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How important is the Theory of Constraints to supply chain management? An assessment of its application and impacts

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ABSTRACT

The Theory of Constraints (TOC) proposes a solution for the supply chain that aims to increase the throughput of sales and reduce inventories. TOC research, however, lacks a conceptual model or method for the application of its practices, has an absence of studies that evaluate consistently the implementation of its performance measures and has a deficiency of empirical evidence to support its improvements. This research aims to address those gaps by simulating a real empirical case to apply the TOC supply chain replenishment system (TOC SCRS) steps. The procedural application of the steps provides a detailed understanding of its impacts and effects. It was found that the system's replenishment and inventory effectiveness can be improved, respectively, in 92% and 62% however in different scenarios. Inventories held in the shops can decrease to 67% while providing significant throughput improvements. Although positive impacts are found, some negative effects are also discovered and discussed.

1. Introduction

Improvement of supply chain performance can be achieved based on the application of diverse methodologies and practices, such as Just-in-Time, lean manufacturing and the Theory of Constraints (Gupta et al., 2022; Pacheco et al., 2021). Among those methodologies, the Theory of Constraints (TOC) proposes a solution for the supply chain (SC) that aims to increase the throughput of sales and reduce inventory levels. In summary, this is accomplished by aggregating stocks at the SC highest point and utilising buffers to manage the replenishment across the supply chain (Gupta & Andersen, 2018; Ikeziri et al., 2019), which is known as the TOC distribution/replenishment solution (Bernardi de Souza & Pires, 2010; Schragenheim, 2010). Although some of the concepts presented in the theory such as decoupling points (Naim & Gosling, 2011), visibility of total SC stock (Berry & Naim, 1996) and positioning of inventories (Jackson & Munson, 2019) have been widely discussed in general supply chain management (SCM), TOC consolidates many of those techniques into a single structured approach.

However, even though the TOC replenishment solution aims to solve many problems related to supply chain distribution, there are still major problems to be addressed by its literature. At the early stages of TOC in the supply chain context, Pérez (1997) claimed that the theory was limited to manufacturing and lacked extrapolation of its concepts and practices in SCM. Similarly, Blackstone (2001) argued that there was no adequate literature addressing the management of the supply chain through the Theory of Constraints. Although there is a growing number of recent studies discussing the subject (Telles et al., 2020; Wei et al., 2017), supply chain management and distribution logistics are the areas where the TOC has been explored the least (Bernardi de Souza & Pires, 2010; Ikeziri et al., 2019). Likewise, Pacheco et al. (2021) state that even though TOC in operations and SCM have been successfully implemented in firms, its literature provides little scientific understanding of the impacts, connections, and the set of elements that enable performance improvement in such environments.

Another common problem in supply chain management is related to its measurement systems. Usually, they tend to optimize the performance of individual processes, therefore, the goals and the measures to control performance are focused on the next downstream node of the SC rather than on the customer (Watson & Polito, 2003). According to the TOC perspective though, the goal of the whole supply chain is to make

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money now and in the future (Costas et al., 2015). To achieve the goal, TOC proposes operational (throughput, inventory, and operating expenses) and global measures (net profit, return over investment, and cash flow) (Goldratt & Cox, 2004). For supply chains, Goldratt et al. (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 et al., 2004). However, the literature on TDD and IDD is sparse and inconclusive, lacking relevant research and practical applications (Gupta & Andersen, 2012). Overall, according to Gupta and Andersen (2018), empirical studies and studies that incorporate TOC implementations and performance measures are still a gap in scientific research.

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

Thus, three main problems can be identified: i) the lack of a conceptual model or method to apply the TOC's practices in supply chains (Tsou, 2013); ii) the lack of studies that evaluate consistently the implementation of TOC in supply chains, including its performance measures (Gupta & Andersen, 2018); and iii) the absence of empirical evidence to support the improvements brought by the application of the 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 stepwise manner (linked to problem i); b) do not point to the causal effects of TOC's intervention in the supply chain (problems i and ii); c) do not assess systematically the impacts of TOC in an empirical study (problems ii and iii); and d) do not assess the supply chain either in aggregated terms or at each of its individual links (problems ii and iii).

Within this context, gaps and problems presented above, the research question that guides this research is defined as: what are the impacts on supply chain performance when applying TOC practices for supply chain management?

This research contributes by addressing the specified problems and filling the gaps in the TOC supply chain literature by providing an application method of TOC in supply chains, assessing this implementation with different performance measures and empirically evidencing its results. The study uses a case of the internal supply chain of a large-sized multinational chemical industry. Using a system dynamics (SD) simulation, a base model is created with the case's current stock and replenishment policies, followed by the application of the TOC replenishment solution to the case. The impacts at shop locations (SC individual links) and at the whole supply chain are recorded and compared to the base model utilising the TOC performance measures.

This paper is structured as follows: after this introduction, the literature background covers the TOC supply chain solution and TOC's performance measures. Next, the methodology section describes the overall framework, the case used in this study, the data analysis process, and the model construction. Then, the results of the simulation are presented comparing the base model and the application of the replenishment solution. Finally, the conclusion summarises the research and points out the academic and empirical implications, as well as future avenues of research.

2. Literature background

Being initially applied in production planning (Goldratt & Cox, 2004), TOC has had its application extended to many other areas such as performance measurement (Seleem et al., 2016) and supply chain management (Gupta et al., 2024; Mishra et al., 2022). 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). Schragenheim (2010), states that the TOC supply chain solution aims to solve common problems such as low inventory turnovers, high investment in stocks, and the lack of finished products all of which cause missing sales, inventory excess and stock obsolescence. According to the author, the TOC solution's purpose is to answer what, where and when to stock, based on frequent replenishment of consumed inventories and strategically placed buffers.

Goldratt (2009) provides the initial concepts about the TOC solution for the supply chain. The main points proposed by the author are the following: i) 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) replenishment orders must be based on actual daily sales to avoid shortages of products; iii) 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) inventory turn must be increased by purchasing smaller lots of the same items and selling quickly to avoid investing money in inventory for longer periods. These main concepts and ideas would serve as the base for the TOC distribution solution. Schragenheim (2010) provides a few more insights into the solution, proposing a six-step method. This research aims to implement the TOC replenishment solution as proposed by the author including the utilisation of TOC's performance measures in SCM as suggested by Bernardi de Souza and Pires (2010). To provide the basic ground of the replenishment solution the following subsections present each of the steps.

2.1. Stock aggregation at the highest level in the supply Chain: the plant/central warehouse (PWH/CWH)

The TOC supply chain replenishment system states that forecast accuracy is dependent on the level of the distribution system – e.g. retailer, regional warehouse, central warehouse, or plant (Kaijun & Wang Yuxia, 2010; K. J. Yuan et al., 2003). Therefore, the TOC-SCRS suggests stock aggregation at the source and the utilisation 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. In the TOC solution, the buffer stock size at the consumption point is kept to a minimum, consequently, the buffer stock at the PWH/CWH needs to be set to higher levels to ensure that when a shop sells a unit, this unit is replaced as soon as possible in a pull system supply chain (Schragenheim, 2010). Statistically, this aggregation ensures more reliability in replenishment than keeping stock at different consumption points (Chang et al., 2015; K. J. Yuan et al., 2003).

2.2. Stock buffer sizes determination for all locations of the chain based on demand, supply, and replenishment lead time

Many mathematical methods have been created to determine the buffer sizes in the supply chain locations (Kaijun & Wang Yuxia, 2010; Lowalekar & Basu, 2020). However, in TOC, setting the exact buffer size is not a relevant issue as long as the buffer is monitored in a timely manner (Yuan et al., 2003). Fundamentally, 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 (Chang, Chang, & Huang, 2014; Modi et al., 2019; Puche et al., 2019).

According to Schragenheim (2010), the maximum stock buffer size is dependent on demand rate and supply responsiveness. The demand rate is the demand for an item per period (day, week, month, etc.). Supply responsiveness refers to how quickly consumed units can be replenished, represented by the replenishment lead time (RLT). Bernardi de Souza and Pires (2010) mention a few other variables to be considered in the buffer size determination, such as average demand within replenishment time, fluctuations of demand, fluctuations of replenishment time, and customer tolerance time.

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 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).

2.3. Increase of the replenishment frequency

TOC-SCRS states that items should be replenished based on actual consumption rather than forecasting. To do so, it is necessary to use replenishment policies based on either daily or the smallest economically feasible order period (Gupta et al., 2024; Lowalekar & Basu, 2020; Modi et al., 2019).

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, & Lei, 2014). According to Schragenheim (2010), differently from 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 trade-off between the additional costs of increasing the frequency of shipments and the cost of having lower availability. Also, in many cases, 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 for the incurred extra cost.

2.4. Manage the flow of inventories through buffers and buffer penetration

Buffer monitoring is realized through 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 coloured differently as green, yellow and red (Chang et al., 2015; Keyvani & Lotfi, 2018; Takami Narita et al., 2021). The colours are set according to the buffer penetration level: green is less than 33 %, yellow is between 33 and 67 %, and red is greater than 67 % (Schragenheim, 2010; Takami Narita et al., 2021). This colour schematic serves as an indication of replenishment urgency with different actions to be taken (Takami Narita et al., 2021). For instance, when the buffer is in the green zone, no action is necessary; 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 (Ikeziri et al., 2023; Simatupang et al., 2004).

2.5. Dynamics buffer management (DBM) utilisation

The buffer penetration indicators also allow to implement the dynamic buffer management. 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 behaviour (Tsou, 2013). The TOC claims that buffer size must be altered based on the changes in the environment (Watson & Polito, 2003) and considers that the ideal levels should be reached over time, after these adjustments (Yuan et al., 2003). Essentially, the dynamic buffer management rule states that over time the buffer should remain in the yellow zone and it must be altered if it remains in the red or green zones for too long (Takami Narita et al., 2021). Staying too long in the green zone means that the buffer stock size is too high and can be reduced (Sun et al., 2013); if it 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 by 33 %, while if the buffer is on TMR it should be increased equally (Ikeziri et al., 2023; Takami Narita et al., 2021). 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. This period should be long enough to let the adjustment occur and short enough to not let a sudden change in demand go unnoticed.

2.6. Set manufacturing Priorities According to urgency in the plant stock buffers

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 utilising 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. Since the model does not consider the manufacturing part of the system, the manufacturing prioritization step is not applied in the model or this study.

2.7. TOC performance metrics

In our study we will use TOC metrics, simulated in the model, to assess the performance of the actions and steps described above. According to the TOC perspective, collaborative performance metrics are required to guarantee that each supply chain component is creating more throughput (Simatupang et al., 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).

Simatupang et al. (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 maximisation. However, it is still 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 the 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* and 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 (Gupta & Andersen, 2012), The TDD guarantees that deliveries are due on time and the IDD continuously promotes actions for inventory reduction. As the aim of the supply chain is to maximise the throughput, the TDD is the main priority and its target is zero. The IDD then functions as a secondary measure and it should be minimised without compromising the TDD (Bernardi de Souza & Pires, 2010).

3. Methodology

In this section, the case selected is described and the overall approach to the simulation model and data analysis are presented. The utilised modelling and simulation tool is System Dynamics (SD). System Dynamics is chosen for this study for being known as a tool that observes systems from a macro level and is utilised for strategic decision-making (Law, 2014). System dynamics makes use of its structural functionalities to develop a computer simulation model that utilises quantitative data (Pidd, 2003). Therefore, SD can be a valuable alternative for simulation studies related to supply chains and TOC as seen in various studies. Hilmola and Gupta (2015) use an SD simulation and apply TOC and throughput accounting (TA) concepts to investigate a product-mix problem; Da Silva Stefano et al. (2022) create an SD model of a supply chain to propose TOC's throughput accounting as a management control mechanism alternative for a transfer price setting; and Machado et al. (2023) also use a systems dynamics model to verify whether decisions based on TA are robust when simultaneous variations occur.

In this study, a system dynamics modelling of the current state of the case – the base scenario – is created. The model is then validated, followed by the inclusion of new variables to simulate the individual application of the steps of the TOC distribution/replenishment solution. Once all relevant steps have been applied, it is possible to evaluate the overall impact 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 allows us to assess individually each one of the TOC's policies, comparing them and measuring their contribution to the overall impact on the supply chain as a whole. On a more general level, the research problem is divided into a conceptual and a technical part. It starts with a literature review to define the problem to be discussed, followed by the definition of the objectives and the case, the creation of the conceptual and simulation models which provide the results to ground the analysis, and finishing with the results and conclusion. This framework is depicted in Fig. 1.

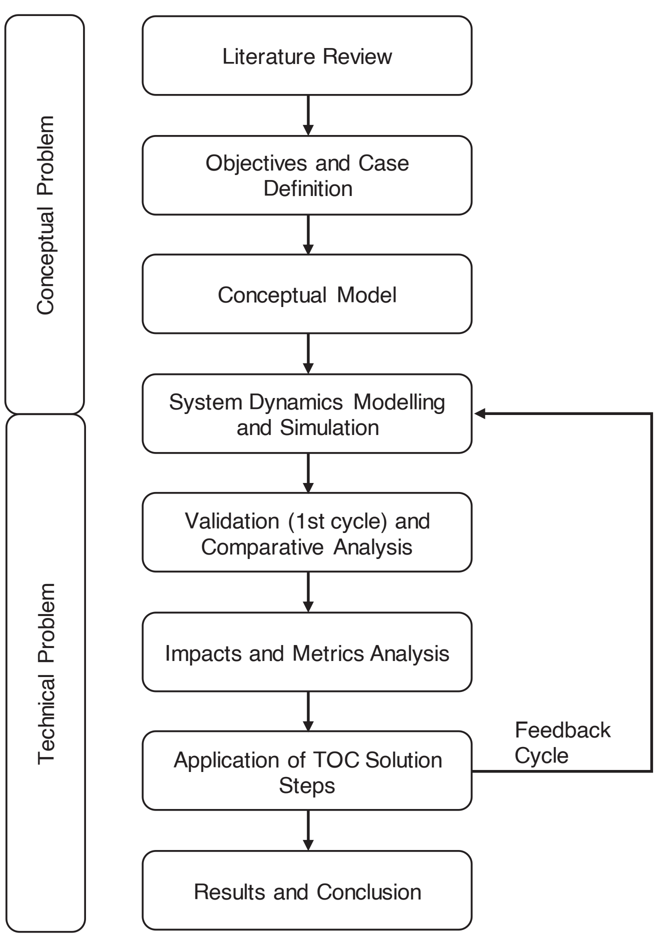

Fig. 1. Research Framework.

3.1. *The case*

The case comprises part of an internal supply chain of a large-sized multinational chemical company, located in Brazil. The country's potential is of strategic interest to the organization and a significant part of the company's global revenue comes from its operations in Brazil. The company has more than 20 manufacturing units, spread among eleven different Brazilian states. Most of its raw materials come from 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 delays in deliveries and even loss of sales. The application of the TOC concepts in the supply chain aims to solve many of those related problems (Goldratt, 2009; Smith & Ptak, 2010) therefore, posing itself as an opportunity for the studied case. In this research, the focus is on the most relevant state for the company in terms of sales, which comprises one production unit (PRD1) – which supplies intermediate products and raw materials to other units – and three mixing units (MIX1, MIX2, MIX3).

To conceptualise the model, data were collected in the field. Two specialists from the sales & operations planning (S&OP) team and one from the fulfilment 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 on replenishment of raw materials such as forecasts, replenishment plans, and raw material consumption. The fulfilment specialist was consulted once – based on the recommendation of the other two specialists due to his position and time within the company – to provide data on the sales order deliveries and delays.

The data sources were varied, including the company's ERP database, logistics, S&OP, and supply department data (in the form of spreadsheets and business intelligence 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 on the structured data and the conceptual model validation. The data collection follows Saunders et al. (2012) and thus is composed of five different techniques, respectively bibliographic, documentary, direct observation, and interviews. The profile of the consulted specialists is presented in Table A in the Appendix, describing their contributions to the research, job positions and their time in the company. Also in the Appendix, Table B provides the variables collected for the research, a brief description of them and their data sources.

3.2. *Data analysis*

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. 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 are in tonnes.

As specified in the data collection section, since there is no accurate control of the sales orders' delays, a proxy variable is utilised 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 et al., 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 in raw materials can cause a direct delay in sales.

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 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), and the inventory levels (at the CWH, at the shops, and the whole SC). Causal impact analysis – as proposed by Brodersen et al. (2015) – is utilised to analyse the system properties and recommend improvements. According to Brodersen et al (2015), a causal inference may be understood as an 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). Fig. 2 summarizes the steps for data analysis and the iteration process to simulate scenarios. For those scenarios, the sensitivity runs are conducted with 30 multiple runs per simulation, resulting in a total of 210 simulation runs.

The scenarios defined for the analyses are shown in the Table 1. From the table, it is possible to note which TOC steps are being applied, which model variables are used or not, and whether the buffer is 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 to organize, summarize, and structure the results data for analysis.

3.3. Model construction

For the construction of the model, the basic SD language is utilised,

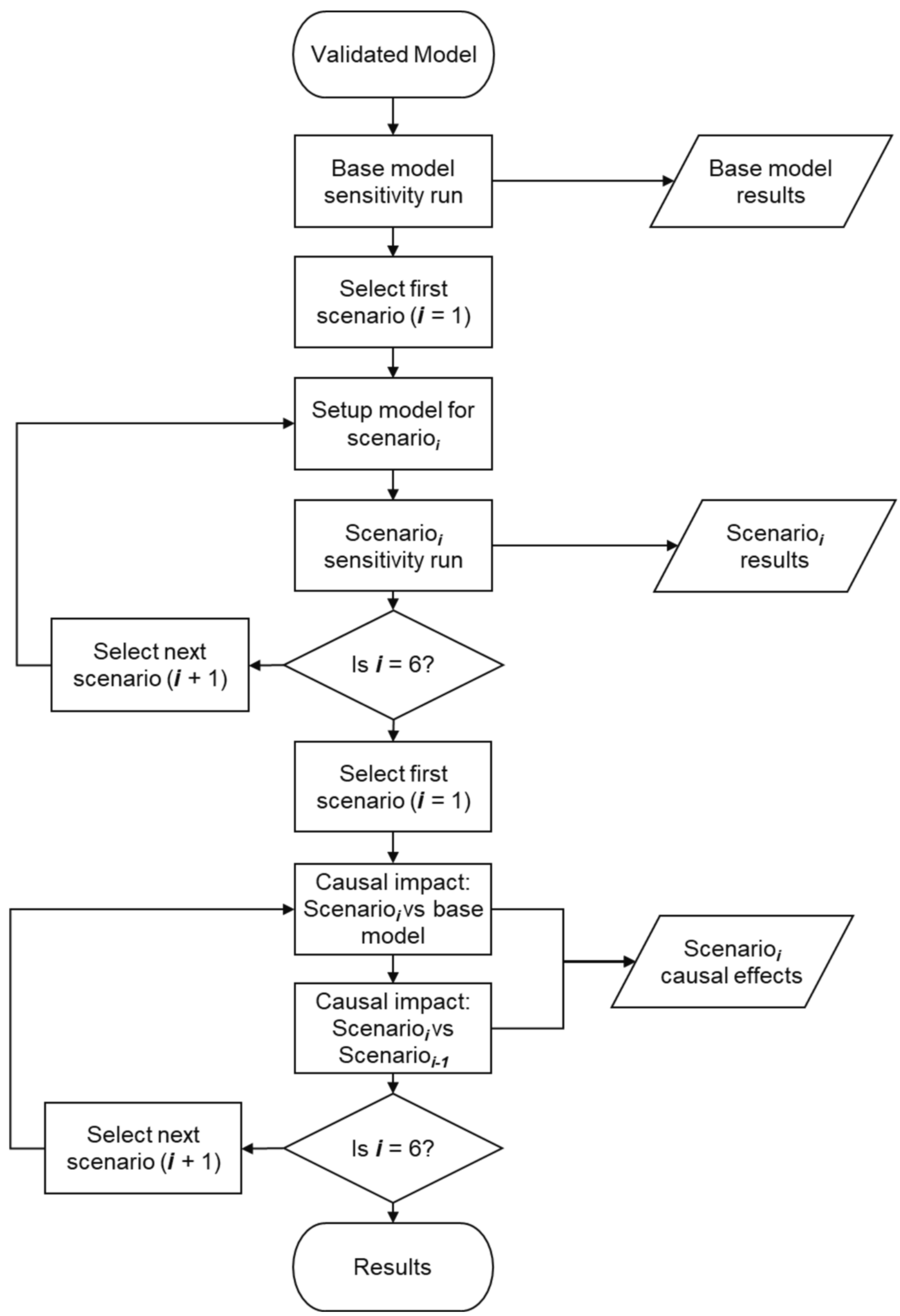

Fig. 2. Data Analysis and Simulation Diagram.

Table 1
Simulation scenarios and model variables.

Scenario	Description	Model variables/parameters						
		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)

consisting of three basic shapes. The rectangles, called stocks, represent resource accumulation. The converters are represented by circles and are additional variables that are not determined by the behaviour of the system. The flows, represented by valves, are a stream of a determined resource that enters or leaves the stocks. The arrows connecting these shapes are called information links, transferring information about a stock or variable to a flow. Aiming to not be extensive, the base model is briefly described and focus is given to the results presented in the next section.

For the model construction, the four units and variables such as the raw material replenishment, the raw material consumption, and the transfers between the units were created. Initially, all the data collected served as a direct input to the model, so randomness was not yet set. This step was conducted to verify the model behaviour, 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 was created, which aims to simulate the forecasting and replenishment process of the company. During this phase, variation was added to the model through the lead times, based on the cumulative distribution function of the historical supply data, forming 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 were simulated in the model as parameters. Thus, running a simulation with or without a specific TOC step was just a matter of adjusting the respective parameters. The same model was utilized for the base model and all the necessary scenarios were simulated by adjusting the respective parameters, assuring replicability of the base values or any required scenario at any moment. The model time unit was weeks, starting at 0 and ending at 55 – approximately one year. The delta time (DT) is set to 1, as a week is deemed enough to capture the main impacts on the system, especially regarding replenishment delays as a one-week delay might incur production planning rescheduling and a late sale. Finally, the model was comprised of four modules. The internal supply chain and the planning and replenishment modules represented the base scenario. A TOC planning module applied the TOC-SCRS steps as well as a hybrid using buffers and forecast data, and a final module was created for the performance measures. Aiming to not overextend the length of the paper, the authors won't detail all of the variables and the model itself, but the source code can be made available upon request. Fig. 3 depicts the whole model while its modules are shown individually in the Appendix in Figures A to E.

3.4. Model validation

To validate the model, the final average stock position was utilised with the TOC parameters disabled. Total inventories of the main raw materials that compose the model were validated. The raw materials were selected based on their purchase volume ratio compared to the total volume of purchases – at least 5 % – and the number of observations available (i.e., the number of purchase orders) – at least 15. These criteria lead to the selection of 6 materials to be validated. Please refer to Table C in the Appendix to see highlighted in blue the selected materials, as well as their volumes and the quantity of observations.

After defining the variables to validate the model, a sensitivity analysis was conducted 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 could arrive 2 weeks later in simulation and the stock positions would not be comparable in the same week. If this happened with a high-volume order, it could significantly impact the overall result. However, the average position at the end of the year needed to be comparable, to provide a good measure for the validation. The mean, standard deviation, and confidence intervals were computed by Stella and set to a 5 % significance. Additionally, a t-student test was conducted to verify the error and check if the sample size was adequate, again with a 5 % significance. The maximum error allowed was 10 %. These data from the validation results are provided in the Appendix, in Table D. All results were within the confidence bounds of the model. No error was greater than the defined maximum error and from the sample size (n) calculation the greater value was 29 for one raw material. As there were 30 samples the number of experiments was enough. Thus, the model was validated.

4. Results

To better understand the impacts of the TOC steps application in the system, the causal impact analysis is conducted. The causal impact estimates the causal effect of a designed intervention on a time series. To do 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 (Piran et al., 2016). The first analysis observes the impacts by comparing the scenarios to the base model.

4.1. Impacts compared to the base model

The analysis is conducted in all six scenarios, always comparing the four variables in each scenario with the base model results. The causal impact results are presented in Table 2, demonstrating the results with the intervention, a prediction without the intervention, the absolute and relative impact, its lower and upper confidence bounds, and the causal significance.

For scenario 1, the aggregation of inventories at the highest point of the supply chain presents an improvement of the TDD and IDD, with no significant impacts on the inventory levels and no changes in the purchase frequency. Those results imply that the loss of throughput can be related to late deliveries to the 'shops', as a simple re-arrangement of

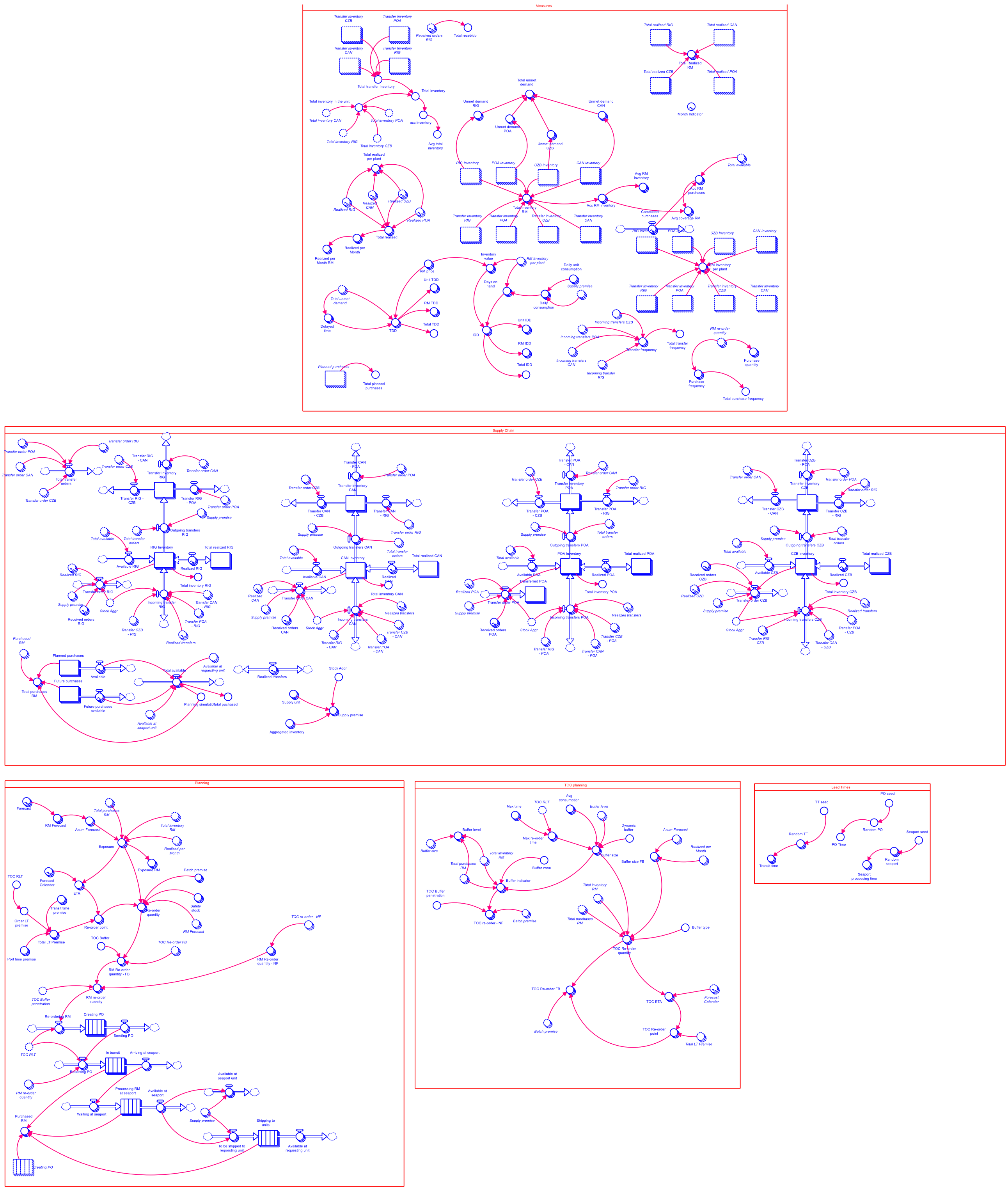

Fig. 3. System Dynamics Model Overview.

inventory positions brings a huge benefit in the throughput. Proof of that is that the inventory-dollar-days increases with no significant impact on total inventory, meaning that the inventory is better positioned and not increasing in total volume. Fig. 4 presents the causal impact plots, where it is possible to note that the TDD improvements are more apparent around week 75, i.e., approximately 20 weeks after the intervention. For the IDD though, the improvements are seen earlier, starting around week 60.

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 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 behaviour for the whole time series. As can be seen in Fig. 5 (c), the inventory level peak is around weeks 66 and 86 – or 13 to 27 in the original time series –, which starts decreasing from that point onwards. The effects of

Table 2
Causal impact results.

Scenario	Variable	Actual (with intervention)	Prediction (without intervention)	Absolute effect	Relative effect	Rel. effect lower bound	Rel. effect upper bound	Causal significance
1	TDD	10.618.725	27.553.153	−16.934.428	−61 %	−82 %	−41 %	Significant
	IDD	246.375.550	406.027.441	−159.651.892	−39 %	−47 %	–32 %	Significant
	Total inventory	11.947.333	11.730.766	216.567	2 %	−3%	7 %	Non-significant
	Purchase freq.	3.390	3.388	2	0 %	−10 %	10 %	Non-significant
2	TDD	10.025.595	27.553.153	−17.527.557	−64 %	−83 %	−43 %	Significant
	IDD	507.496.726	406.027.441	101.469.285	25 %	18 %	32 %	Significant
	Total inventory	16.293.975	11.730.766	4.563.209	39 %	34 %	44 %	Significant
	Purchase freq.	12.583	3.388	9.195	271 %	262 %	282 %	Significant
3	TDD	31.621.247	27.553.153	4.068.094	15 %	−5%	35 %	Non-significant
	IDD	349.907.088	406.027.441	−56.120.353	−14 %	−21 %	−6%	Significant
	Total inventory	12.349.795	11.730.766	619.029	5 %	0 %	11 %	Significant
	Purchase freq.	11.166	3.388	7.778	230 %	219 %	240 %	Significant
4	TDD	49.583.943	27.553.153	22.030.790	80 %	61 %	100 %	Significant
	IDD	225.752.325	406.027.441	−180.275.116	−44 %	−51 %	−37 %	Significant
	Total inventory	9.622.627	11.730.766	−2.108.139	−18 %	–23 %	−13 %	Significant
	Purchase freq.	10.478	3.388	7.090	209 %	199 %	220 %	Significant
5	TDD	2.235.824	27.553.153	−25.317.329	−92 %	−113 %	−72 %	Significant
	IDD	481.128.918	406.027.441	75.101.476	18 %	12 %	25 %	Significant
	Total inventory	17.668.210	11.730.766	5.937.444	51 %	46 %	55 %	Significant
	Purchase freq.	4.170	3.388	782	23 %	13 %	33 %	Significant
6	TDD	3.721.721	27.553.153	–23.831.432	−86 %	−105 %	−65 %	Significant
	IDD	733.238.213	406.027.441	327.210.771	81 %	74 %	87 %	Significant
	Total inventory	20.172.628	11.730.766	8.441.862	72 %	67 %	77 %	Significant
	Purchase freq.	9.793	3.388	6.405	189 %	179 %	200 %	Significant

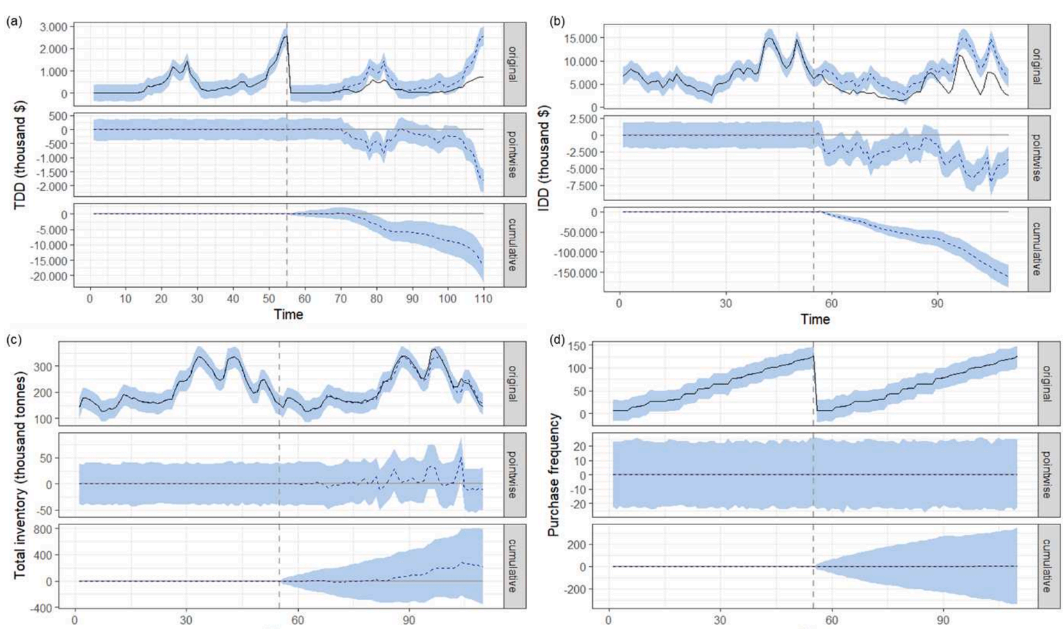

Fig. 4. Causal impact plots for Scenario 1.

seasonality in 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 total period is 39 %. From the plots, it is also possible to note that the time it takes to observe the results is similar to the ones found in scenario 1 for both TDD and IDD. Regarding inventory levels and the purchase

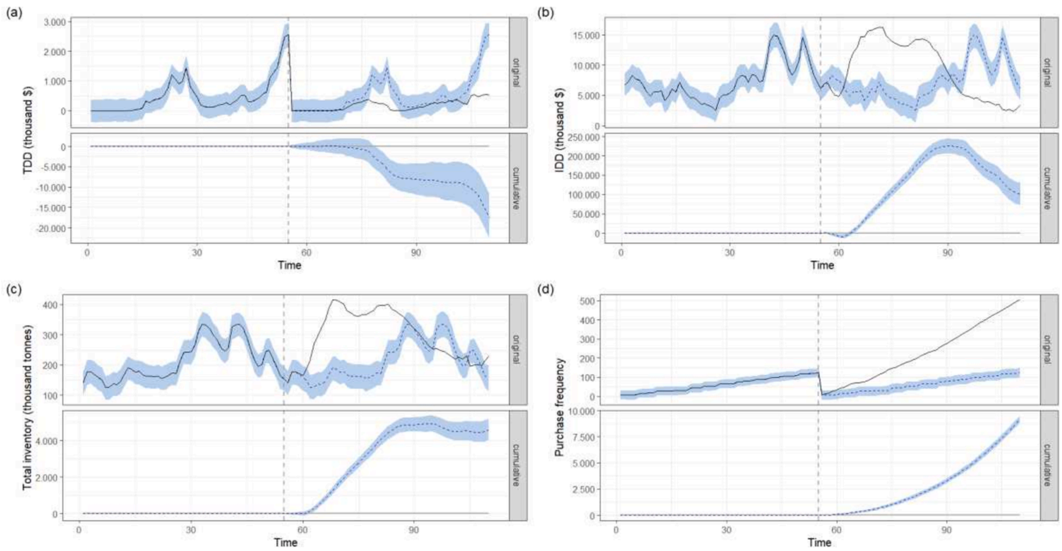

Fig. 5. Causal impact plots for scenario 2.

frequency, the increase occurs right after the intervention, approximately at time 60, i.e., about 5 weeks after the intervention.

Scenario 3 implements the utilisation of the buffer penetration concept. The causal plots for this comparison are presented in Fig. 6. Part (a) demonstrates TDD behaviour for this scenario. Following the cumulative effect, the TDD is improved during the normal season but increases 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 improves both IDD and inventory may compromise the throughput (TDD).

Scenario 4, the last scenario where the TOC solution is purely applied in the system, looks similar to the previous step. Both the inventory-dollar-days and the inventory levels improve, and the IDD is even better than in scenario 1. However, as in scenario 3, the TDD is impacted. Part (a) of Fig. 7 demonstrates the problems with seasonality. As can be noted, the cumulative TDD is 'under control' and even better than the base scenario until the high demand point. From that point, the losses increase, causing a great impact at the end of the period. The effects on the TDD are observed approximately at time 70 which decreases until around time 90. From that point 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.

At 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 protected 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, consequently increasing the IDD. This is caused by the increase in inventory levels by the utilisation of buffers, as the traditional TOC buffers are conservative with safety measures to be less dependent on forecasts and secure throughput. Thus, to find a better model to deal with the system's seasonality, two other scenarios are tested.

Scenario 5, which uses forecast-based buffers, presents the highest impact on the TDD. IDD and total inventory increase in comparison to the base model. It presents a TDD improvement of 92 %, along with a mean increase in inventory of 51 % and an IDD increase of 18 %. The inventory increase for this scenario is greater than any increase found in

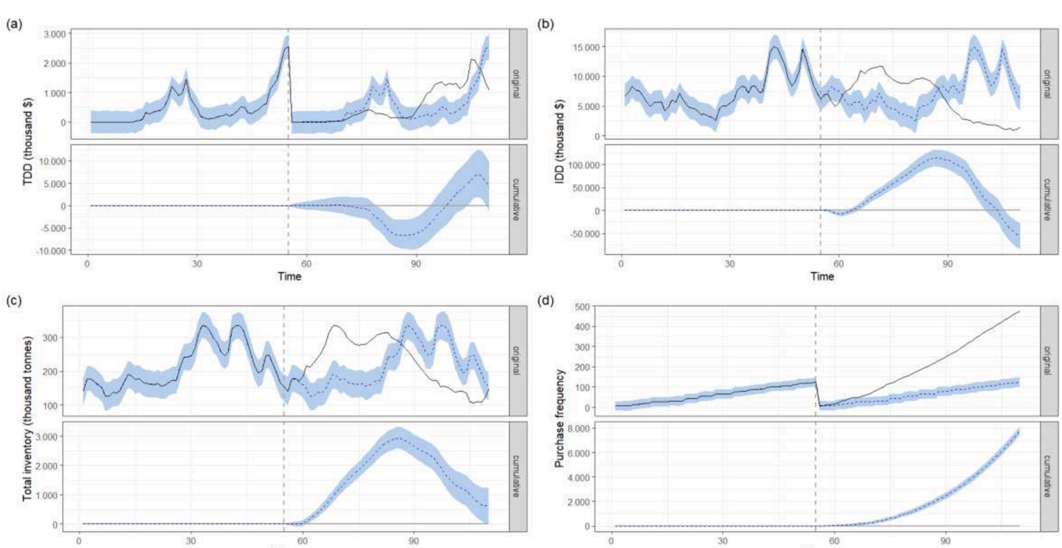

Fig. 6. Causal impacts plots for scenario 3.

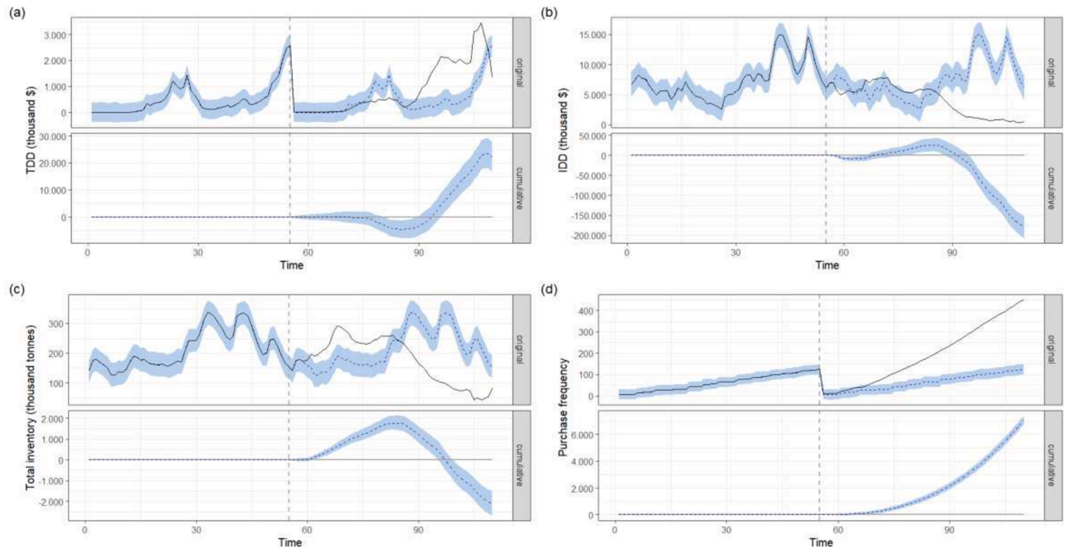

Fig. 7. Causal impacts plots for scenario 4.

the previous scenarios. However, the high impact on the throughput might compensate for the increases in inventory. It is important to note that 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 Fig. 8, inventory levels increase especially during the high season and start decreasing once this period has passed.

Scenario 6 combines the utilisation of the forecast-based buffers with traditional TOC buffers. Forecast-based buffers are used during the high season, while the TOC buffers are used during the normal season. Scenario 6 presents the second-best TDD value, but at the same time has the highest inventory levels. Fig. 9 presents the causal impact plots for scenario 6. TOC buffers build up the stock before high season, protecting the throughput. When the forecast-based buffers start acting there is not enough time to return to the previous inventory levels and both inventory and IDD start decreasing only at the end of the period. Both scenarios 5 and 6 present the same patterns found previously regarding the time taken for the effects to be noticed. The IDD starts improving around week 70, while all the other variables start to increase from time 60 onwards.

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. Thus, the replenishment frequency seems to be more than a constraint than a TOC solution step.

In summary, besides the already mentioned scenarios 2 and 3, scenario 5 presents good results as well. With a significant impact of 92 % in throughput, the absolute increase of 51 % in inventory levels might be worth considering for application in the case.

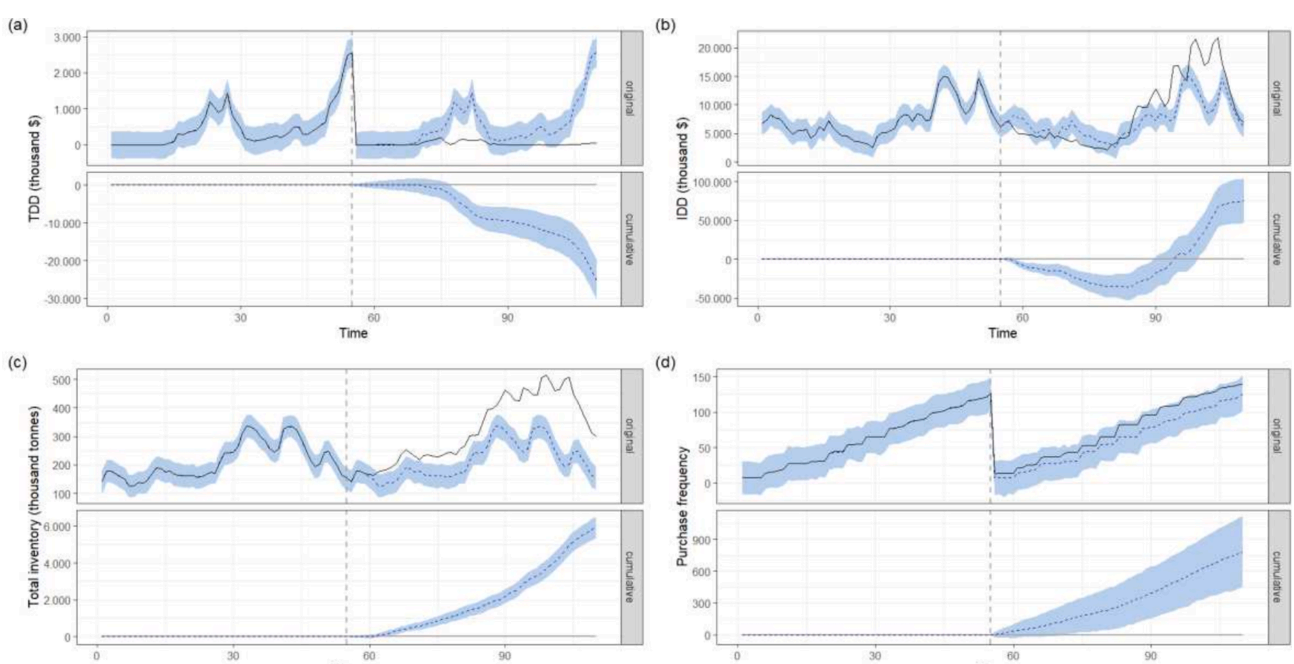

Fig. 8. Causal impacts plots for scenario 5.

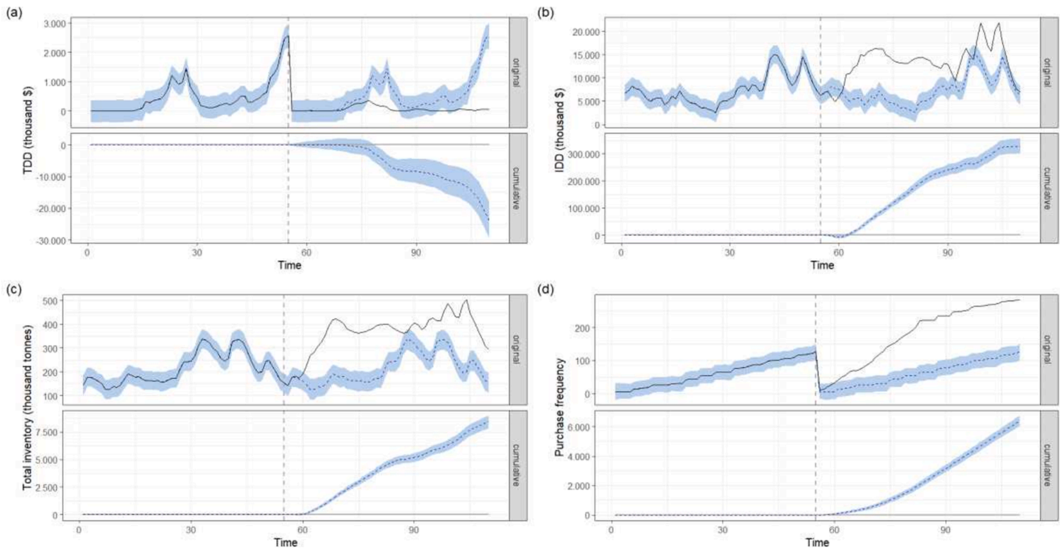

Fig. 9. Causal impact plots for scenario 6.

4.2. Incremental step application impacts comparison

Other than analysing and measuring the effects of the TOC implementation in comparison to the base scenarios, a few comparisons among scenarios are also conducted. This allows, 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 is presented in Table 3.

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 though is to mention that the determination of buffer sizes, which is conducted in scenario 2, serves as a structure for both steps 4 and 5, which are represented in scenarios 3 and 4. To replenish the buffers, the purchase frequency increases significantly as well. Fig. 10 shows the comparison of the distributions for scenarios 1 and 2.

Next, scenarios 3 and 4 are compared to scenarios 2 and 3, respectively. Fig. 11 presents the distributions for scenarios 2 and 3 (a), 3 and 4

Table 3
Incremental causal impact.

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

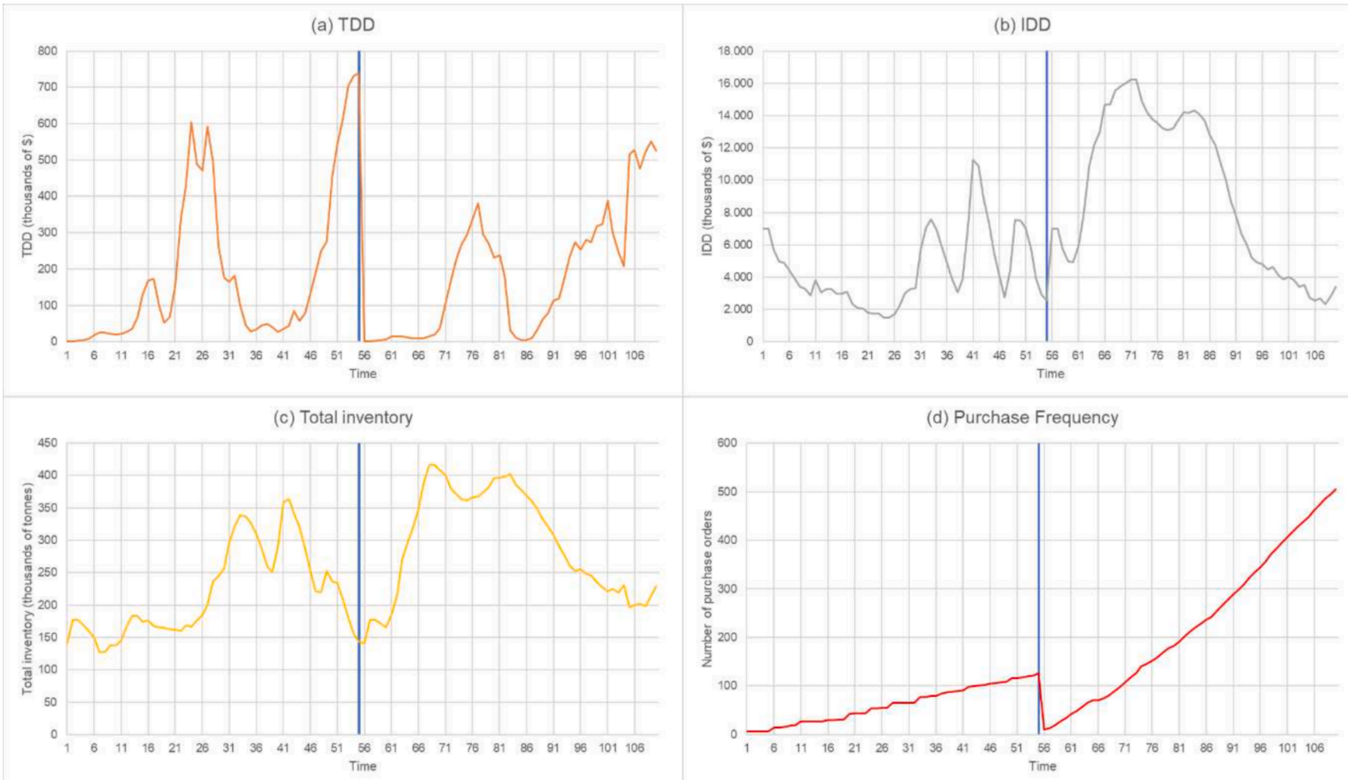

Fig. 10. Scenarios 1 and 2 distributions.

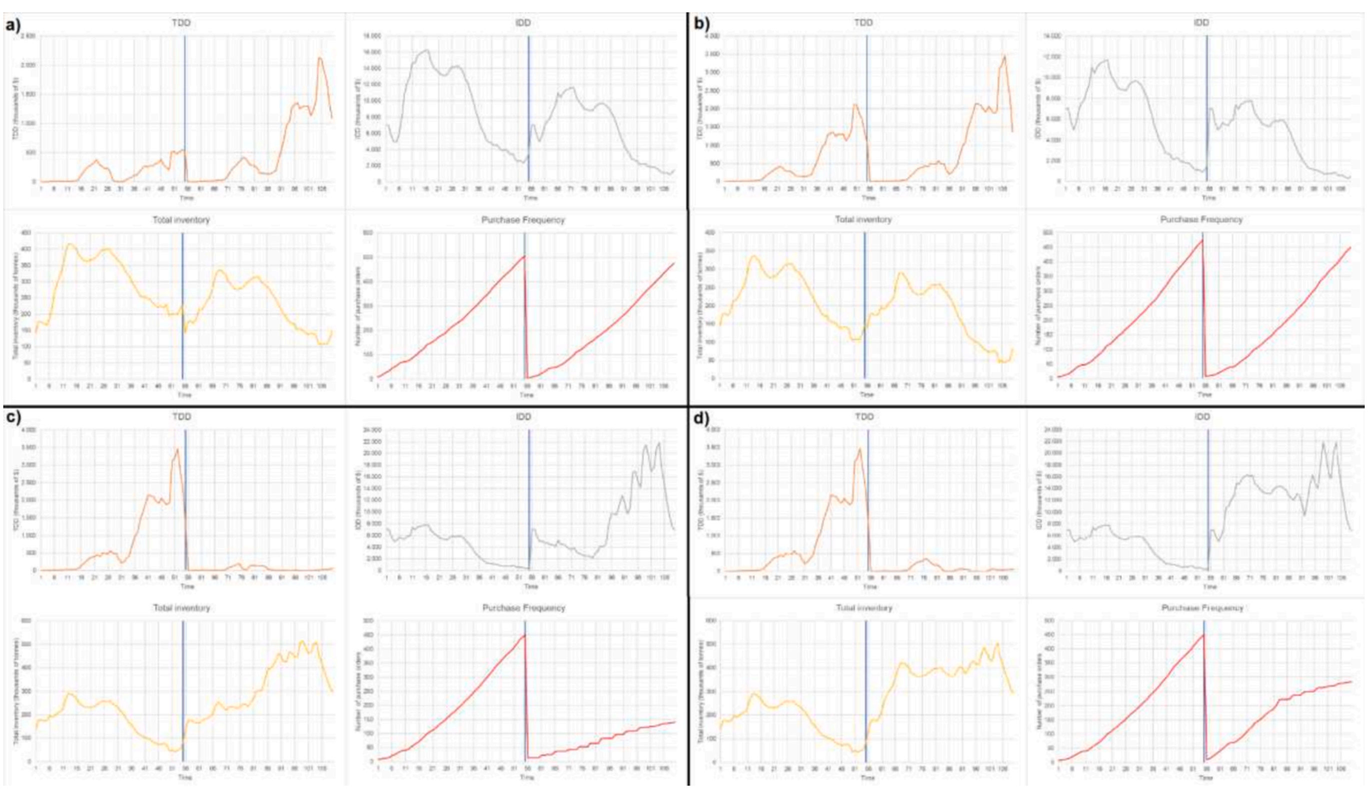

Fig. 11. Scenarios and distributions comparison.

(b), 4 and 5 (c), and 4 and 6 (d) – these are also shown individually in the Appendix in Figures F to I. Following the analyses conducted previously, the charts present the previous scenario distribution before the intervention point, while the scenario being analysed is shown after the intervention time.

Both scenarios 3 and 4 present improvements in the IDD and inventory levels but restrictive values for the throughput in comparison to the 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. The purchase frequency remains the same as in the previous step.

In the hybrid scenarios, improvements can be noted when compared to the traditional TOC steps. This indicates that the hybrid solutions, especially 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 a 95 % improvement. Both IDD and inventories start increasing especially during the high season, which can be observed at around time 80 onwards.

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

In summary, it can be noted that the TOC steps always try to prioritize the throughput, but the seasonality impacts the solution, especially the ones that use buffers. With inventory aggregation, the throughput, IDD, and inventory levels are improved. In step 3, with the utilisation of buffers and the decrease of the replenishment type, the TDD improves when compared to the base model. Although the improvement in TDD from steps 2 to 3 is not significant, the buffer utilisation serves as a base to construct the other TOC steps as well as the hybrid scenarios. 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 scenarios 5 and 6, which worsens the inventory levels and IDD but improves the throughput significantly. In scenario 5, which utilises TOC buffer levels based on the forecast and not solely in demand, the throughput is higher than in the other scenarios, but the IDD and inventory levels increase. It presents a 92 % improvement in the TDD, an 18 % increase in the IDD and a 51 % increase in the cumulative inventory levels when compared to the base scenario. Thus, the relative impact on the TDD surpasses all the increments in the IDD and the inventory levels. Finally, regarding the replenishment frequency, except for scenario 2, all the other scenarios significantly increase it. Thus, as stated before, the replenishment frequency is more a requirement of the solution than an implementation step.

5. Discussion of the results and managerial implications

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

5.1. Managerial and practical implications

The long lead times, delays in replenishment, lost sales, and fierce competition of the studied case presented a huge opportunity for supply chain performance improvement. As a big multinational company with many foreign suppliers composing its supply chain, those operational improvements can take time and often are costly and risky. Therefore, simulation and modelling serve as proper tools for more assertive, cheaper and safer decisions regarding 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 be achieved, impacting directly the company's results. At first, the implementation of the aggregated inventories at the highest level of the supply chain demonstrates an excellent increase in the throughput with no statistically significant increases in inventory levels. On the contrary, what is perceived is a huge reduction of inventories in the shops or, in other words, the requesting units. An observed 67 % decrease in inventory in the 3 smaller plants might be attractive for the business.

The utilisation of buffers can also contribute to improving the results of the company's supply chain. The application of forecast-based buffers also shows that better results can be achieved through the application of TOC concepts, achieving up to 92 % improvement in the TDD. However, to achieve this impact an increase in inventories would be necessary. Then, two valuable options derive from this research as suggestions for 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 another that maximises the throughput and, consequently, increases the total level of inventories in the SC. A thoughtful comparison was presented in this research, which can support the manager's decision for whichever path is chosen, be it the maximum prioritisation of the throughput, or a middle-term solution that would not impact the overall inventory level.

The practicality and applicability of these solutions and improvements found in the model also need to be taken into consideration by the managers. The improvements in throughput, for instance, either by aggregation or via buffers require an increase in inventory levels – either at the smaller plants or in total. This of course would have financial implications (as the company would have to purchase and stock more raw materials) as well as physical constraints such as storage space which could be expanded by external warehouses which in turn would bring additional costs into the picture. The replenishment frequency is also something that needs to be addressed by managers. In the case studied, many of the raw materials are imported and transported in vessels across the ocean which might constrain high-frequency deliveries, unless an alternative is found which might, again, incur additional costs.

Additionally, the model simulates only one part of the complete supply chain of the organization. The regional state where the case is located represents almost 30 % of the operations of the company in the country. In that sense, the 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 other states as well. Not only that, but the concepts and practices herein could be extended to the international levels too, demonstrating huge opportunities for improvement.

Lastly, in a more general sense, the research can also demonstrate to other managers some of the benefits and challenges of the application of TOC practices in the supply chain. Nevertheless, it presents managers with steps that can be taken to improve the throughput of their supply chains, highlighting some aspects regarding trade-offs on inventory levels and the requirements for delivery frequency in similar MTO scenarios.

5.2. Academic contributions

Even though there are many studies demonstrating the benefits of applying TOC practices at production and factory levels, the studies regarding its application and impacts on supply chains are rather limited and, therefore, not fully reported and comprehended (Gupta & Snyder, 2009; Ikeziri et al., 2019; Puche et al., 2016). This paper fulfils this gap by 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 its initial context – retail and distribution (Ikeziri et al., 2019) – to another strategic sector – MTO. TOC research within the SC perspective has been very specific, focusing on parts of the replenishment solution such as manufacturing level operations (Gupta & Andersen, 2018; Telles et al., 2020), inventory impacts and improvements (Chang, Chang, & Huang, 2014; Chang et al., 2015), buffer management (Tsou, 2013), and replenishment frequency (Wu et al., 2012, 2014). Our research advances research of TOC in SCM, by providing a holistic view of its impacts on the supply chain and its links, analysing not only inventory levels but also how well positioned those are – through the IDD – and the SC throughput performance – the TDD.

All TOC steps presented a significant impact on at least one of the key variables, but they also presented some of the theory's flaws, especially when dealing with abrupt changes in demand. It was noted that the buffers' performance is 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 6 – affected positively the system's throughput, but compromised inventories and IDD. This suggests that Schragenheim's (2010) proposition might not be as 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 on 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 an empirical case, some general findings regarding the objectives of each TOC solution step can be pointed out. It is important to note though, that those findings may 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 Table 4.

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 relevant is 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. The IDD, improves to almost 40 % in the stock aggregation, meaning that the inventories are better positioned throughout the supply chain. 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 noted that throughput takes more time to be perceived in the system after the implementation of the steps when compared to IDD and inventory levels. The TDD took up to 20 weeks to have an observable increase or decrease. Regarding the IDD and inventories though, those impacts could be observed in approximately 5 weeks. This is not only relevant to the academic context but to managers as well, as this can provide a good perception of 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 to 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. Thus, it seems to function like a reality check or a pre-requisite to move into those other initiatives.

6. Conclusions

The TOC replenishment solution aims to solve many problems related to supply chain distribution by increasing the throughput of sales and reducing inventory levels (Bernardi de Souza & Pires, 2010; Ikeziri et al., 2019). Although promising, TOC's literature hadn't yet presented a method to apply its practices in supply chains (Tsou, 2013), studies that evaluated consistently the implementation of TOC in supply chains, including its performance measures (Gupta & Andersen, 2018), and, therefore, had an absence of empirical evidence to support the improvements brought by its application (Gupta & Boyd, 2008). All these gaps are tackled in this paper, which presents an application method for TOC in supply chains, assesses its implementation with different performance measures and empirically evidences its results.

This research assesses each one of the TOC SCRS steps and evaluates its impacts, using a simulation study of an empirical case. A system dynamics model was created, simulating the actual scenario of the company and other scenarios that simulate the application of the TOC solution in a stepwise manner. The procedural application of the steps provides a detailed understanding of its impacts and effects in the defined case. Additionally, the causal impact technique is utilised to measure TOC's impact on the supply chain, providing good visual resources to assess those impacts, as well as meaningful data to support the negative and positive effects of its interventions on the system.

The TOC steps are modelled, 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 inventories with better efficiency levels – measured through the IDD. Still, inventories in the shops can decrease up to 67 % while providing significant throughput improvements. Additionally, two other scenarios are proposed 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 buffer utilisation are analysed and the TOC SC suggestion to deal with those is also tested. As demonstrated, the results are only satisfactory and other scenarios tend to present better results. Some insightful considerations, contributions and options are made to the company and managers in general that might help improve its supply chain operations. We highlight the challenges around the application of the concepts, mainly with the increases in inventory levels and replenishment frequency that need careful consideration before putting into practice the steps described in this research.

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 raw-material consumption to calculate throughput losses. However, as an MTO company, 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 their prioritization – could not

Table 4
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 increases safety measures to do so, i.e., inventories	Throughput	Inventory-dollar-days and total SC inventory 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, and 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 their optimal point	Inventory-dollar-days and total SC inventory levels	Throughput

be assessed.

For future avenues of study, many scenarios can be suggested. Within the company context, 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 reproduced in other similar scenarios – MTO, high level of international suppliers, etc. – to refute or corroborate the results presented. Moreover, any other empirical applications of TOC with quantitative measures of impacts are welcome and could be used for comparison and improvement of the theory.

CRediT authorship contribution statement

Gustavo Stefano: Writing – original draft, Validation, Investigation, Formal analysis, Data curation, Conceptualization. **Daniel Pacheco Lacerda:** Writing – review & editing, Methodology, Formal analysis. **Maria Isabel Wolf Motta Morandi:** . **Ricardo Augusto Cassel:** Writing – review & editing, Visualization. **Juliano Denicol:** Writing – review & editing, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

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Table A
Specialists' profiles.

Position	Support in the research	Company time
Senior S&OP coordinator	Provided an overall view of planning and forecasting processes	9 years
S&OP coordinator	Provided a detailed understanding of the department activities plus the data of raw material replenishment, including forecasts replenishment orders, and consumption	10 years
Fulfilment coordinator	Provided data on sales orders deliveries, including expected times and delays	9 years

Table B
Variables collected.

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. data
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	Provides the expected transit time by origin (country and seaport)	S&OP knowledge database

Table C
Observations and purchase volumes by raw material.

Raw material	# Observations	Purchase volume	Volume % of total
RM A	84	549.377,14	37 %
RM B	50	263.782,00	18 %
RM C	26	2.196,00	0 %
RM D	23	106.640,00	7 %
RM E	21	3.772,00	0 %
RM F	20	124.908,44	8 %
RM G	17	94.952,00	6 %
RM H	15	69.673,68	5 %
RM I	14	84.000,00	6 %
RM J	11	312,00	0 %
RM K	9	30.054,00	2 %
RM L	9	44.630,00	3 %
RM M	8	28.643,00	2 %
RM N	8	33.041,00	2 %
RM O	8	216,00	0 %
RM P	6	144,00	0 %
RM Q	4	98,00	0 %
RM R	3	13.220,00	1 %
RM S	3	1.056,00	0 %
RM T	3	72,00	0 %
RM U	3	12.751,00	1 %
RM V	3	1.008,00	0 %
RM X	3	8.796,00	1 %
RM Y	3	69,00	0 %
RM Z	3	82,50	0 %
RM AA	3	72,00	0 %
RM AB	2	48,00	0 %
RM AC	1	4.400,00	0 %
Total	**363**	**14.78.013,755**	100 %

* The light blue highlight indicates the selected raw materials for the validation

Table D
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	NA
RM A	65.022	64.422	8.109	46.100	77.300	2,0452	3.028	6.502	7
RM B	19.494	18.418	5.148	8.830	27.800	2,0452	1.922	1.949	29
RM D	16.818	18.788	1.206	16.300	20.600	2,0452	450	1.682	2
RM F	17.744	16.518	1.871	11.300	18.300	2,0452	699	1.774	5
RM G	16.535	22.095	3.016	14.900	26.800	2,0452	1.126	1.653	14
RM H	8.774	8.221	1.252	5.780	10.800	2,0452	467	877	9

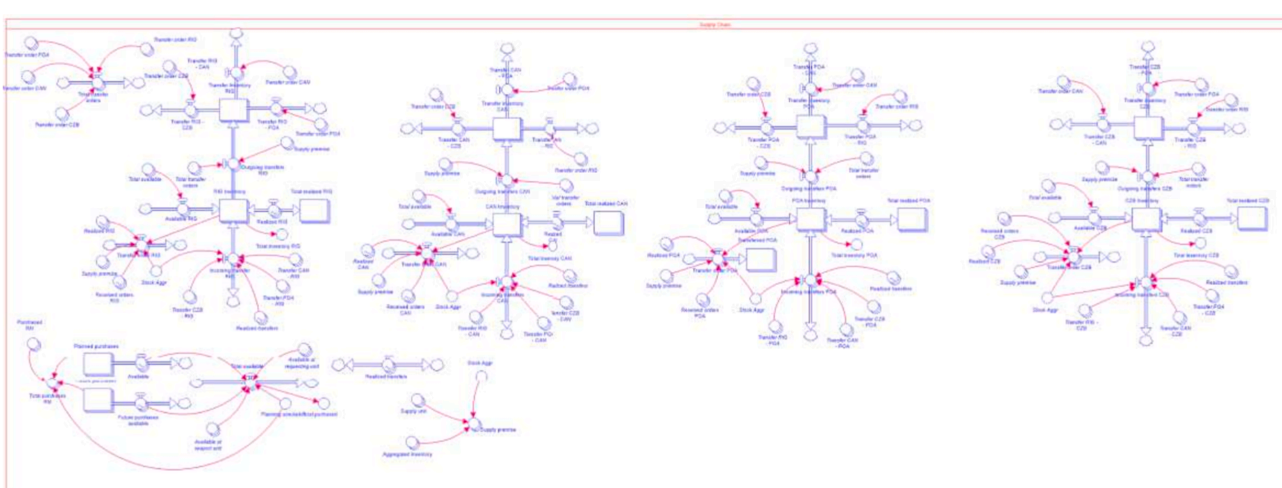

Fig. A. Supply Chain Model Component

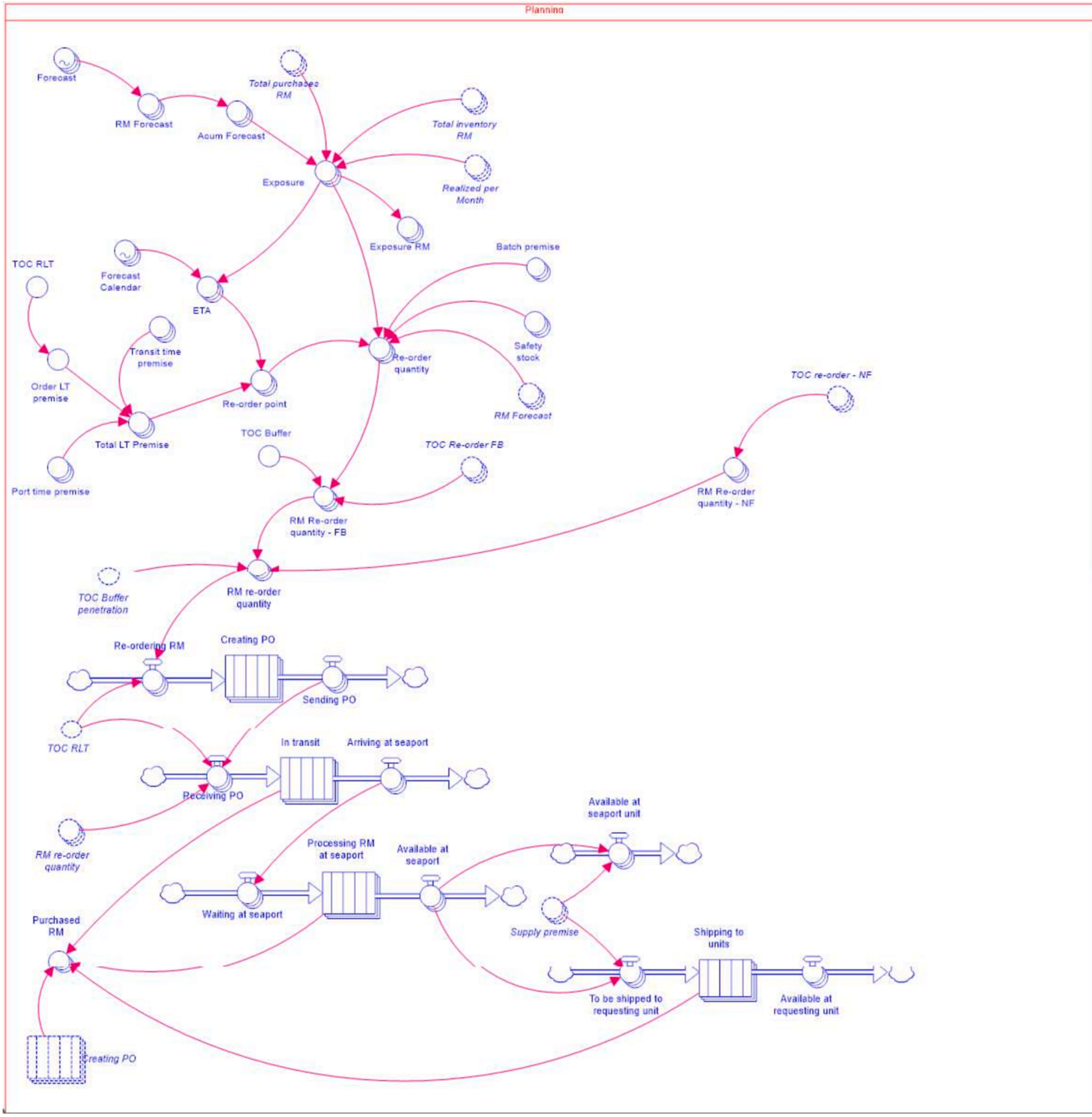

Fig. B. Planning Model Component

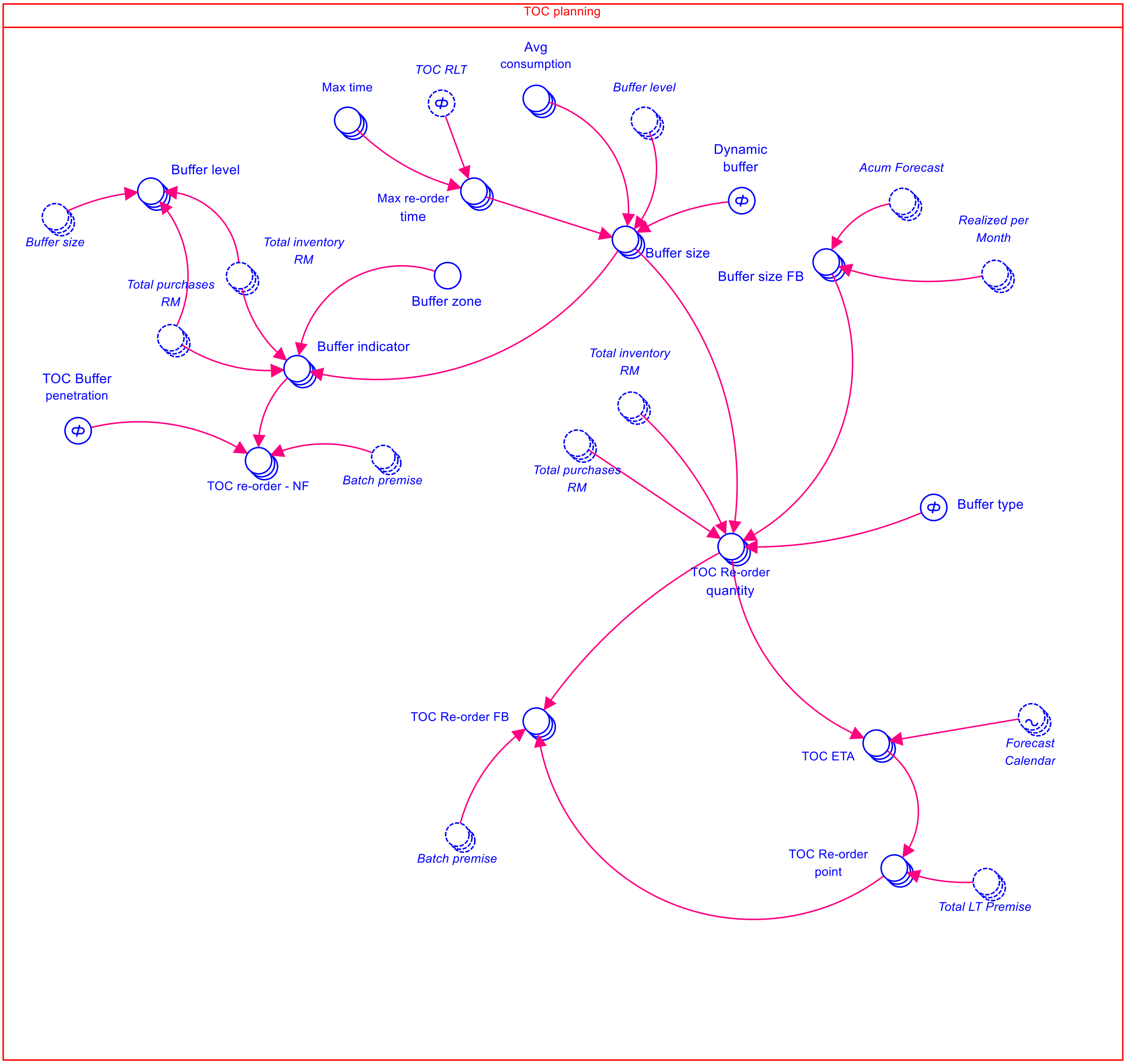

Fig. C. TOC Planning Model Component

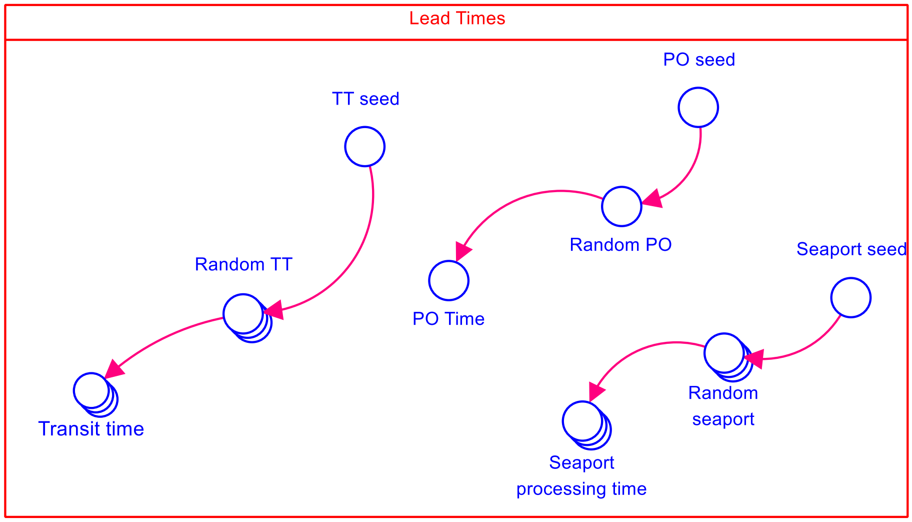

Fig. D. Lead Times Model Component

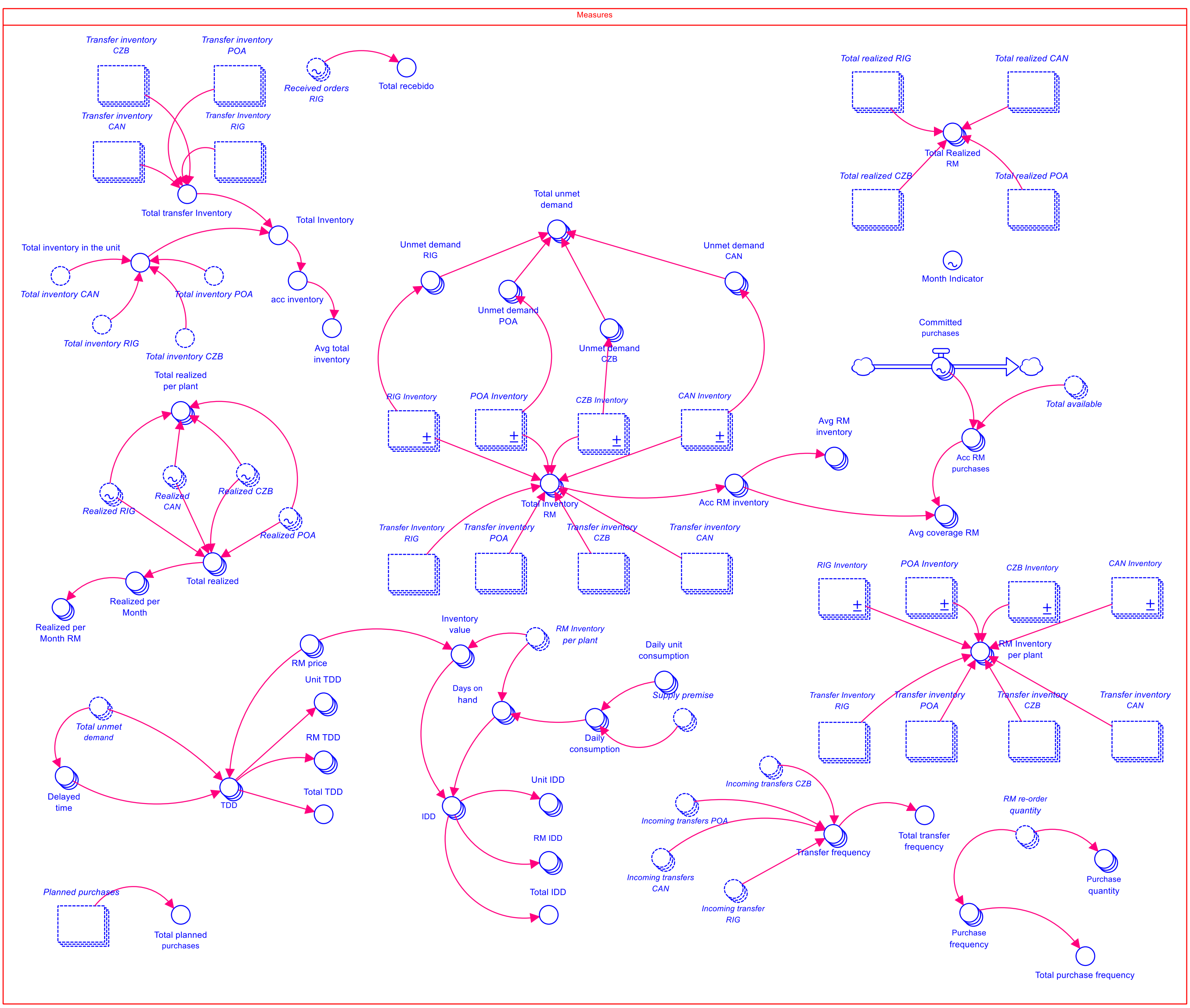

Fig. E. Measures Model Component

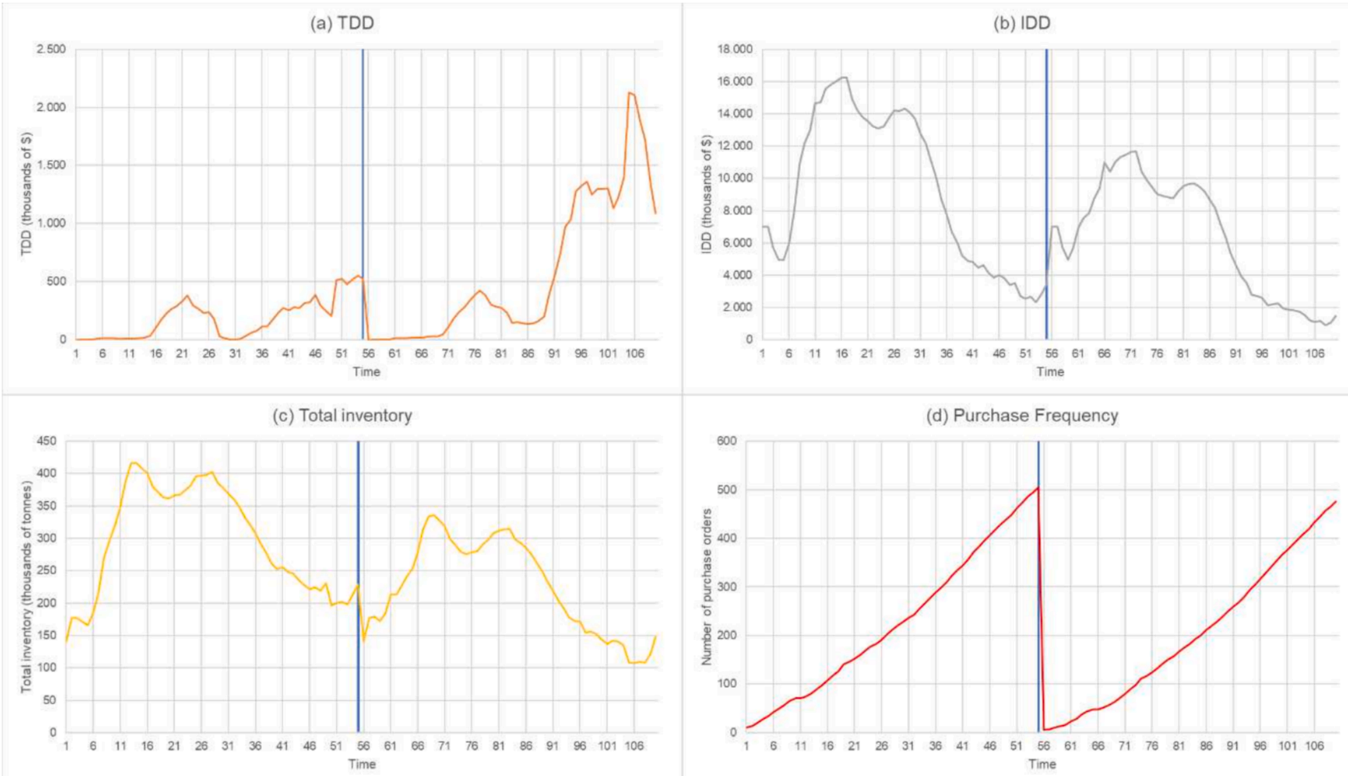

Fig. F. Scenarios 2 and 3 distributions comparison.

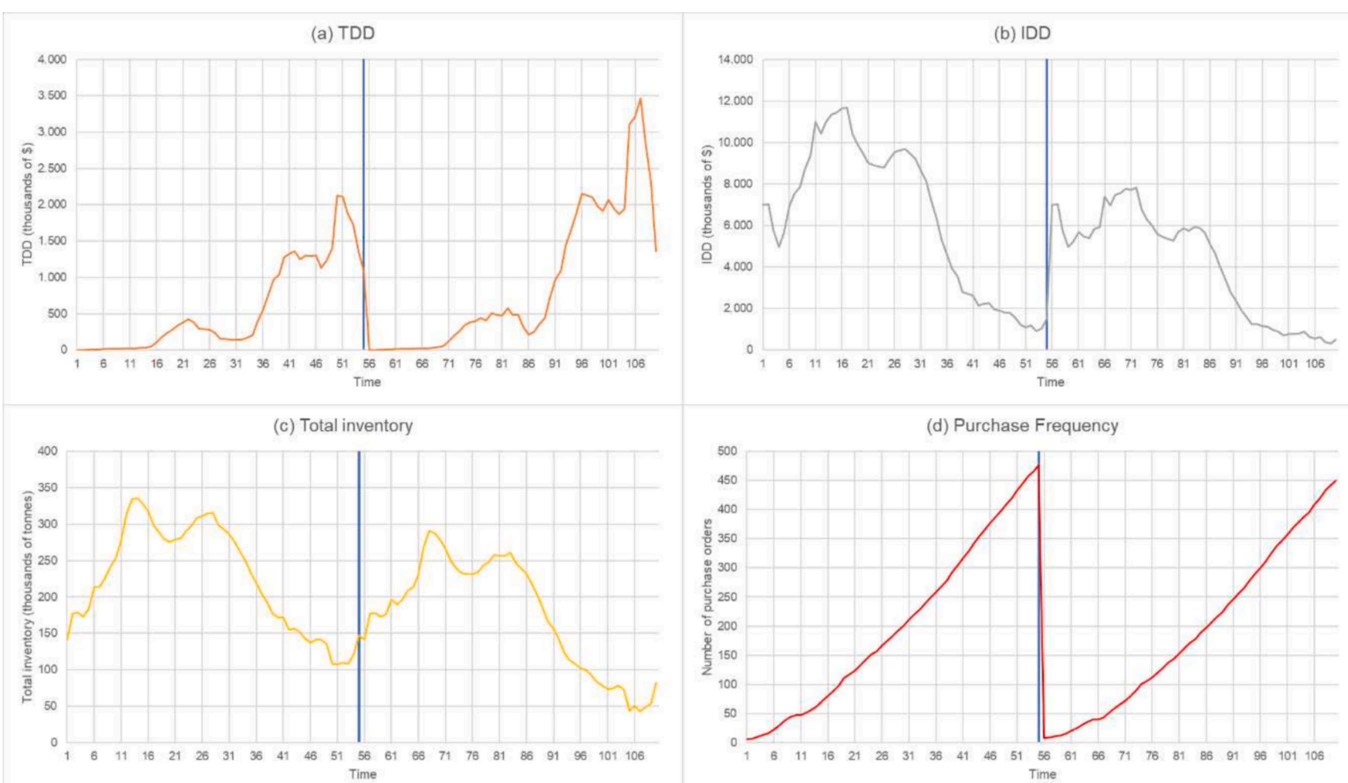

Fig. G. Scenarios 3 and 4 distributions comparison.

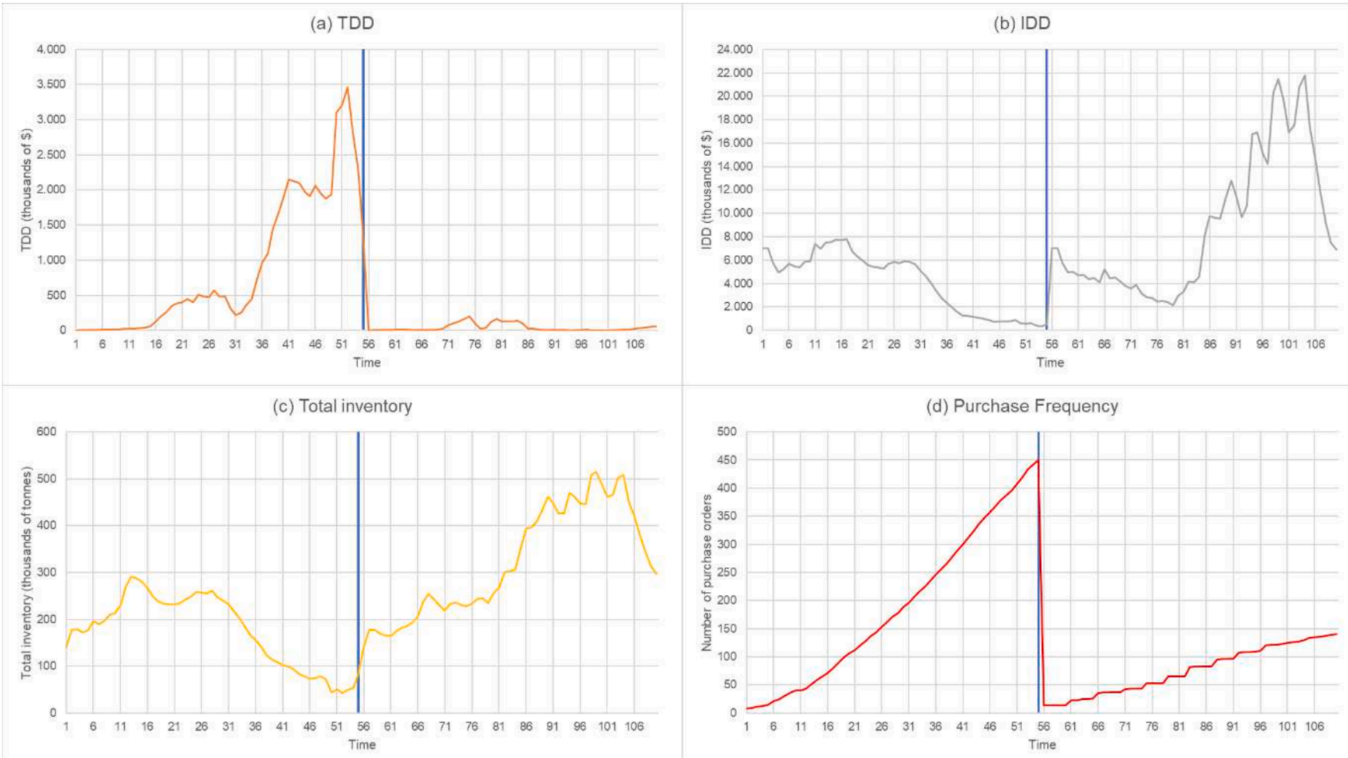

Fig. H. Scenarios 4 and 5 distributions comparison.

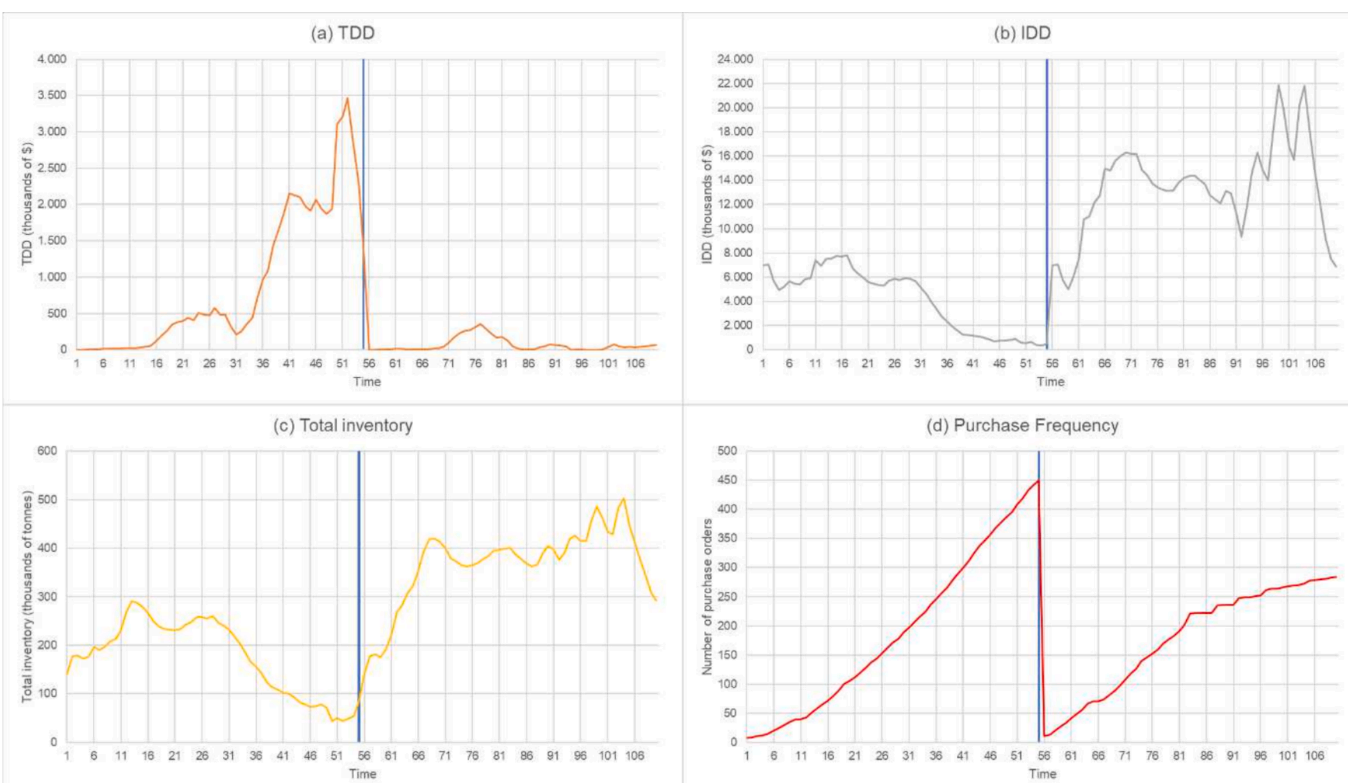

Fig. I. Scenarios 4 and 6 distributions comparison.

Data availability

The data that has been used is confidential.

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