0%	25%
	1	1	25%	25%	50%
	2	1	25%	50%	75%
	4	1	25%	75%	100%
KRISTALON 06 12 36	1	2	25%	0%	25%
	2	4	50%	25%	75%
	3	2	25%	75%	100%
KRISTALON 13 40 13	1	2	67%	0%	67%
	3	1	33%	67%	100%
KRISTALON 15 05 30	1	1	50%	0%	50%
	10	1	50%	50%	100%
NAM	1	1	33%	0%	33%
	2	1	33%	33%	67%
	3	1	33%	67%	100%
NIP GR	1	1	33%	0%	33%
	2	2	67%	33%	100%
PG MIX 14 16 18	1	1	17%	0%	17%
	2	4	67%	17%	83%
	3	1	17%	83%	100%
SAM GR	0	5	33%	0%	33%
	1	9	60%	33%	93%
	2	1	7%	93%	100%
SAM STD	1	1	100%	0%	100%
SSP GR	1	4	29%	0%	29%
	2	10	71%	29%	100%

Raw Material	Processing time (weeks)	Observations	Probability	Probability range	
				From	To
TSP GR	1	10	59%	0%	59%
	2	7	41%	59%	100%
UREIA ADBLUE	0	5	24%	0%	24%
	1	8	38%	24%	62%
	2	5	24%	62%	86%
	3	3	14%	86%	100%
UREIA GR	1	32	64%	0%	64%
	2	16	32%	64%	96%
	3	2	4%	96%	100%
YBELA AXAN	1	11	48%	0%	48%
	2	9	39%	48%	87%
	3	3	13%	87%	100%
YLIVA NITRABOR	1	3	33%	0%	33%
	2	4	44%	33%	78%
	3	1	11%	78%	89%
	6	1	11%	89%	100%
YMILA 13 24 12	1	4	44%	0%	44%
	2	3	33%	44%	78%
	3	2	22%	78%	100%
YMILA 16 16 16	1	15	75%	0%	75%
	3	5	25%	75%	100%
YMILA 19 04 19	1	2	25%	0%	25%
	2	4	50%	25%	75%
	6	2	25%	75%	100%
YMILA 21 07 14	2	1	33%	0%	33%
	6	2	67%	33%	100%
YMILA 22 04 12	1	2	100%	0%	100%
YTERA CALCINIT	1	4	15%	0%	15%
	2	4	15%	15%	31%
	3	17	65%	31%	96%
	4	1	4%	96%	100%
YVERA 40	1	2	25%	0%	25%
	2	6	75%	25%	100%

Source: the author (2020).

APPENDIX I – SYSTEM DYNAMICS MODEL OVERVIEW

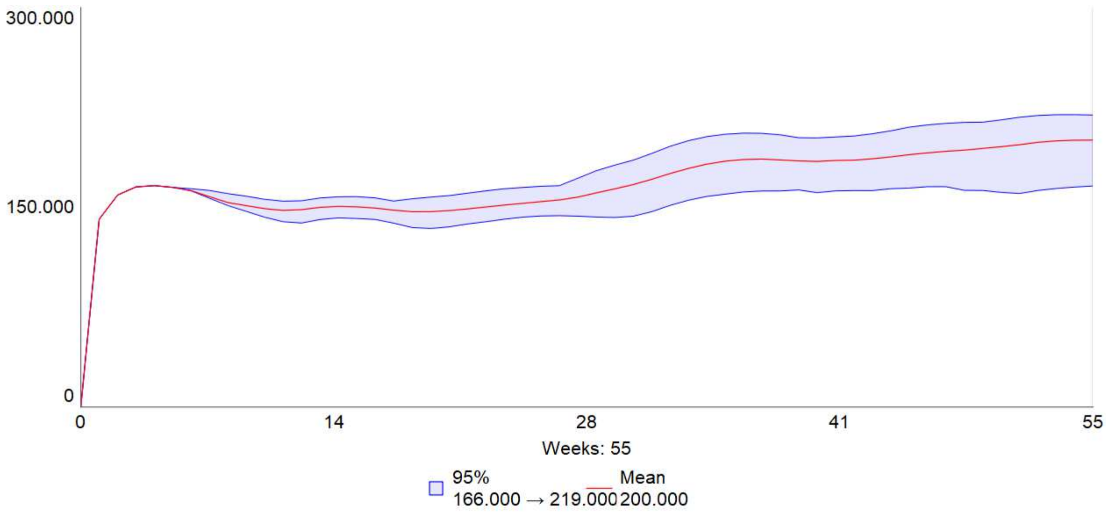
Figure 57 – System Dynamics Model



Source: the author (2020).

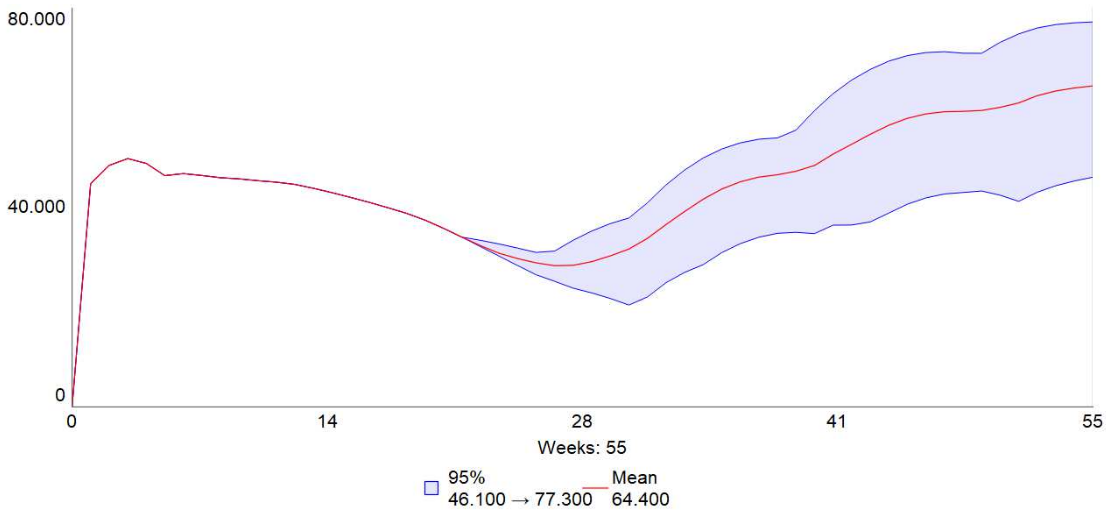
APPENDIX J – CONFIDENCE INTERVALS OF RESULTS

Figure 58 – Average total inventory confidence intervals



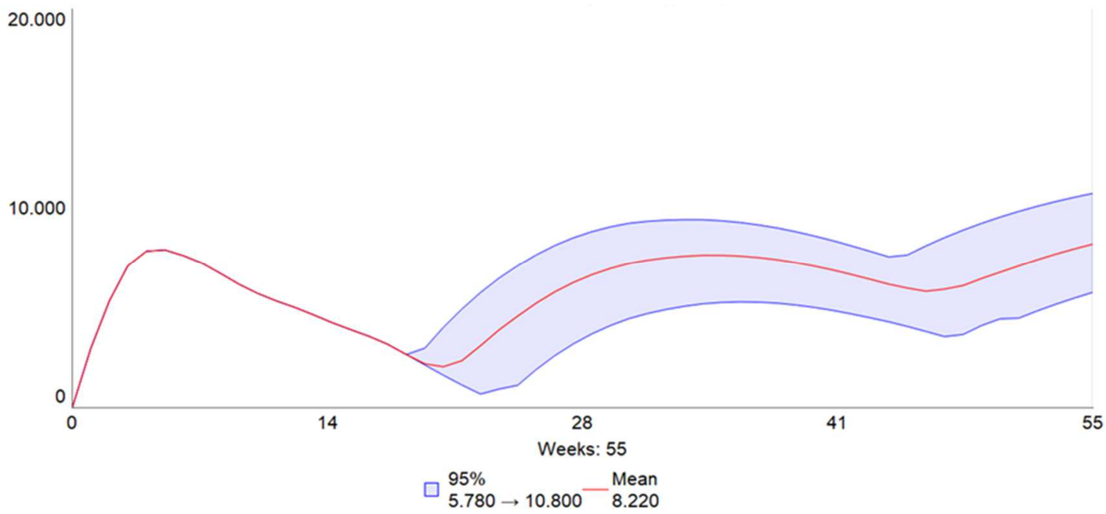
Source: the author (2020).

Figure 59 – confidence invervals for KCL GR



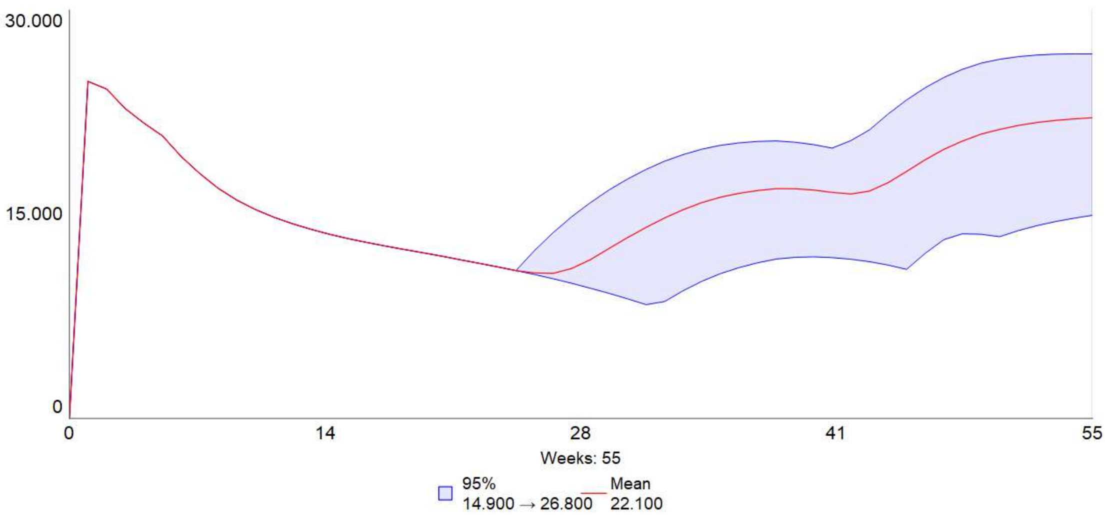
Source: the author (2020).

Figure 60 – Confidence intervals for SAM GR



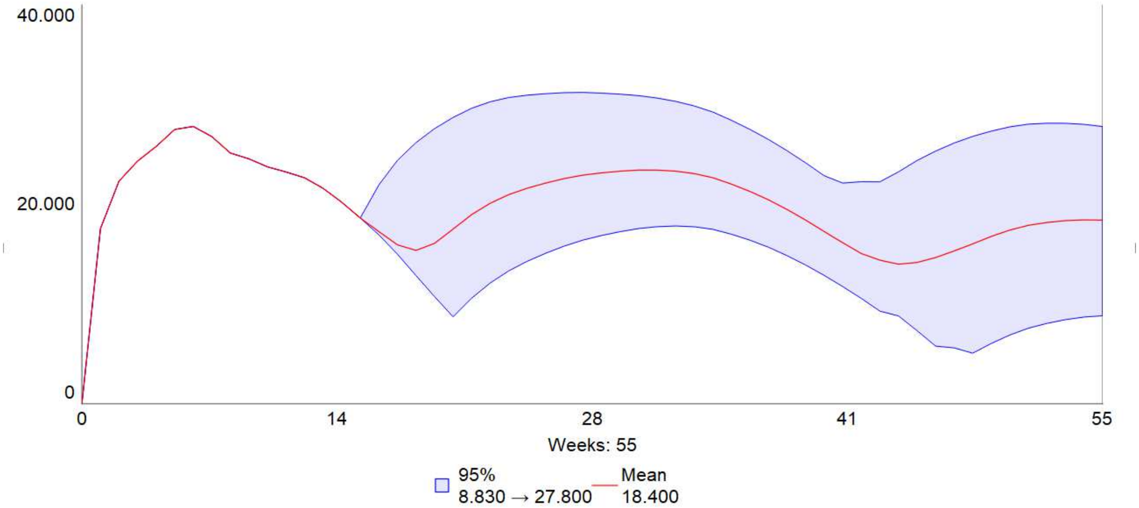
Source: the author (2020).

Figure 61 – Confidence intervals for TSP GR



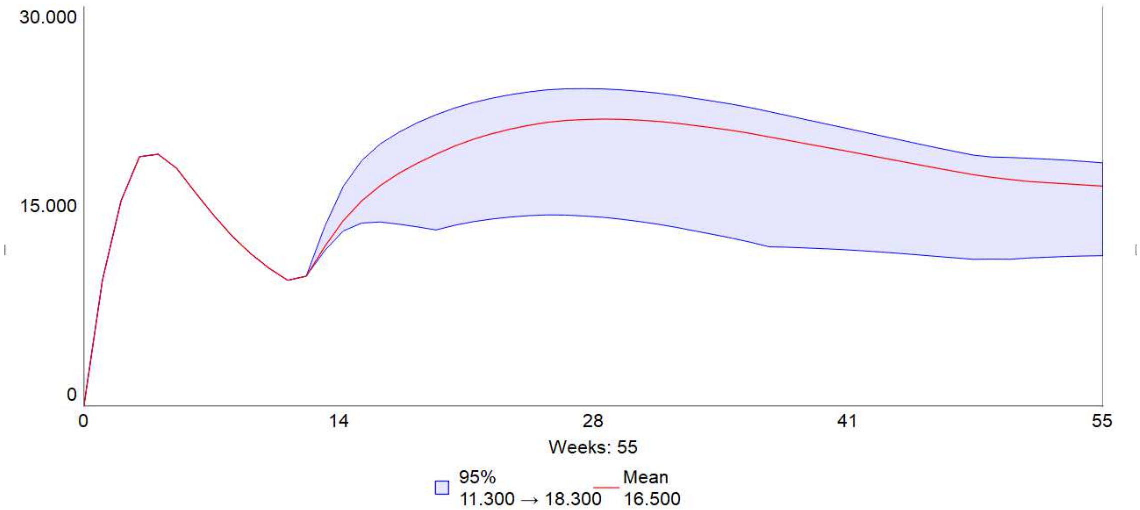
Source: the author (2020).

Figure 62 – Confidence intervals for UREIA GR



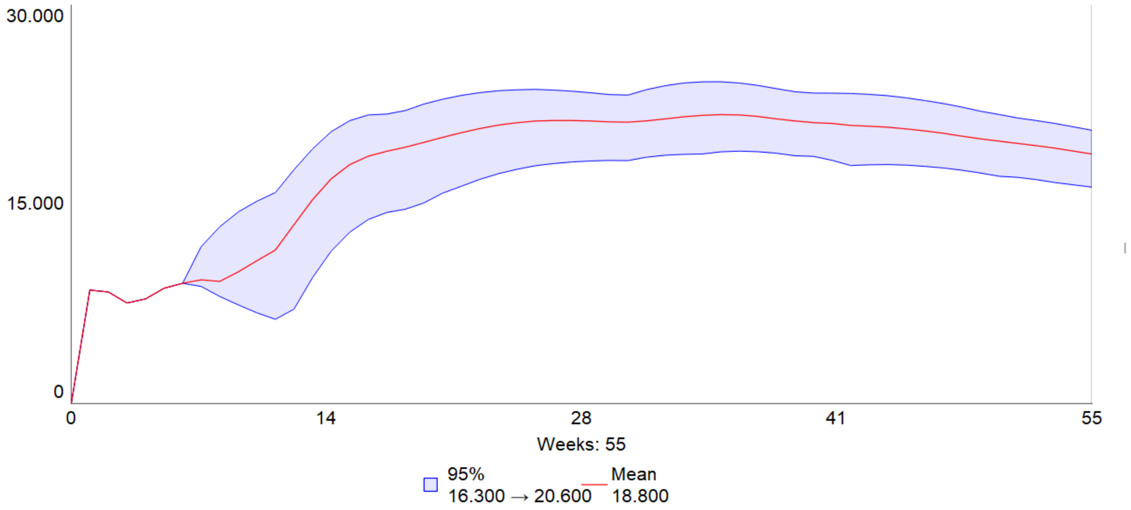
Source: the author (2020).

Figure 63 – Confidence intervals for YMILA 16 16 16



Source: the author (2020).

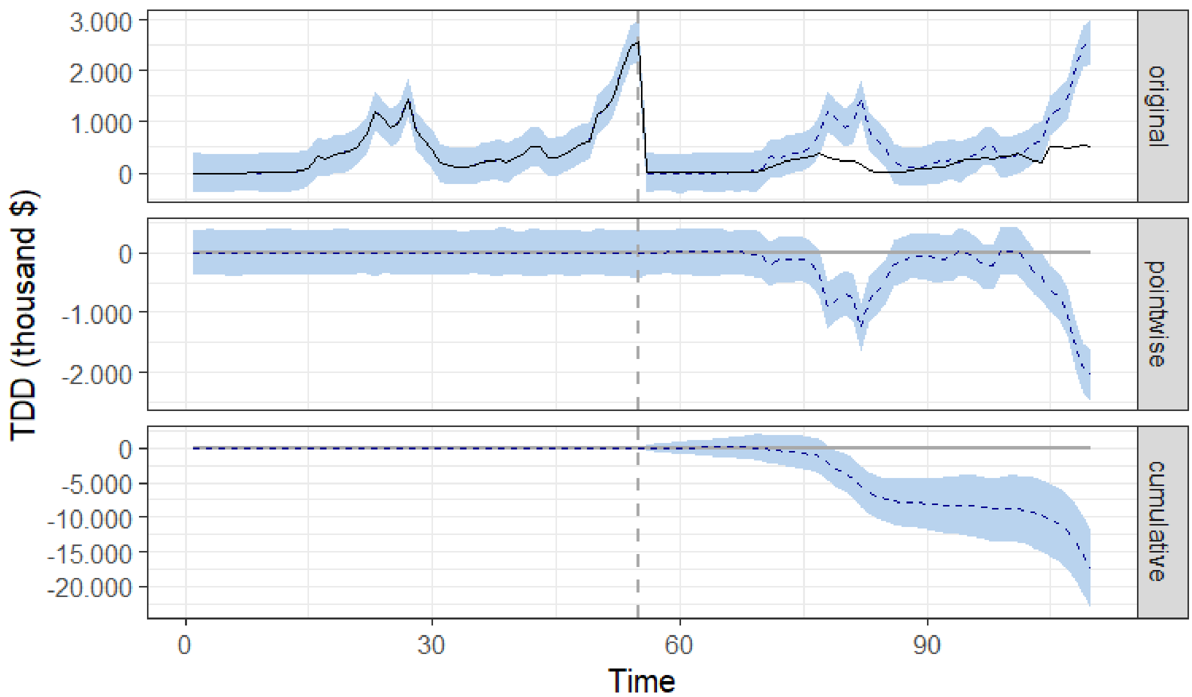
Figure 64 – Confidence intervals for YBELA AXAN



Source: the author (2020).

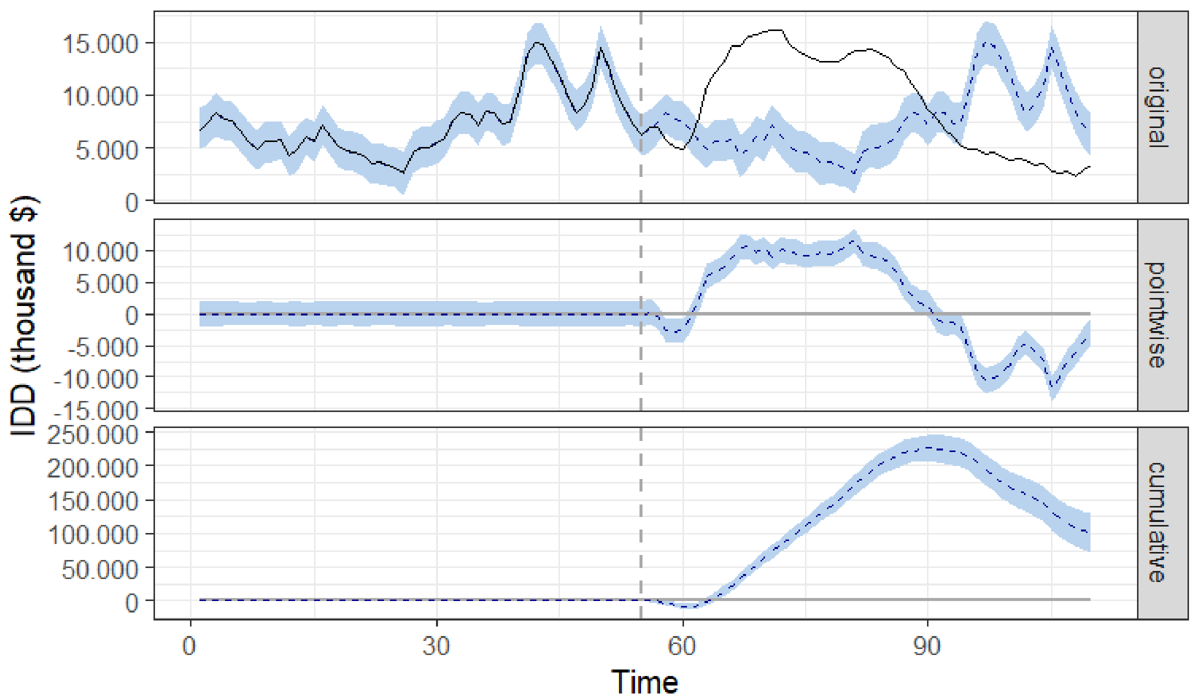
APPENDIX K – CAUSAL IMPACT PLOTS

Figure 65 – TDD impact for scenario 2 compared to the base model



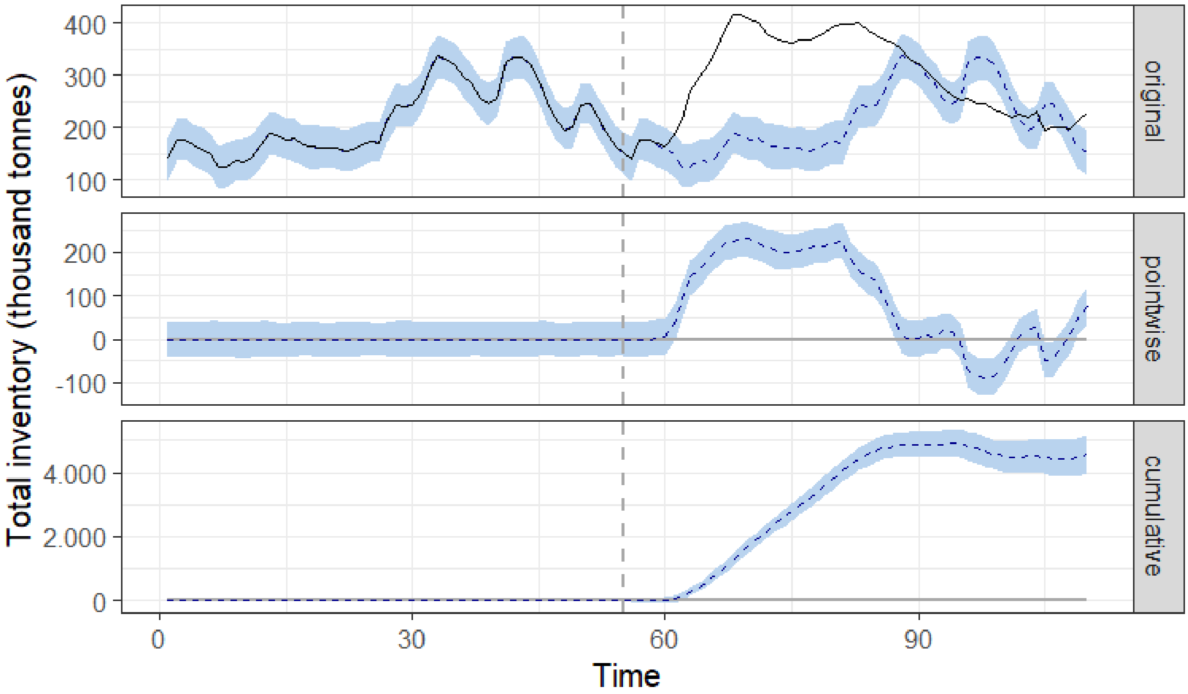
Source: the author (2020).

Figure 66 – IDD impact for scenario 2 compared to the base model1



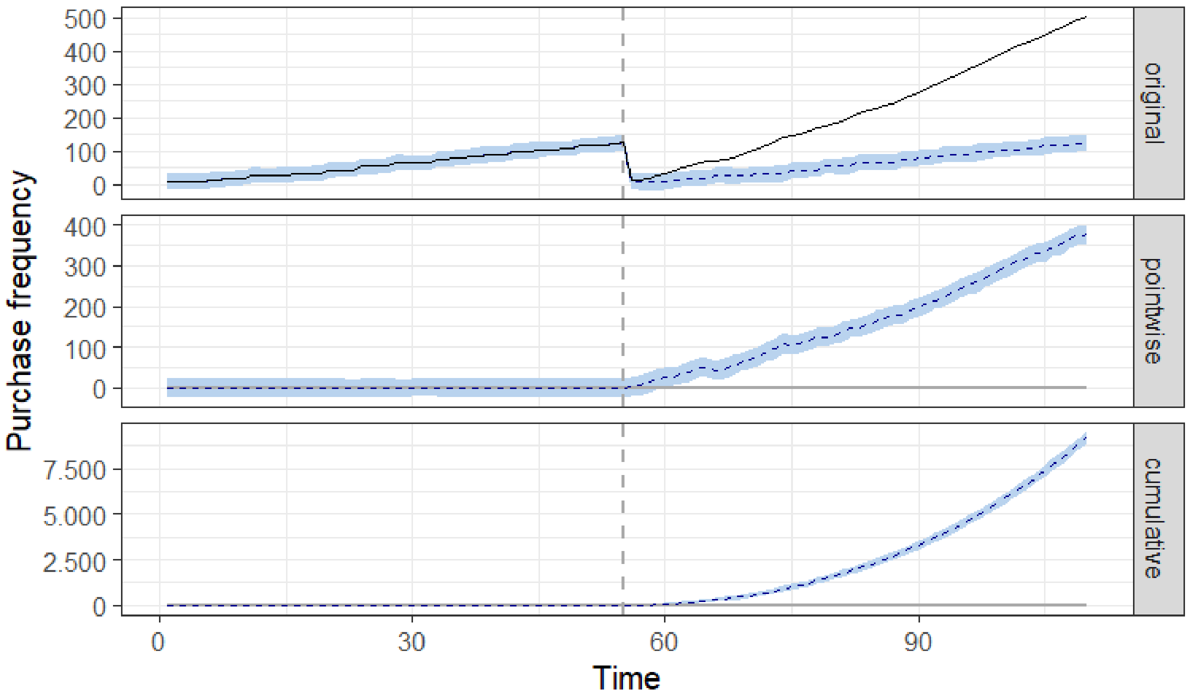
Source: the author (2020).

Figure 67 – Total inventory impact for scenario 2 compared to the base model



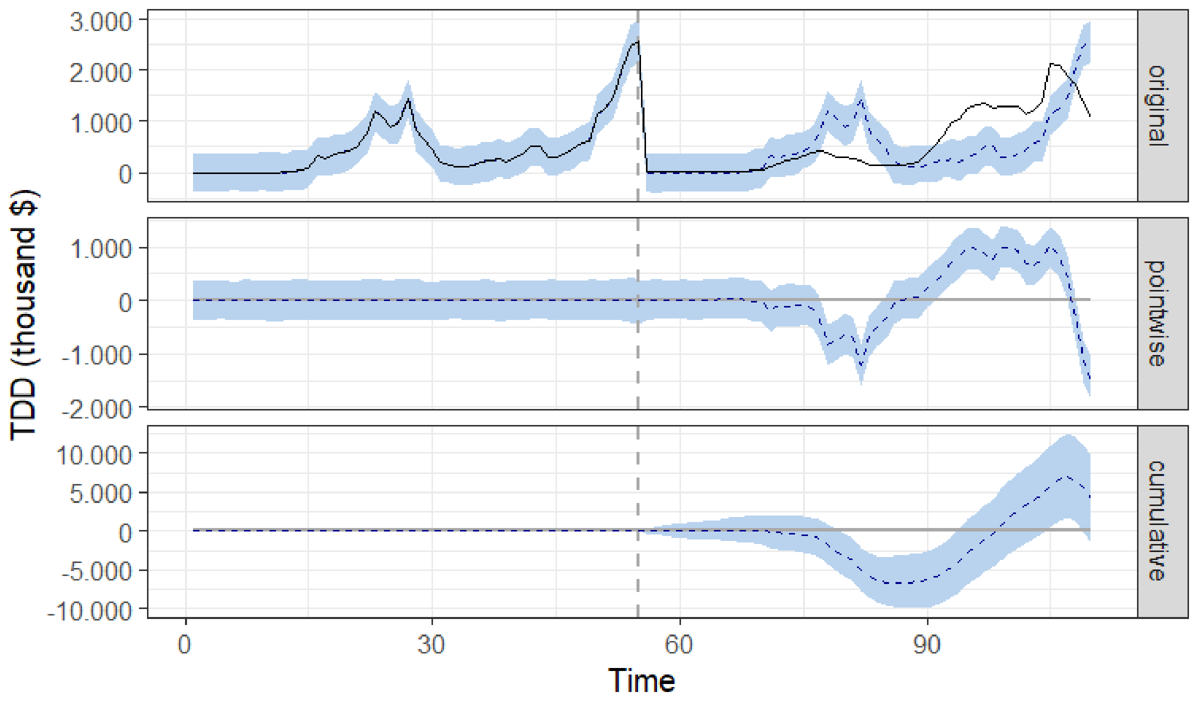
Source: the author (2020).

Figure 68 – Purchase frequency impact for scenario 2 compared to the base model



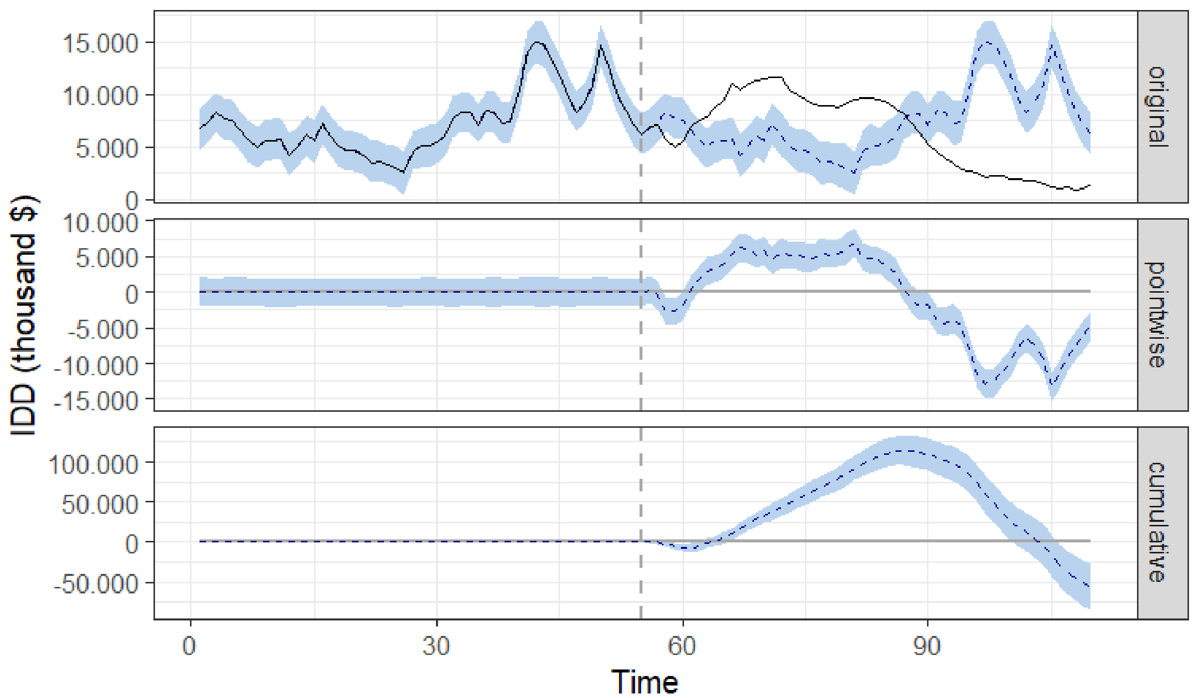
Source: the author (2020).

Figure 69 – TDD impact for scenario 3 compared to the base model



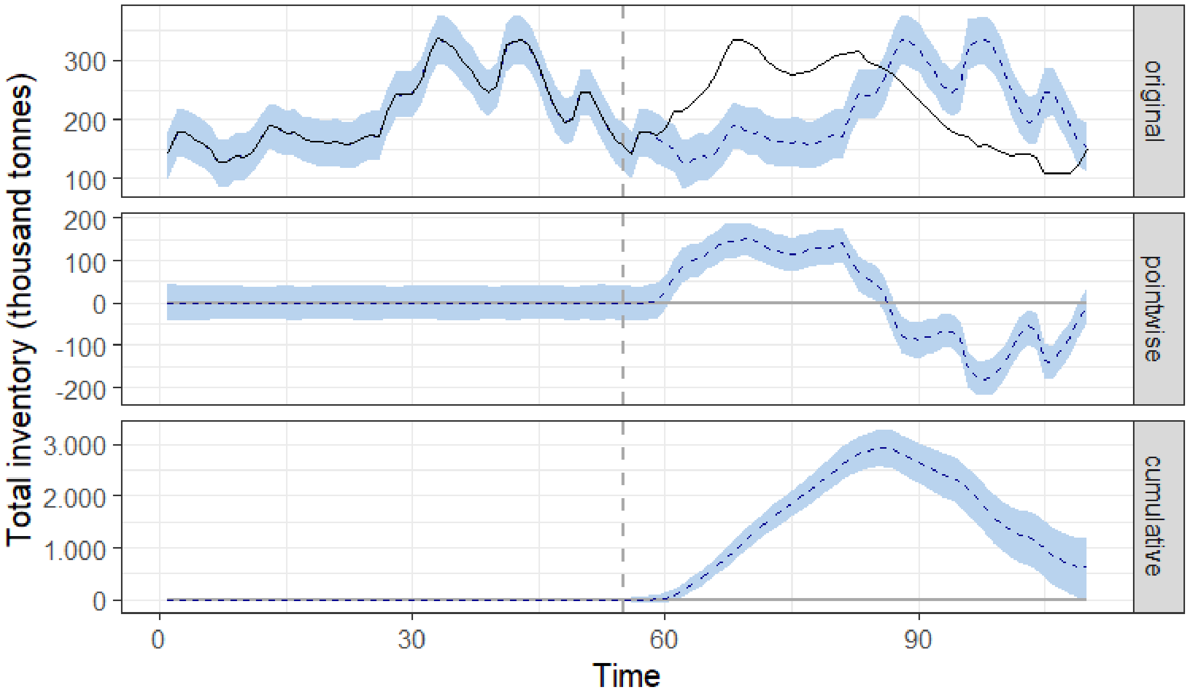
Source: the author (2020).

Figure 70 – IDD impact for scenario 3 compared to the base model



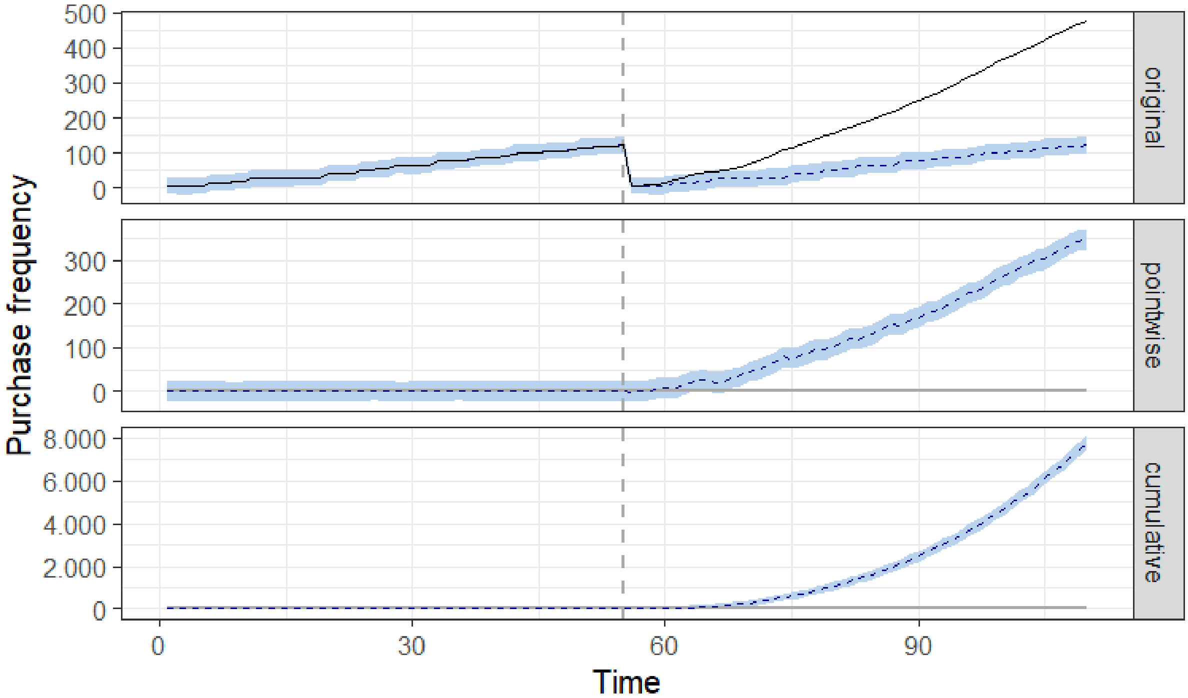
Source: the author (2020).

Figure 71 – Total inventory impact for scenario 3 compared to the base model



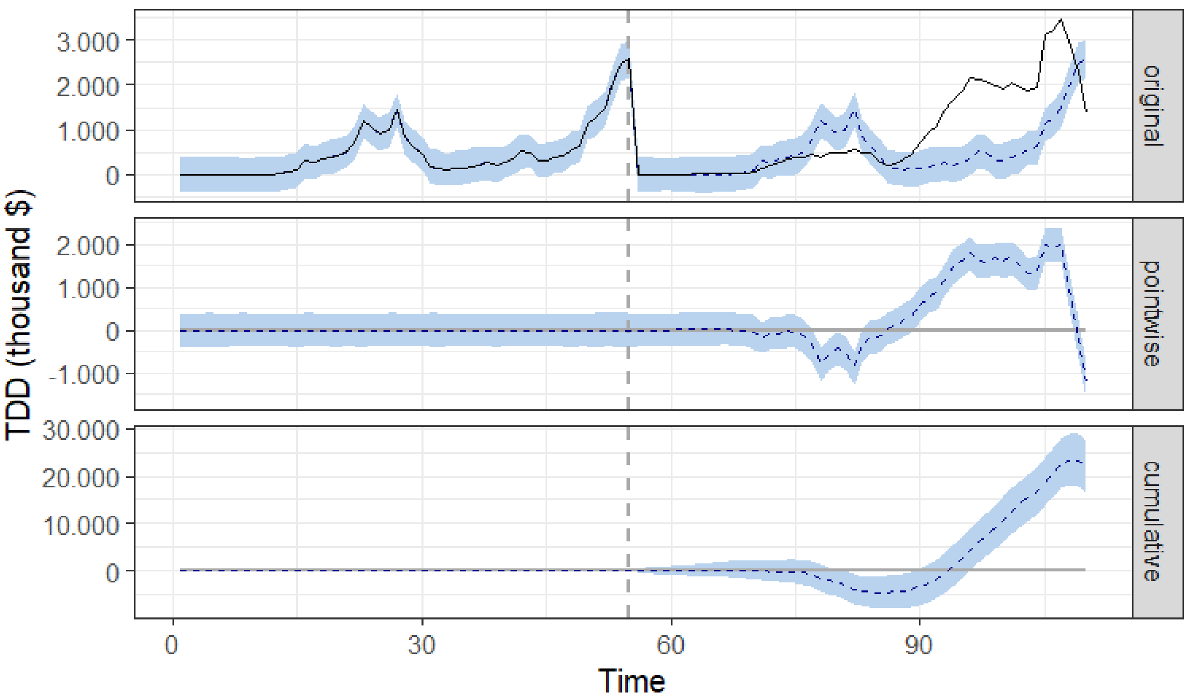
Source: the author (2020).

Figure 72 – Purchase frequency impact for scenario 3 compared to the base model



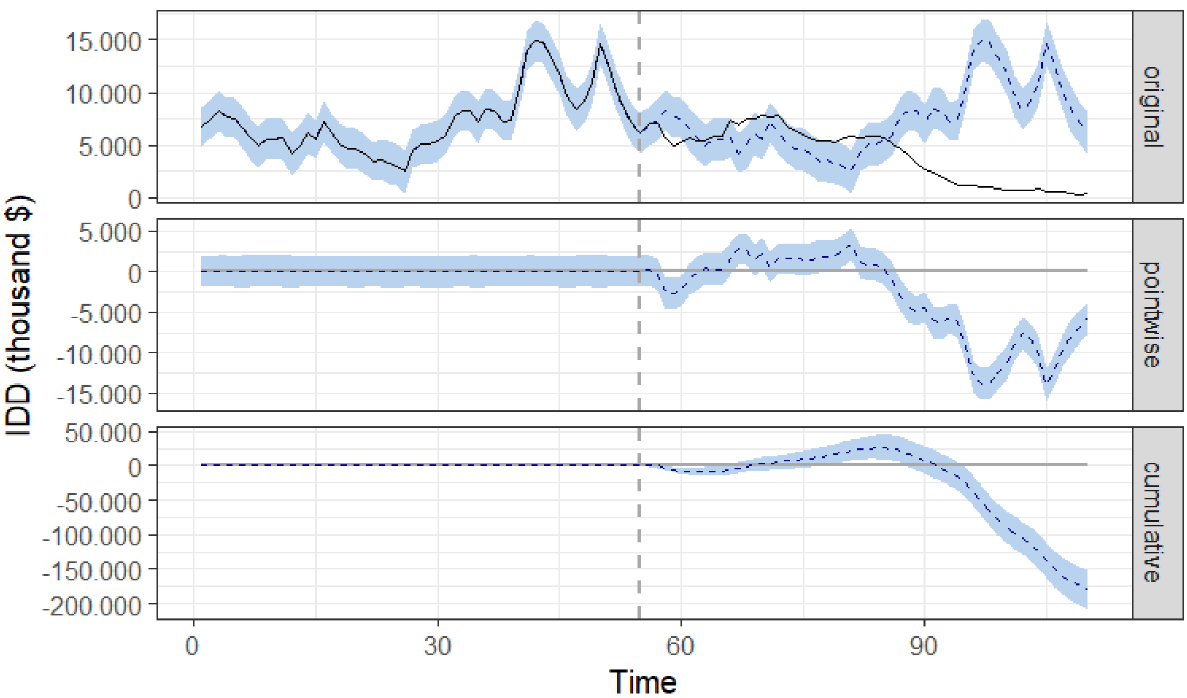
Source: the author (2020).

Figure 73 – TDD impact for scenario 4 compared to the base model



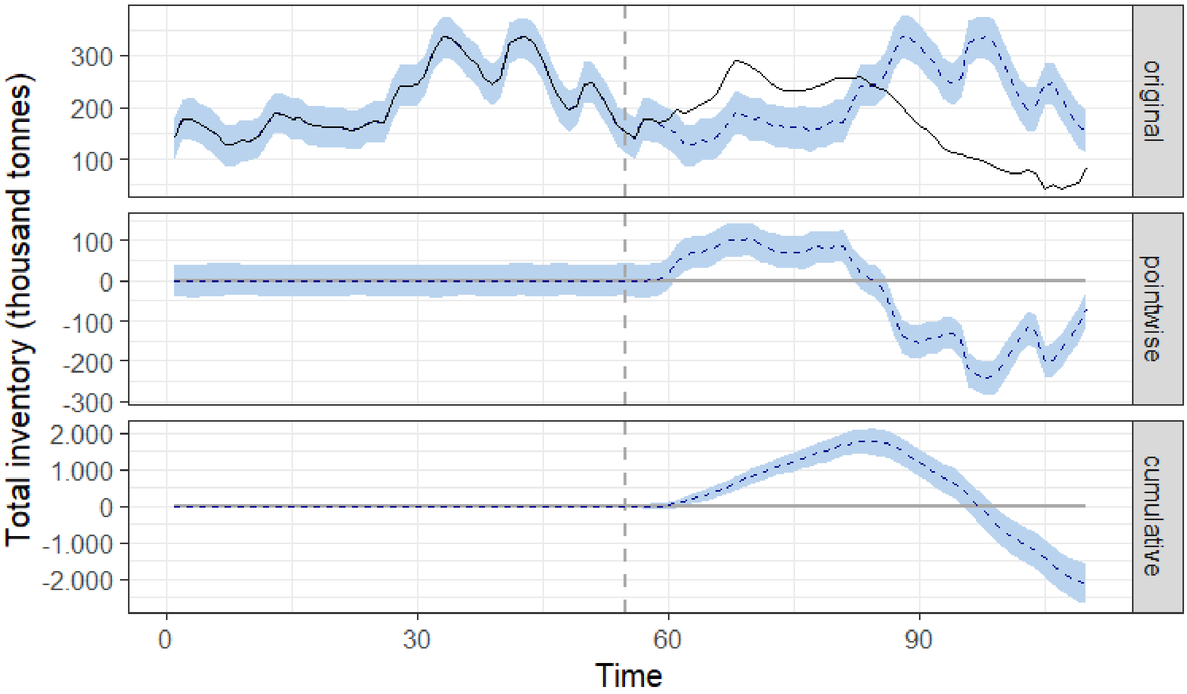
Source: the author (2020).

Figure 74 – IDD impact for scenario 4 compared to the base model



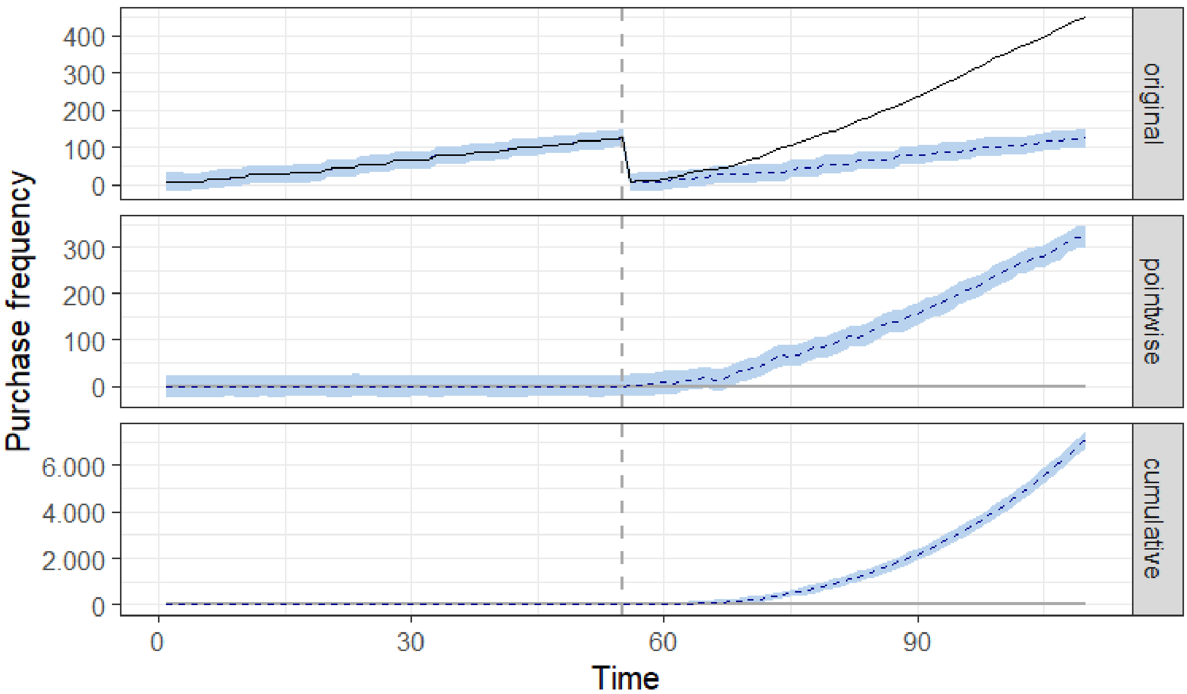
Source: the author (2020).

Figure 75 – Total inventory impact for scenario 4 compared to the base model



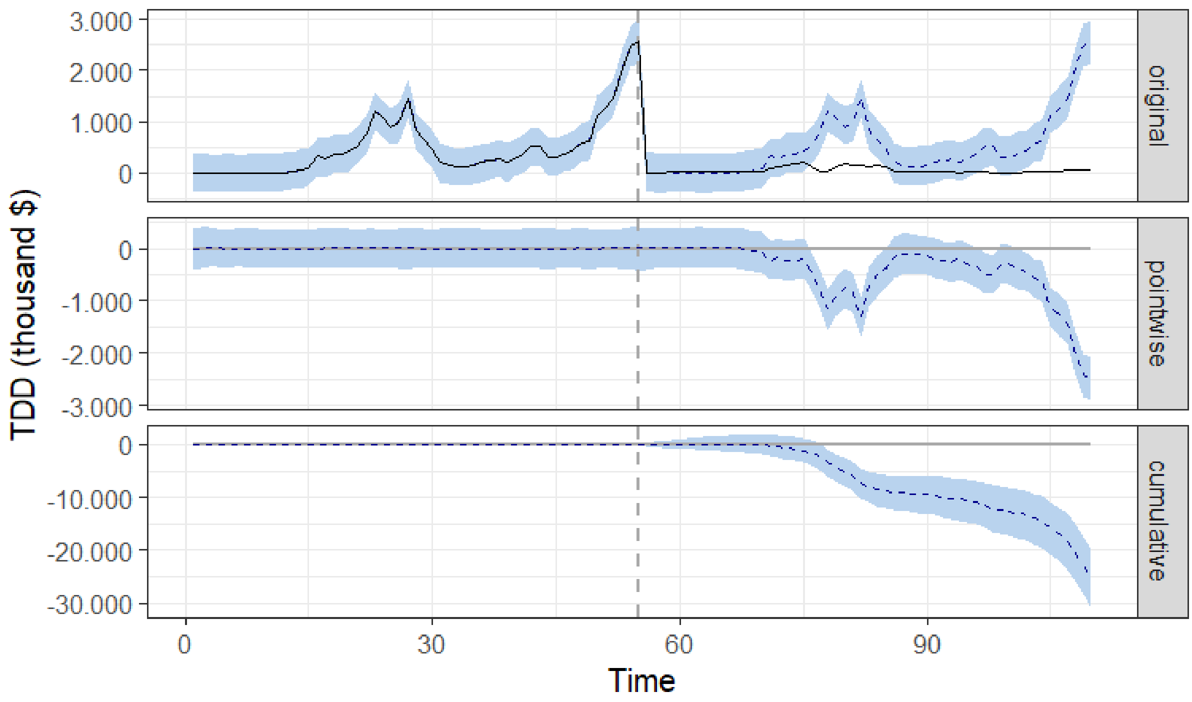
Source: the author (2020).

Figure 76 – Purchase frequency impact for scenario 4 compared to the base model



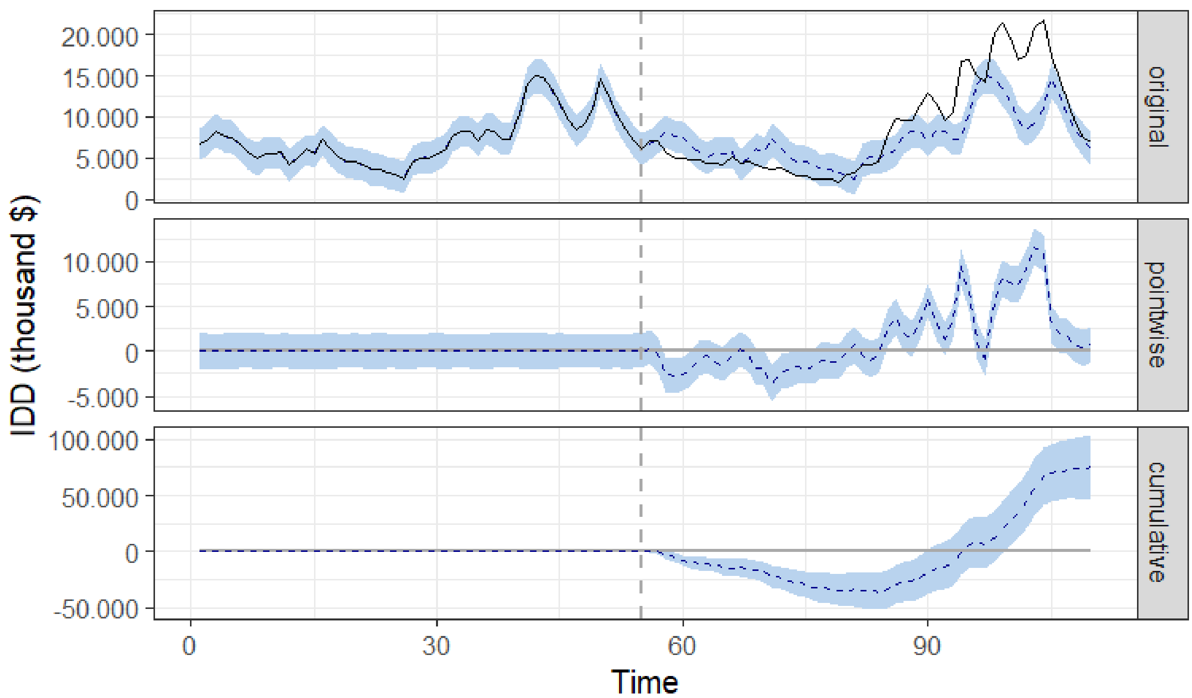
Source: the author (2020).

Figure 77 – TDD impact for scenario 5 compared to scenario the base model



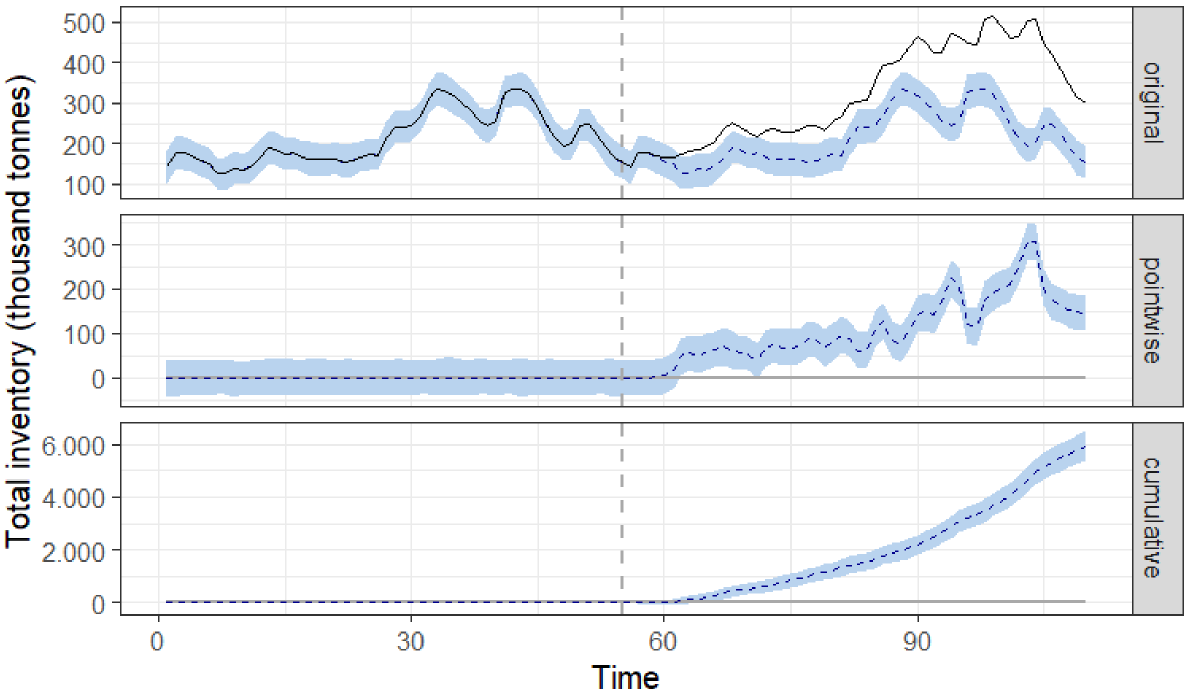
Source: the author (2020).

Figure 78 – IDD impact for scenario 5 compared to the base model



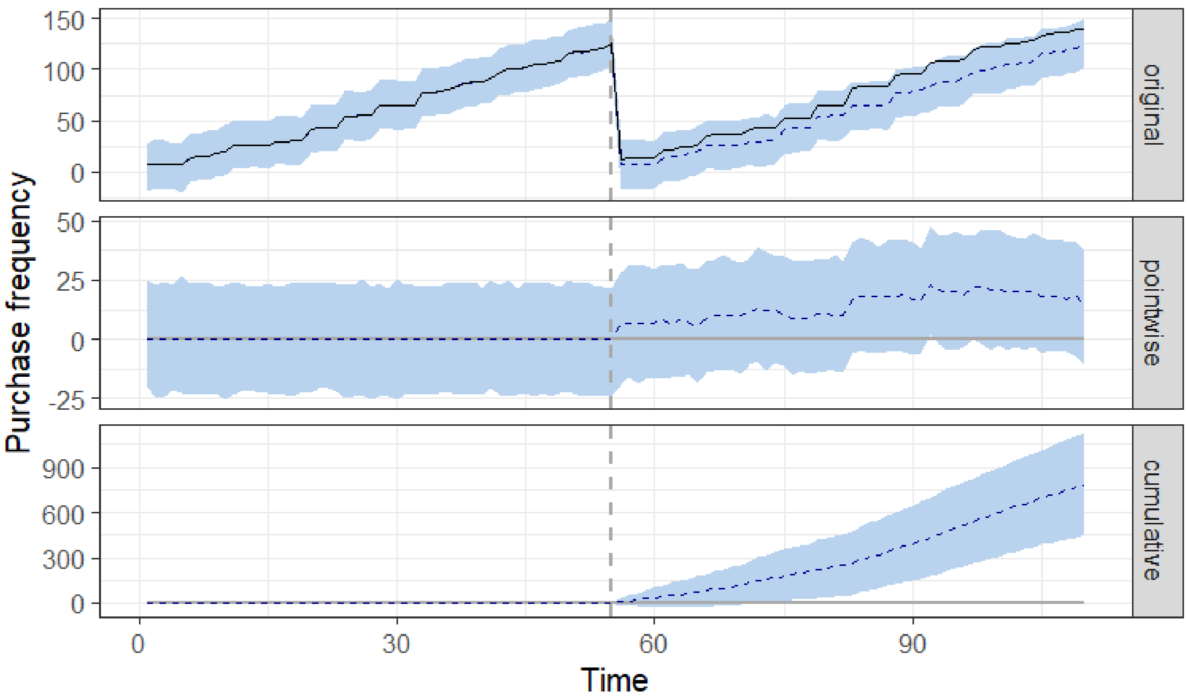
Source: the author (2020).

Figure 79 – Total inventory impact for scenario 5 compared to the base model



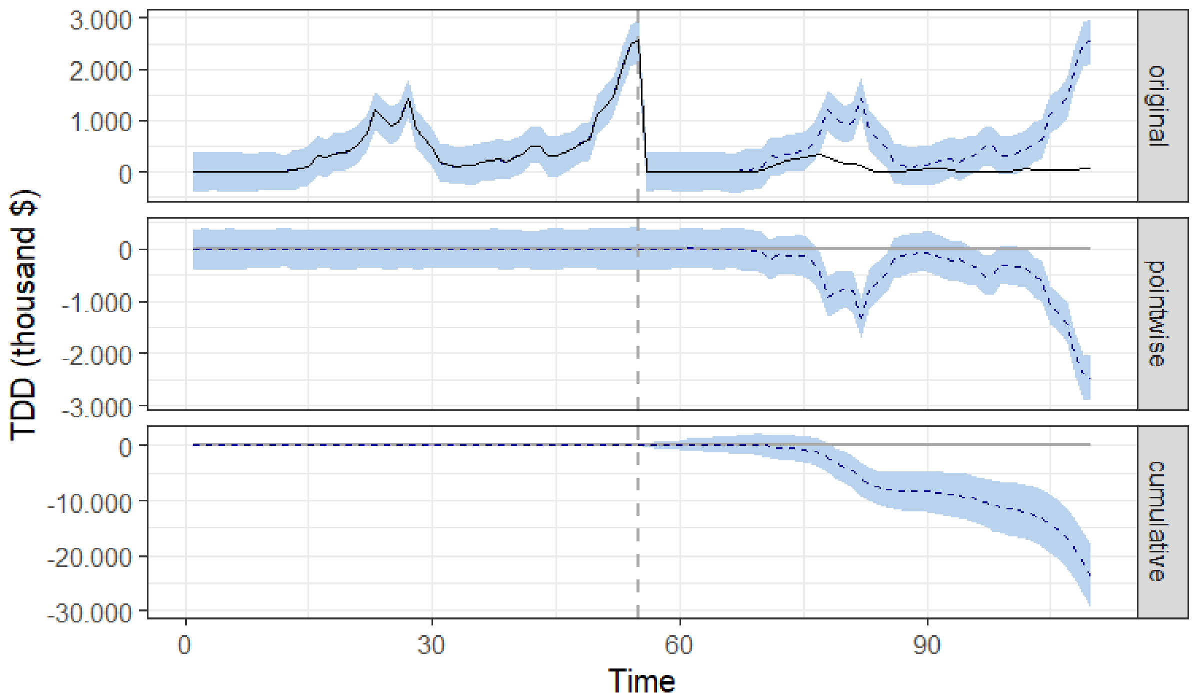
Source: the author (2020).

Figure 80 – Purchase frequency impact for scenario 5 compared to the base model



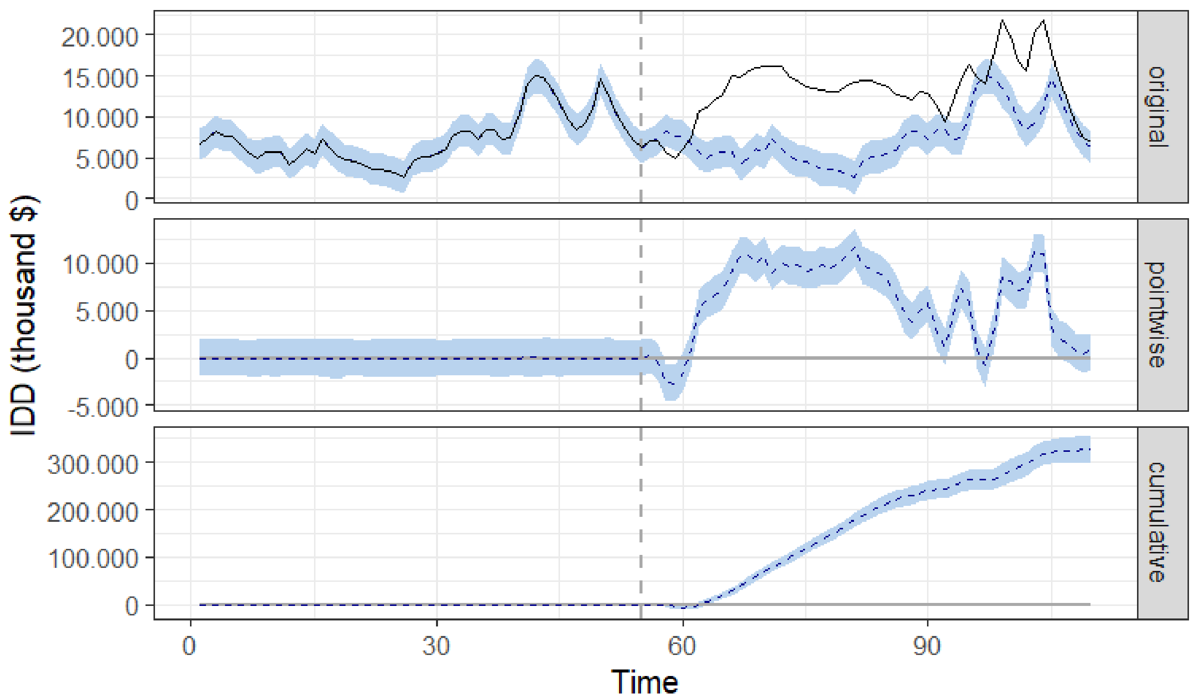
Source: the author (2020).

Figure 81 – TDD impact for scenario 6 compared to scenario the base model



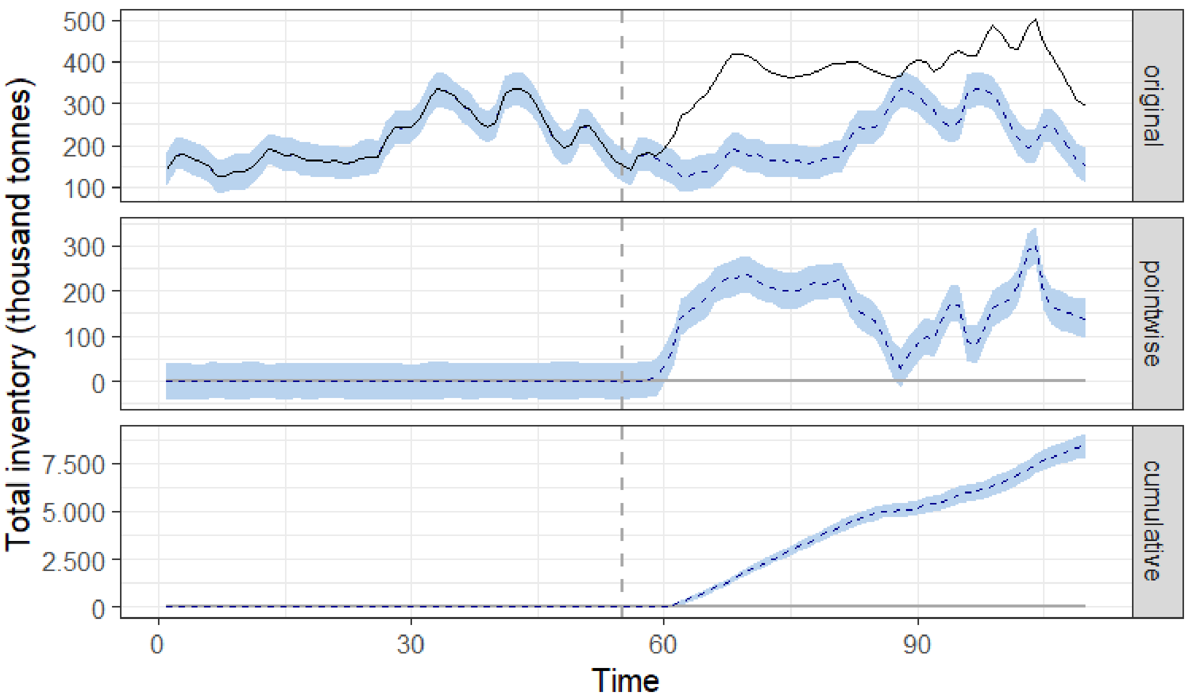
Source: the author (2020).

Figure 82 – IDD impact for scenario 6 compared to scenario the base model



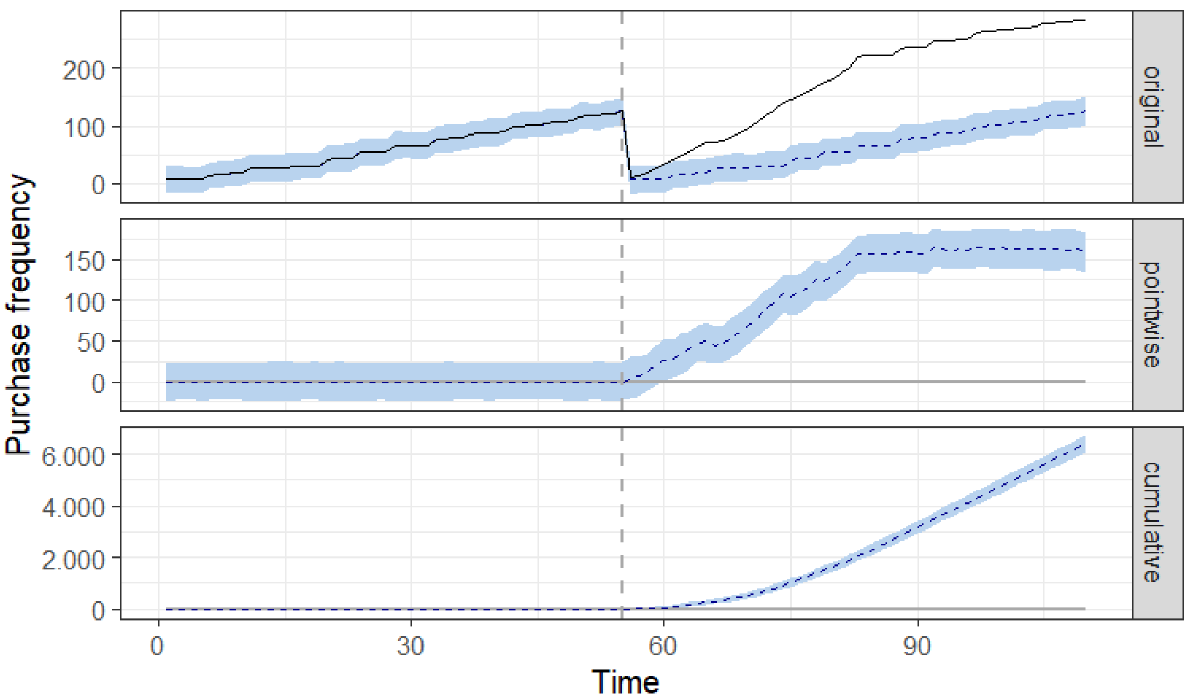
Source: the author (2020).

Figure 83 – Total inventory impact for scenario 6 compared to the base model



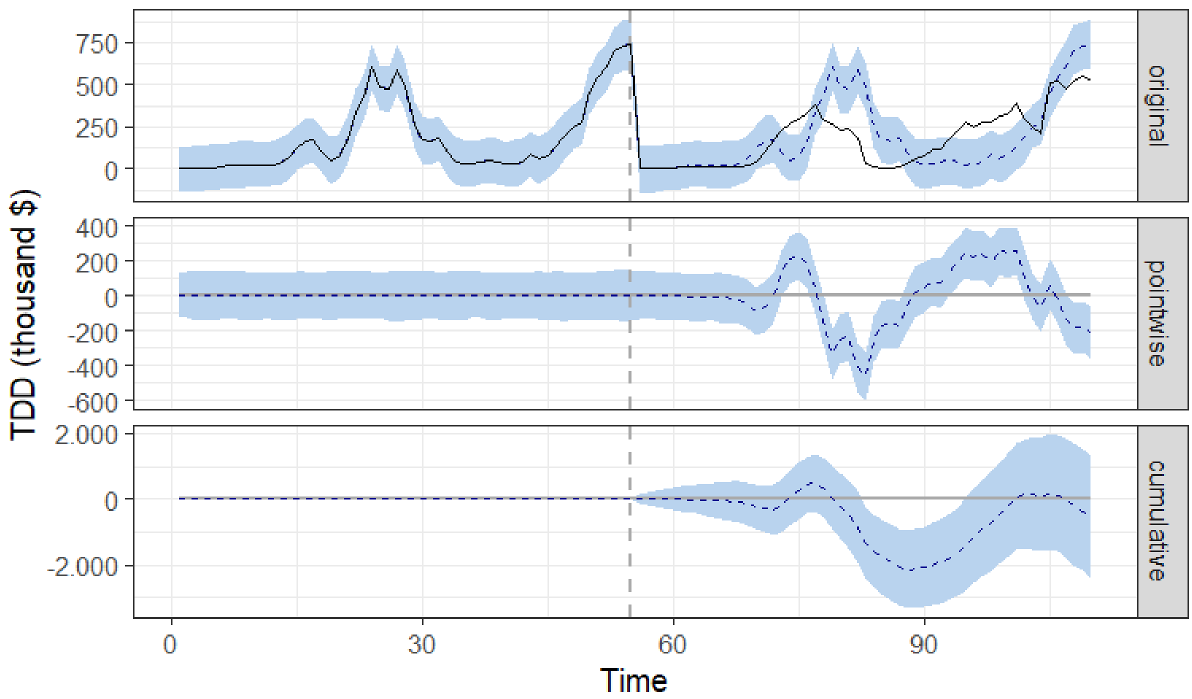
Source: the author (2020).

Figure 84 – Purchase frequency impact for scenario 6 compared to the base model



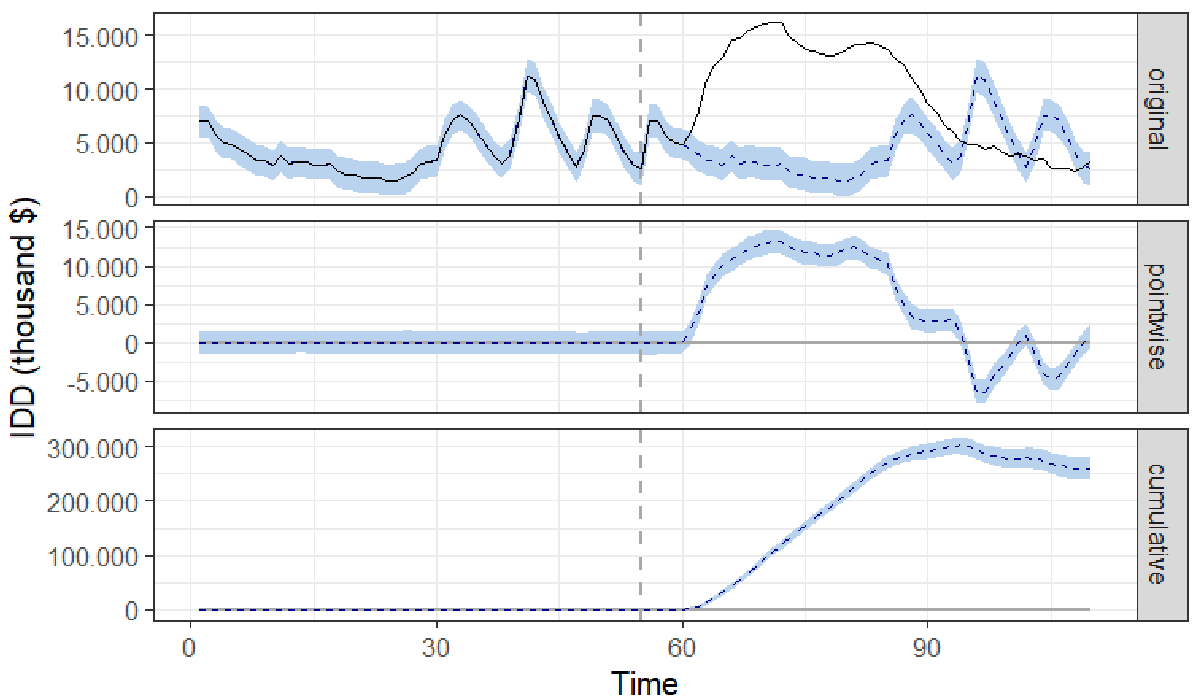
Source: the author (2020).

Figure 85 – TDD impact for scenario 2 compared to scenario 1



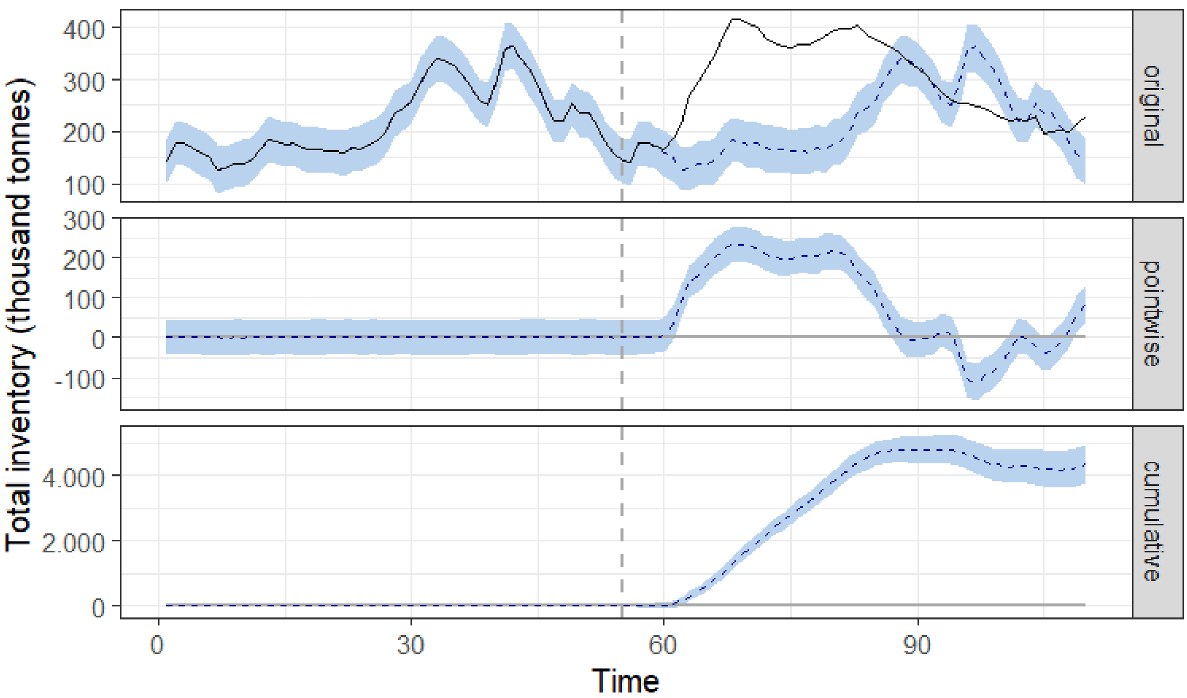
Source: the author (2020).

Figure 86 – IDD impact for scenario 2 compared to scenario 1



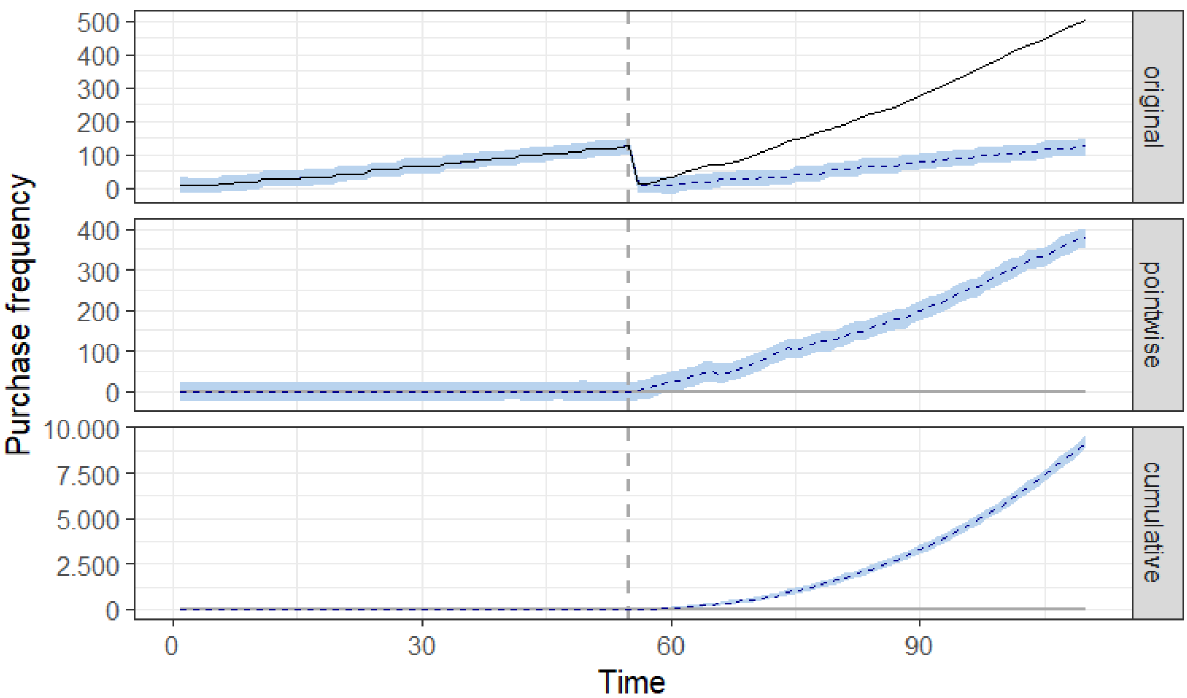
Source: the author (2020).

Figure 87 – Total inventory impact for scenario 2 compared to scenario 1



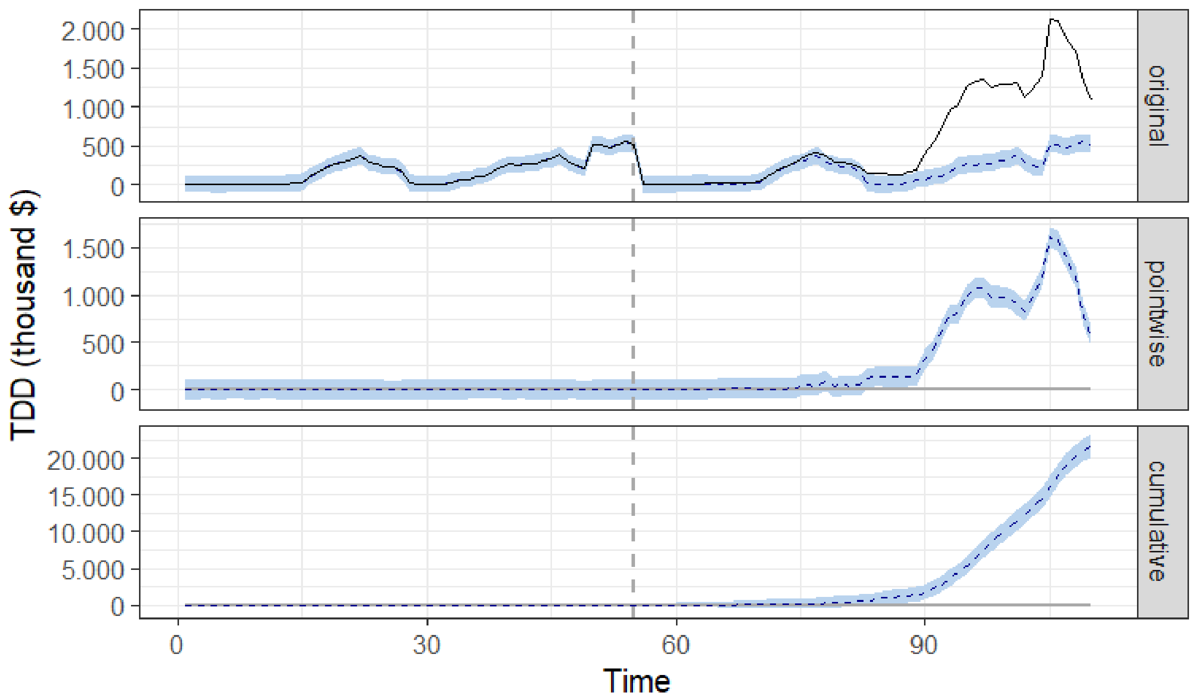
Source: the author (2020).

Figure 88 – Purchase frequency impact for scenario 2 compared to scenario 1



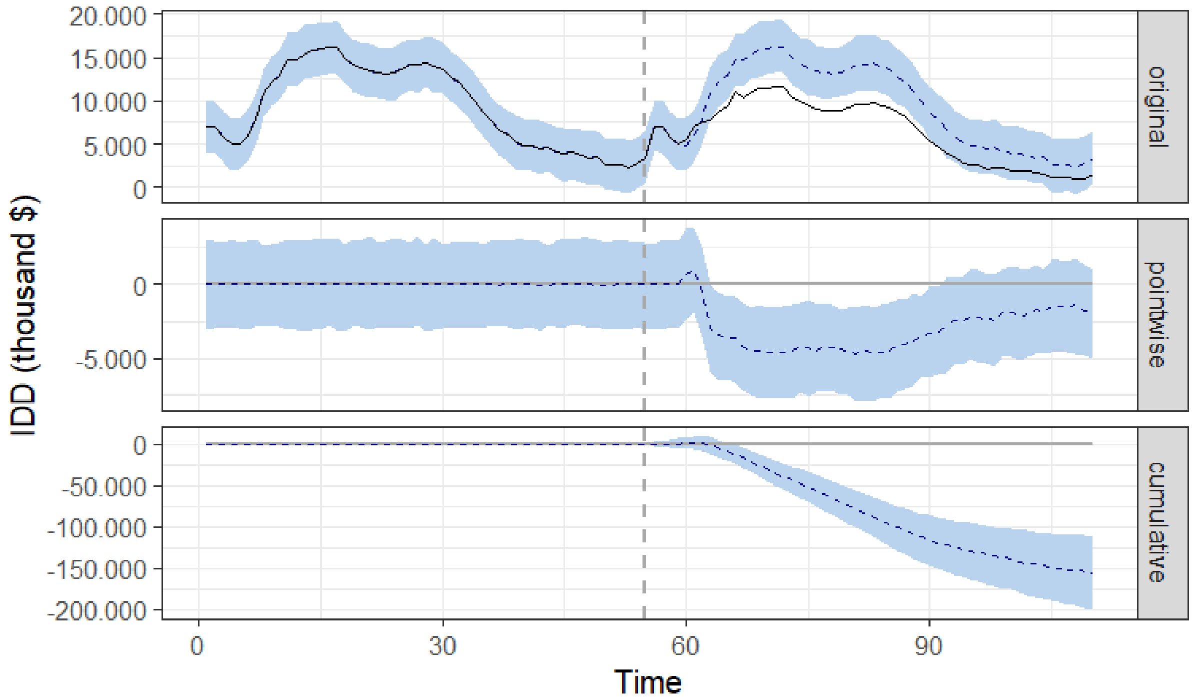
Source: the author (2020).

Figure 89 – TDD impact for scenario 3 compared to scenario 2



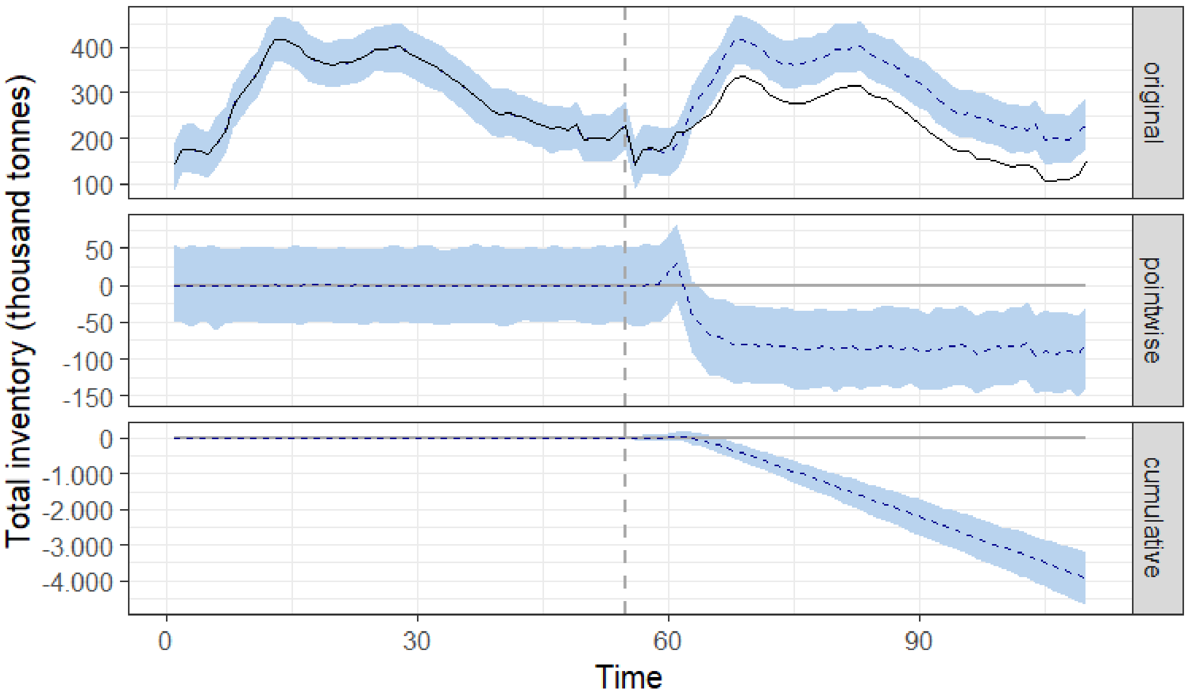
Source: the author (2020).

Figure 90 – IDD impact for scenario 3 compared to scenario 2



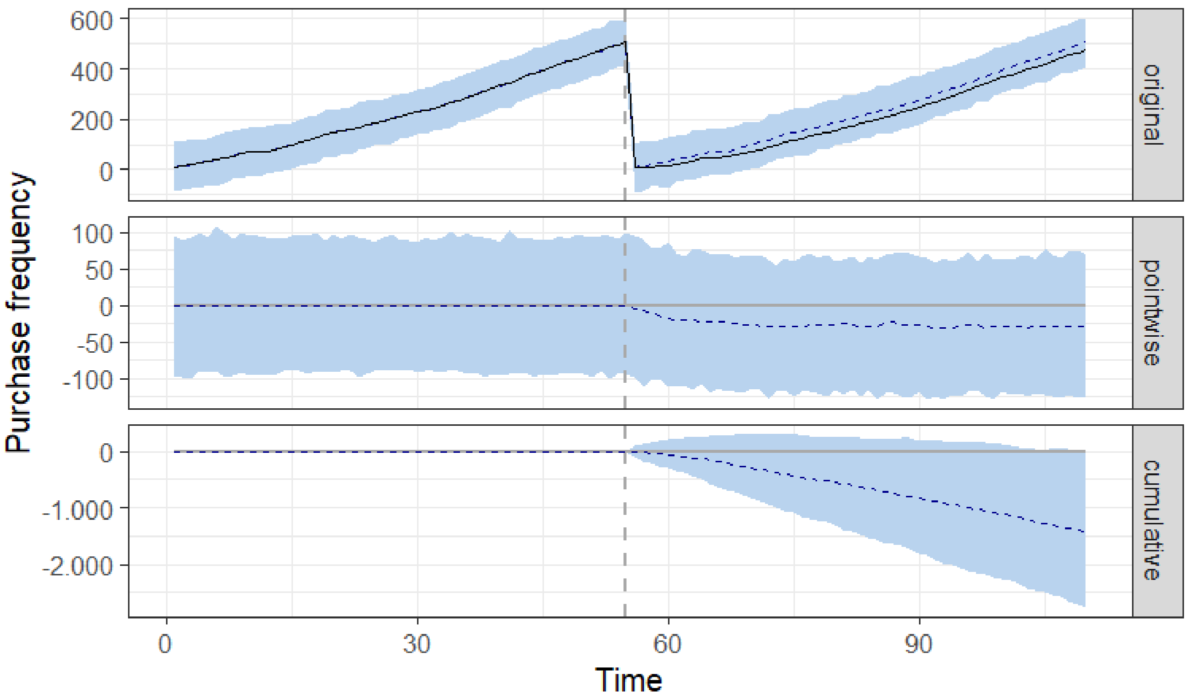
Source: the author (2020).

Figure 91 – Total inventory impact for scenario 3 compared to scenario 2



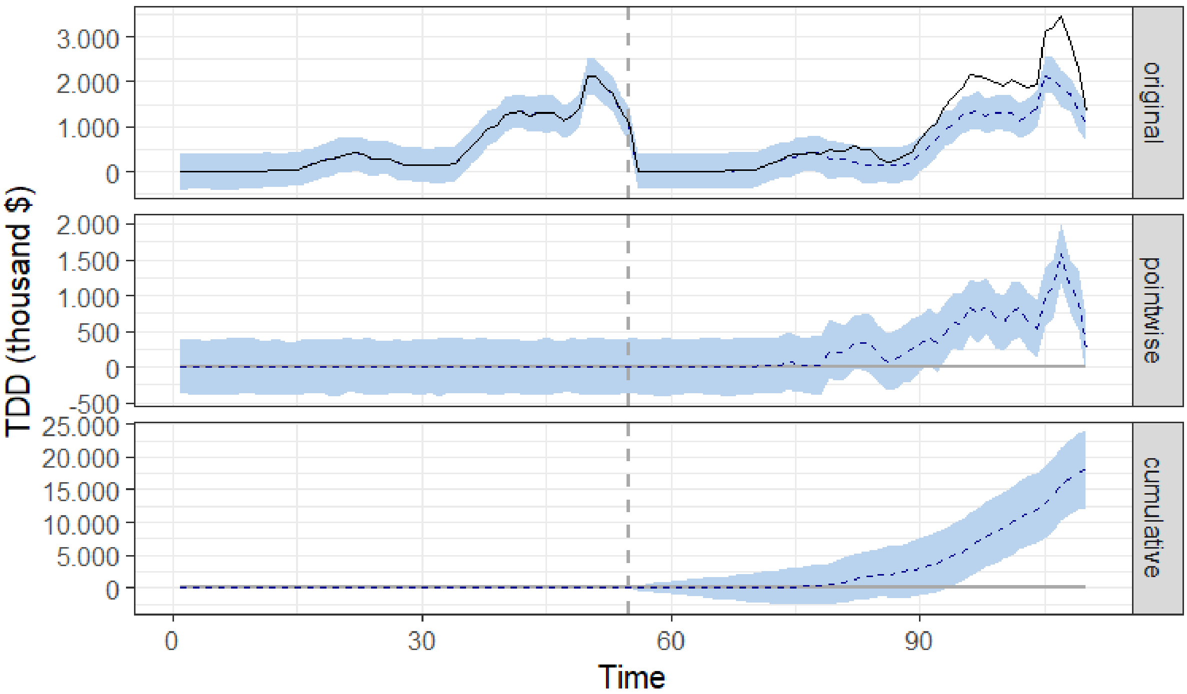
Source: the author (2020).

Figure 92 – Purchase frequency impact for scenario 3 compared to scenario 2



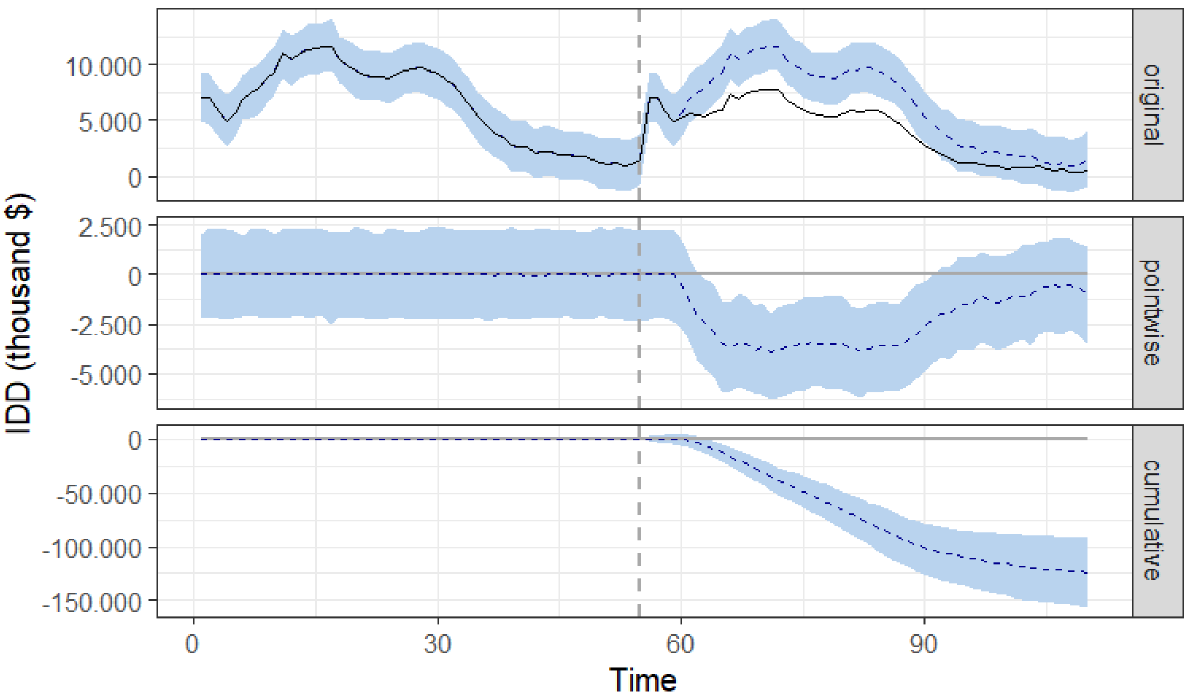
Source: the author (2020).

Figure 93 – TDD impact for scenario 4 compared to scenario 3



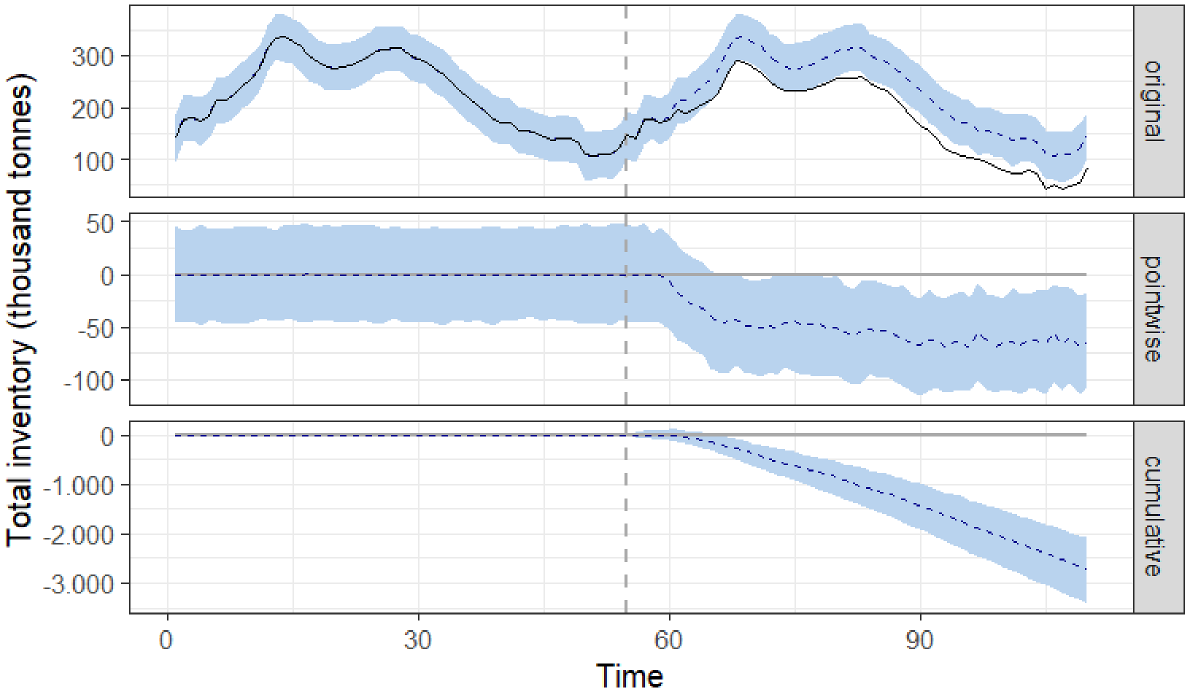
Source: the author (2020).

Figure 94 – IDD impact for scenario 4 compared to scenario 3



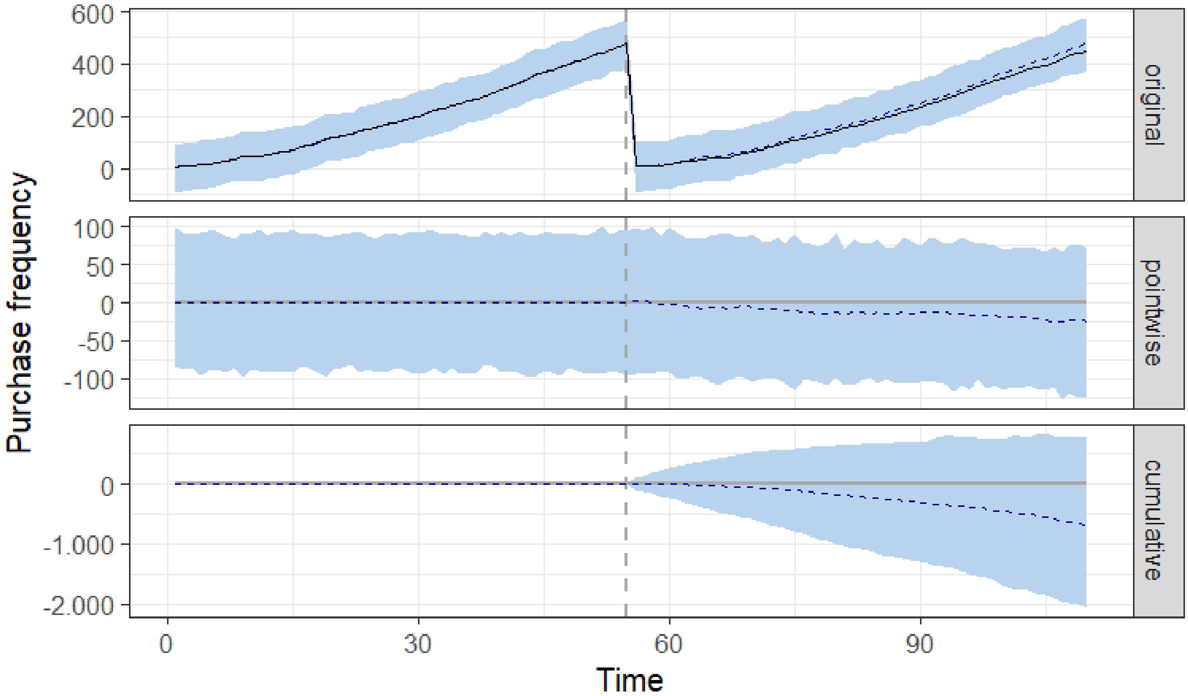
Source: the author (2020).

Figure 95 – Total inventory impact for scenario 4 compared to scenario 3



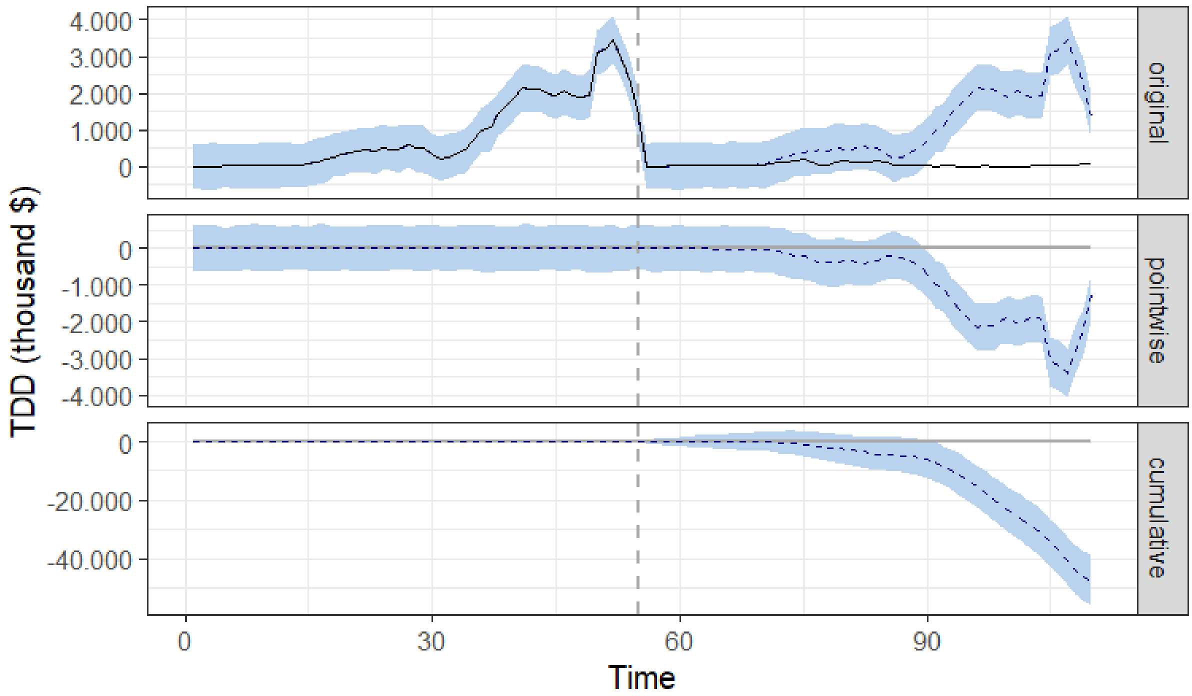
Source: the author (2020).

Figure 96 – Purchase frequency impact for scenario 4 compared to scenario 3



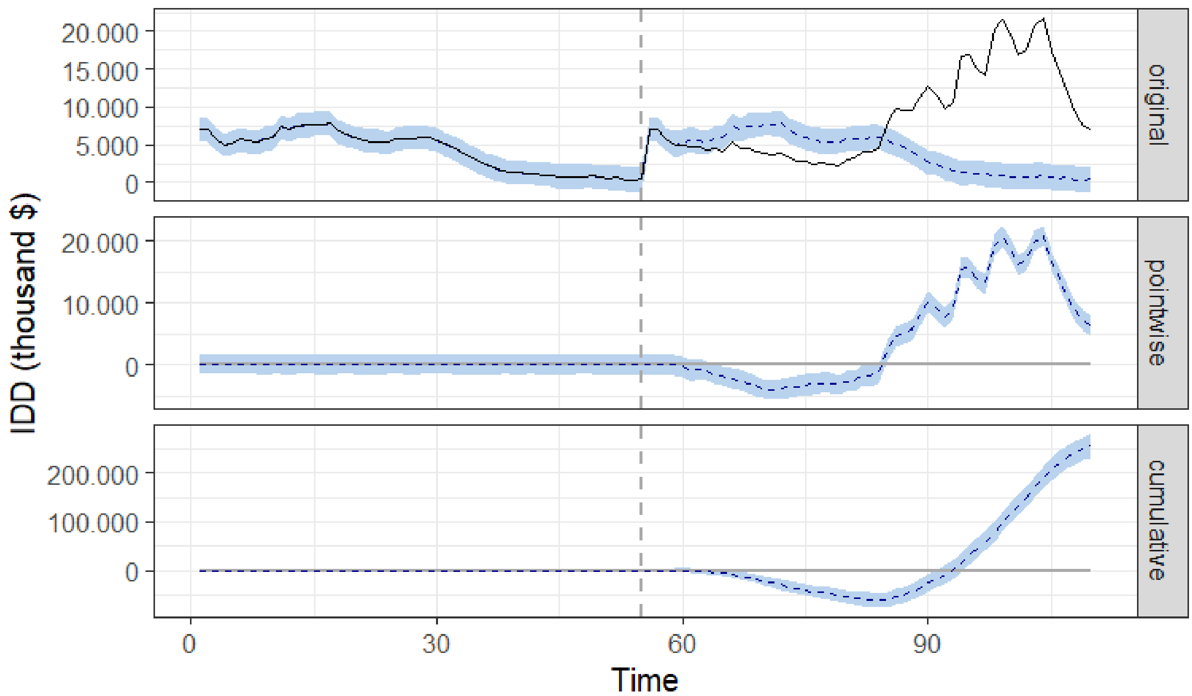
Source: the author (2020).

Figure 97 – TDD causal impact for scenario 5 compared to scenario 4



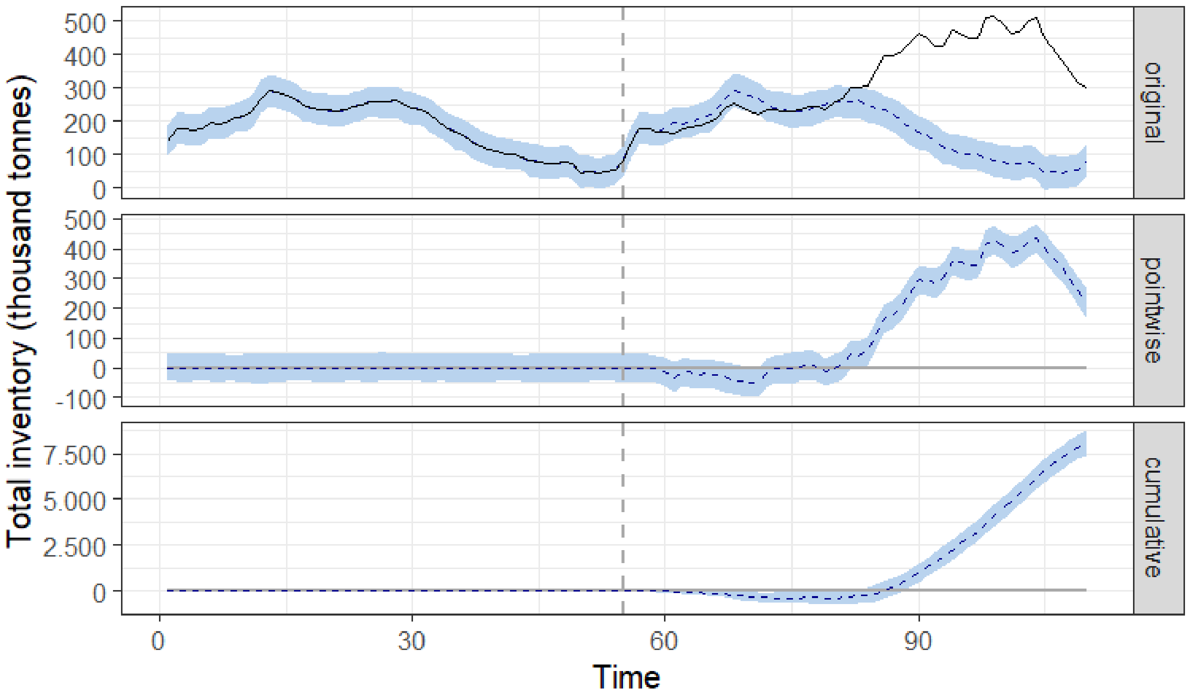
Source: the author (2020).

Figure 98 – IDD impact for scenario 5 compared to scenario 4



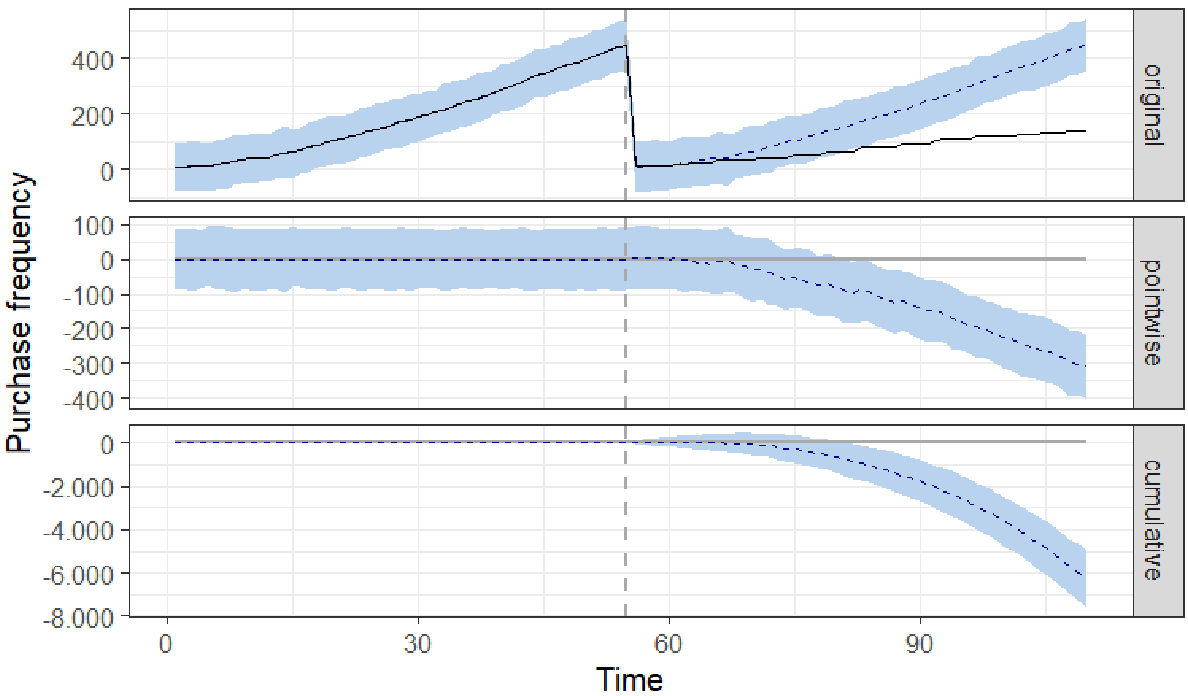
Source: the author (2020).

Figure 99 – Total inventory impact for scenario 5 compared to scenario 4



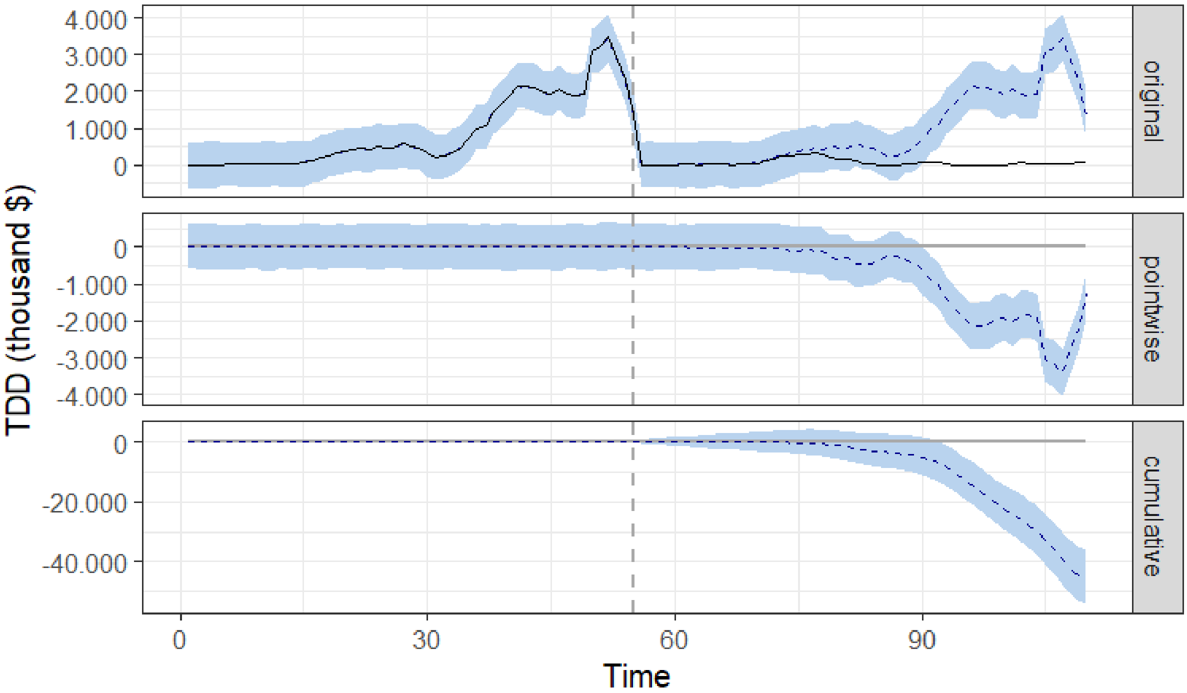
Source: the author (2020).

Figure 100 – Purchase frequency impact for scenario 5 compared to scenario 4



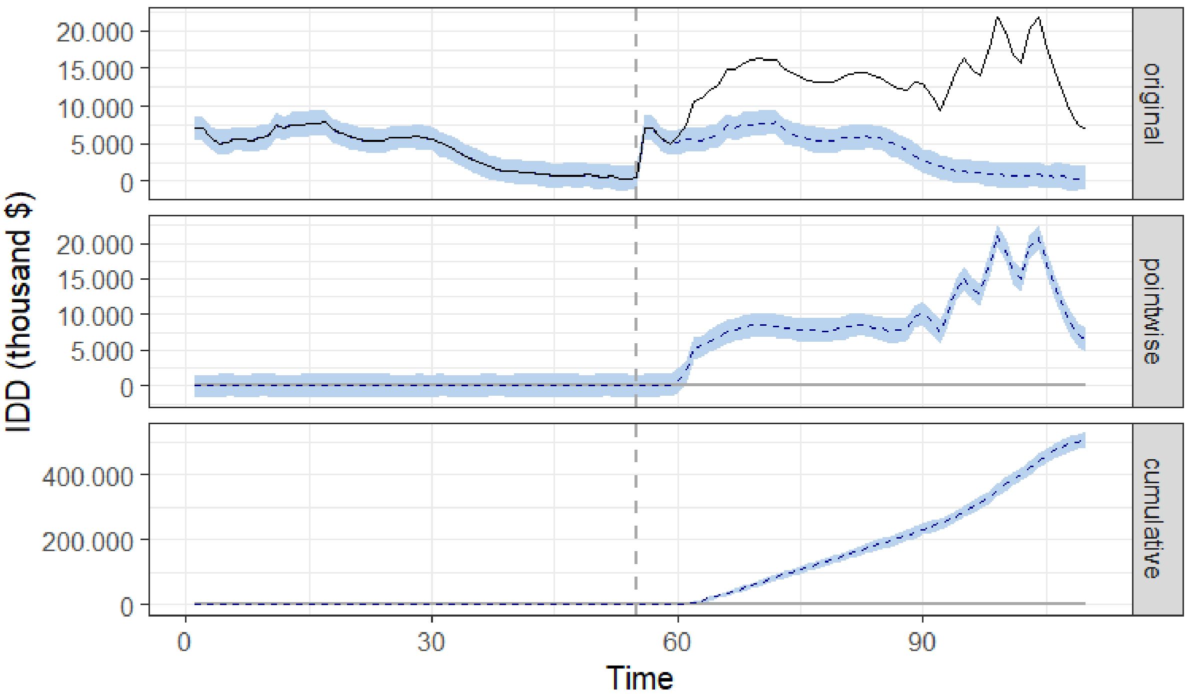
Source: the author (2020).

Figure 101 – TDD impact for scenario 6 compared to scenario 4



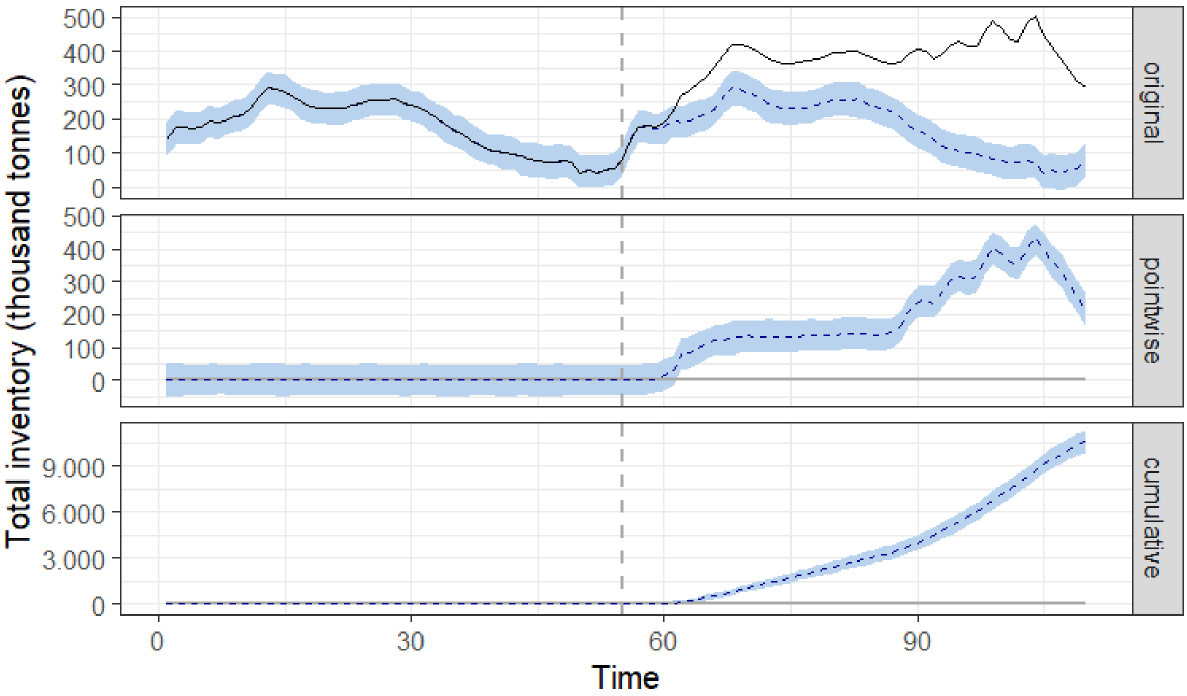
Source: the author (2020).

Figure 102 – IDD impact for scenario 6 compared to scenario 4



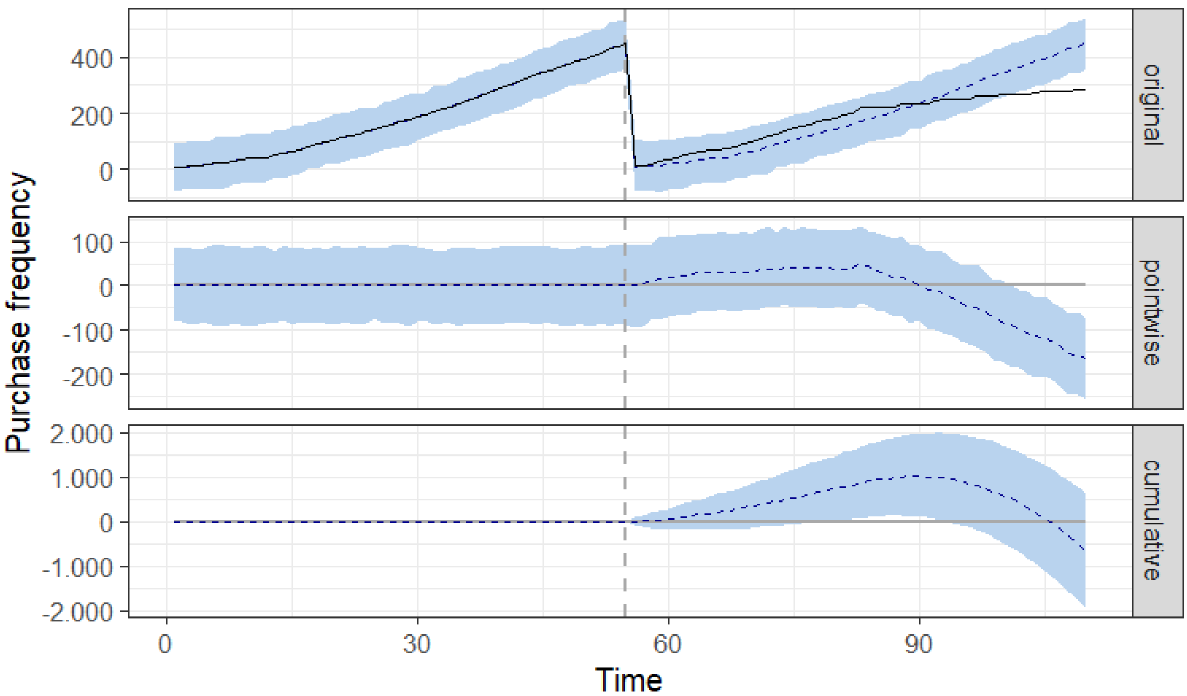
Source: the author (2020).

Figure 103 – Total inventory impact for scenario 6 compared to scenario 4



Source: the author (2020).

Figure 104 – Purchase frequency impact for scenario 6 compared to scenario 4



Source: the author (2020).

APPENDIX L – CAUSAL IMPACT RESULTS

Scen.	Var.	Avg / Cum	Actual (with interv.)	Prediction (w/o interv.)	Prediction lower bound	Prediction upper bound	Prediction s.d.	Absolute effect	Absolute effect lower bound	Absolute effect upper bound	Absolute effect s.d.	Rel. eff.	Rel. eff. LB	Rel. eff. UB	Rel. eff. s.d.	p-value
2 - 1	TDD	Avg	193.068	500.966	400.205	602.032	51.956	-307.899	-408.964	-207.137	51.956	-61%	-82%	-41%	10%	0,0010
2 - 1	TDD	Cum	10.618.725	27.553.153	22.011.262	33.111.740	2.857.605	-16.934.428	-22.493.016	-11.392.538	2.857.605	-61%	-82%	-41%	10%	0,0010
2 - 1	IDD	Avg	4.479.555	7.382.317	6.847.199	7.920.827	264.596	-2.902.762	-3.441.271	-2.367.643	264.596	-39%	-47%	-32%	4%	0,0010
2 - 1	IDD	Cum	246.375.550	406.027.441	376.595.933	435.645.475	14.552.790	-159.651.892	-189.269.925	-130.220.383	14.552.790	-39%	-47%	-32%	4%	0,0010
3 - 1	TDD	Avg	182.284	500.966	398.378	596.091	50.183	-318.683	-413.808	-216.094	50.183	-64%	-83%	-43%	10%	0,0010
3 - 1	TDD	Cum	10.025.595	27.553.153	21.910.770	32.785.015	2.760.058	-17.527.557	-22.759.420	-11.885.175	2.760.058	-64%	-83%	-43%	10%	0,0010
3 - 1	IDD	Avg	9.227.213	7.382.317	6.852.075	7.901.268	265.279	1.844.896	1.325.945	2.375.139	265.279	25%	18%	32%	4%	0,0010
3 - 1	IDD	Cum	507.496.726	406.027.441	376.864.099	434.569.758	14.590.367	101.469.285	72.926.968	130.632.627	14.590.367	25%	18%	32%	4%	0,0010
3 - 1	Inv.	Avg	296.254	213.287	202.577	223.833	5.407	82.967	72.422	93.677	5.407	39%	34%	44%	3%	0,0010
3 - 1	Inv.	Cum	16.293.975	11.730.766	11.141.727	12.310.792	297.385	4.563.209	3.983.184	5.152.248	297.385	39%	34%	44%	3%	0,0010
3 - 1	Freq.	Avg	229	62	55	68	3	167	161	174	3	271%	262%	282%	5%	0,0010
3 - 1	Freq.	Cum	12.583	3.388	3.031	3.721	174	9.195	8.862	9.552	174	271%	262%	282%	5%	0,0010
4 - 1	TDD	Avg	574.932	500.966	398.618	598.618	51.372	73.965	-23.686	176.313	51.372	15%	-5%	35%	10%	0,0764
4 - 1	TDD	Cum	31.621.247	27.553.153	21.924.016	32.923.967	2.825.479	4.068.094	-1.302.721	9.697.230	2.825.479	15%	-5%	35%	10%	0,0764
4 - 1	IDD	Avg	6.361.947	7.382.317	6.840.581	7.901.931	269.166	-1.020.370	-1.539.984	-478.634	269.166	-14%	-21%	-6%	4%	0,0010
4 - 1	IDD	Cum	349.907.088	406.027.441	376.231.954	434.606.193	14.804.134	-56.120.353	-84.699.105	-26.324.866	14.804.134	-14%	-21%	-6%	4%	0,0010
4 - 1	Inv.	Avg	224.542	213.287	201.482	224.620	5.549	11.255	-78	23.060	5.549	5%	0%	11%	3%	0,0269
4 - 1	Inv.	Cum	12.349.795	11.730.766	11.081.513	12.354.097	305.194	619.029	-4.302	1.268.282	305.194	5%	0%	11%	3%	0,0269
4 - 1	Freq.	Avg	203	62	55	68	3	141	135	148	3	230%	219%	240%	5%	0,0010
4 - 1	Freq.	Cum	11.166	3.388	3.046	3.738	175	7.778	7.428	8.120	175	230%	219%	240%	5%	0,0010
5 - 1	TDD	Avg	901.526	500.966	400.667	593.746	51.567	400.560	307.780	500.860	51.567	80%	61%	100%	10%	0,0010
5 - 1	TDD	Cum	49.583.943	27.553.153	22.036.667	32.656.054	2.836.202	22.030.790	16.927.889	27.547.276	2.836.202	80%	61%	100%	10%	0,0010
5 - 1	IDD	Avg	4.104.588	7.382.317	6.861.799	7.876.853	260.297	-3.277.729	-3.772.265	-2.757.211	260.297	-44%	-51%	-37%	4%	0,0010
5 - 1	IDD	Cum	225.752.325	406.027.441	377.398.922	433.226.895	14.316.313	-180.275.116	-207.474.569	-151.646.597	14.316.313	-44%	-51%	-37%	4%	0,0010
5 - 1	Inv.	Avg	174.957	213.287	202.189	224.078	5.565	-38.330	-49.121	-27.233	5.565	-18%	-23%	-13%	3%	0,0010

Scen.	Var.	Avg / Cum	Actual (with interv.)	Prediction (w/o interv.)	Prediction lower bound	Prediction upper bound	Prediction s.d.	Absolute effect	Absolute effect lower bound	Absolute effect upper bound	Absolute effect s.d.	Rel. eff.	Rel. eff. LB	Rel. eff. UB	Rel. eff. s.d.	p-value
5 - 1	Inv.	Cum	9.622.627	11.730.766	11.120.419	12.324.286	306.100	-2.108.139	-2.701.659	-1.497.792	306.100	-18%	-23%	-13%	3%	0,0010
5 - 1	Freq.	Avg	191	62	55	68	3	129	123	135	3	209%	199%	220%	5%	0,0010
5 - 1	Freq.	Cum	10.478	3.388	3.035	3.726	177	7.090	6.752	7.443	177	209%	199%	220%	5%	0,0010
6 - 1	TDD	Avg	40.651	500.966	401.255	605.093	51.556	-460.315	-564.442	-360.603	51.556	-92%	-113%	-72%	10%	0,0010
6 - 1	TDD	Cum	2.235.823	27.553.153	22.068.999	33.280.125	2.835.553	-25.317.329	-31.044.301	-19.833.175	2.835.553	-92%	-113%	-72%	10%	0,0010
6 - 1	IDD	Avg	8.747.799	7.382.317	6.865.495	7.890.400	258.642	1.365.481	857.399	1.882.303	258.642	18%	12%	25%	4%	0,0010
6 - 1	IDD	Cum	481.128.918	406.027.441	377.602.242	433.971.993	14.225.293	75.101.476	47.156.925	103.526.676	14.225.293	18%	12%	25%	4%	0,0010
6 - 1	Inv.	Avg	321.240	213.287	202.933	223.354	5.295	107.954	97.886	118.308	5.295	51%	46%	55%	2%	0,0010
6 - 1	Inv.	Cum	17.668.210	11.730.766	11.161.293	12.284.470	291.217	5.937.444	5.383.740	6.506.916	291.217	51%	46%	55%	2%	0,0010
6 - 1	Freq.	Avg	76	62	55	68	3	14	8	20	3	23%	13%	33%	5%	0,0010
6 - 1	Freq.	Cum	4.170	3.388	3.045	3.718	175	782	452	1.125	175	23%	13%	33%	5%	0,0010
7 - 1	TDD	Avg	67.668	500.966	394.055	593.998	51.283	-433.299	-526.330	-326.387	51.283	-86%	-105%	-65%	10%	0,0010
7 - 1	TDD	Cum	3.721.721	27.553.153	21.673.007	32.669.876	2.820.585	-23.831.432	-28.948.155	-17.951.286	2.820.585	-86%	-105%	-65%	10%	0,0010
7 - 1	IDD	Avg	13.331.604	7.382.317	6.903.349	7.878.486	259.001	5.949.287	5.453.118	6.428.255	259.001	81%	74%	87%	4%	0,0010
7 - 1	IDD	Cum	733.238.213	406.027.441	379.684.210	433.316.714	14.245.042	327.210.771	299.921.499	353.554.002	14.245.042	81%	74%	87%	4%	0,0010
7 - 1	Inv.	Avg	366.775	213.287	202.466	223.517	5.325	153.488	143.258	164.309	5.325	72%	67%	77%	2%	0,0010
7 - 1	Inv.	Cum	20.172.628	11.730.766	11.135.636	12.293.415	292.897	8.441.862	7.879.214	9.036.992	292.897	72%	67%	77%	2%	0,0010
7 - 1	Freq.	Avg	178	62	55	68	3	116	110	123	3	189%	179%	200%	5%	0,0010
7 - 1	Freq.	Cum	9.793	3.388	3.029	3.729	177	6.405	6.064	6.764	177	189%	179%	200%	5%	0,0010
3 - 2	TDD	Avg	182.284	192.800	158.316	226.920	17.994	-10.516	-44.636	23.968	17.994	-5%	-23%	12%	9%	0,2903
3 - 2	TDD	Cum	10.025.595	10.603.993	8.707.377	12.480.590	989.672	-578.397	-2.454.994	1.318.219	989.672	-5%	-23%	12%	9%	0,2903
3 - 2	IDD	Avg	9.227.213	4.479.161	4.079.702	4.860.982	194.881	4.748.052	4.366.231	5.147.512	194.881	106%	97%	115%	4%	0,0010
3 - 2	IDD	Cum	507.496.726	246.353.877	224.383.584	267.354.019	10.718.480	261.142.849	240.142.708	283.113.143	10.718.480	106%	97%	115%	4%	0,0010
3 - 2	Inv.	Avg	296.254	217.138	205.862	227.986	5.792	79.117	68.269	90.392	5.792	36%	31%	42%	3%	0,0010
3 - 2	Inv.	Cum	16.293.975	11.942.563	11.322.434	12.539.206	318.578	4.351.413	3.754.769	4.971.541	318.578	36%	31%	42%	3%	0,0010
3 - 2	Freq.	Avg	229	62	55	68	3	167	161	174	3	271%	261%	282%	5%	0,0010
3 - 2	Freq.	Cum	12.583	3.388	3.014	3.726	179	9.195	8.857	9.569	179	271%	261%	282%	5%	0,0010
4 - 3	TDD	Avg	574.932	182.076	152.826	210.806	14.966	392.856	364.126	422.106	14.966	216%	200%	232%	8%	0,0010
4 - 3	TDD	Cum	31.621.247	10.014.154	8.405.437	11.594.318	823.152	21.607.093	20.026.929	23.215.809	823.152	216%	200%	232%	8%	0,0010

Scen.	Var.	Avg / Cum	Actual (with interv.)	Prediction (w/o interv.)	Prediction lower bound	Prediction upper bound	Prediction s.d.	Absolute effect	Absolute effect lower bound	Absolute effect upper bound	Absolute effect s.d.	Rel. eff.	Rel. eff. LB	Rel. eff. UB	Rel. eff. s.d.	p-value
4 - 3	IDD	Avg	6.361.947	9.221.384	8.409.108	9.989.875	410.701	-2.859.437	-3.627.928	-2.047.161	410.701	-31%	-39%	-22%	4%	0,0010
4 - 3	IDD	Cum	349.907.088	507.176.113	462.500.949	549.443.120	22.588.547	-157.269.024	-199.536.032	-112.593.861	22.588.547	-31%	-39%	-22%	4%	0,0010
4 - 3	Inv.	Avg	224.542	296.096	282.004	309.915	7.161	-71.555	-85.373	-57.462	7.161	-24%	-29%	-19%	2%	0,0010
4 - 3	Inv.	Cum	12.349.795	16.285.296	15.510.206	17.045.308	393.830	-3.935.501	-4.695.513	-3.160.411	393.830	-24%	-29%	-19%	2%	0,0010
4 - 3	Freq.	Avg	203	229	204	252	13	-26	-49	-1	13	-11%	-22%	0%	6%	0,0227
4 - 3	Freq.	Cum	11.166	12.573	11.194	13.874	702	-1.407	-2.708	-28	702	-11%	-22%	0%	6%	0,0227
5 - 4	TDD	Avg	901.526	574.297	469.294	678.719	53.113	327.229	222.807	432.233	53.113	57%	39%	75%	9%	0,0010
5 - 4	TDD	Cum	49.583.943	31.586.330	25.811.143	37.329.556	2.921.224	17.997.613	12.254.387	23.772.800	2.921.224	57%	39%	75%	9%	0,0010
5 - 4	IDD	Avg	4.104.588	6.358.547	5.768.867	6.951.824	307.184	-2.253.959	-2.847.237	-1.664.279	307.184	-35%	-45%	-26%	5%	0,0010
5 - 4	IDD	Cum	225.752.325	349.720.067	317.287.674	382.350.345	16.895.137	-123.967.742	-156.598.020	-91.535.348	16.895.137	-35%	-45%	-26%	5%	0,0010
5 - 4	Inv.	Avg	174.957	224.429	211.852	236.188	6.226	-49.472	-61.231	-36.895	6.226	-22%	-27%	-16%	3%	0,0010
5 - 4	Inv.	Cum	9.622.627	12.343.612	11.651.875	12.990.352	342.450	-2.720.985	-3.367.725	-2.029.248	342.450	-22%	-27%	-16%	3%	0,0010
5 - 4	Freq.	Avg	191	203	178	229	13	-12	-38	13	13	-6%	-19%	6%	6%	0,1622
5 - 4	Freq.	Cum	10.478	11.157	9.783	12.581	702	-679	-2.103	695	702	-6%	-19%	6%	6%	0,1622
6 - 4	TDD	Avg	40.651	900.536	738.292	1.061.600	84.119	-859.885	-1.020.949	-697.641	84.119	-95%	-113%	-77%	9%	0,0010
6 - 4	TDD	Cum	2.235.823	49.529.483	40.606.064	58.388.017	4.626.536	-47.293.659	-56.152.193	-38.370.240	4.626.536	-95%	-113%	-77%	9%	0,0010
6 - 4	IDD	Avg	8.747.799	4.103.058	3.664.840	4.540.212	219.064	4.644.741	4.207.586	5.082.959	219.064	113%	103%	124%	5%	0,0010
6 - 4	IDD	Cum	481.128.918	225.668.168	201.566.198	249.711.678	12.048.511	255.460.750	231.417.240	279.562.720	12.048.511	113%	103%	124%	5%	0,0010
6 - 4	Inv.	Avg	321.240	174.863	161.792	187.516	6.570	146.377	133.725	159.448	6.570	84%	76%	91%	4%	0,0010
6 - 4	Inv.	Cum	17.668.210	9.617.471	8.898.557	10.313.358	361.323	8.050.739	7.354.852	8.769.653	361.323	84%	76%	91%	4%	0,0010
6 - 4	Freq.	Avg	76	190	167	213	12	-115	-138	-91	12	-60%	-72%	-48%	6%	0,0010
6 - 4	Freq.	Cum	4.170	10.470	9.161	11.742	656	-6.300	-7.572	-4.991	656	-60%	-72%	-48%	6%	0,0010
7 - 4	TDD	Avg	67.668	900.536	717.688	1.067.379	88.397	-832.868	-999.711	-650.020	88.397	-92%	-111%	-72%	10%	0,0010
7 - 4	TDD	Cum	3.721.721	49.529.483	39.472.824	58.705.835	4.861.857	-45.807.762	-54.984.114	-35.751.103	4.861.857	-92%	-111%	-72%	10%	0,0010
7 - 4	IDD	Avg	13.331.604	4.103.058	3.667.202	4.533.311	219.588	9.228.546	8.798.292	9.664.402	219.588	225%	214%	236%	5%	0,0010
7 - 4	IDD	Cum	733.238.213	225.668.168	201.696.085	249.332.132	12.077.334	507.570.044	483.906.081	531.542.128	12.077.334	225%	214%	236%	5%	0,0010
7 - 4	Inv.	Avg	366.775	174.863	161.735	188.342	6.789	191.912	178.433	205.040	6.789	110%	102%	117%	4%	0,0010
7 - 4	Inv.	Cum	20.172.628	9.617.471	8.895.418	10.358.816	373.413	10.555.157	9.813.812	11.277.210	373.413	110%	102%	117%	4%	0,0010
7 - 4	Freq.	Avg	178	190	167	213	12	-12	-35	11	12	-6%	-18%	6%	6%	0,1653

Scen.	Var.	Avg / Cum	Actual (with interv.)	Prediction (w/o interv.)	Prediction lower bound	Prediction upper bound	Prediction s.d.	Absolute effect	Absolute effect lower bound	Absolute effect upper bound	Absolute effect s.d.	Rel. eff.	Rel. eff. LB	Rel. eff. UB	Rel. eff. s.d.	p-value
7 - 4	Freq.	Cum	9.793	10.470	9.172	11.705	664	-677	-1.912	621	664	-6%	-18%	6%	6%	0,1653
2 - 1	Inv.	Avg	217.224	213.287	202.610	224.003	5.611	3.938	-6.778	14.614	5.611	2%	-3%	7%	3%	0,2428
2 - 1	Inv.	Cum	11.947.333	11.730.766	11.143.571	12.320.145	308.616	216.567	-372.811	803.762	308.616	2%	-3%	7%	3%	0,2428
2 - 1	Freq.	Avg	62	62	55	68	3	0	-6	6	3	0%	-10%	10%	5%	0,4835
2 - 1	Freq.	Cum	3.390	3.388	3.044	3.722	176	2	-332	346	176	0%	-10%	10%	5%	0,4835

Source: the author (2020).