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Supply Chain Risk Management: an Interactive Simulation Model in a Big Data Context

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Abstract

Aligned with the Industry 4.0 research and innovation agenda, a Decision Support System is currently being developed with the purpose of enhancing decision-making in risk scenarios at Supply Chains. It is comprised of a Big Data Warehouse and a simulation model. The former stores and provides integrated real data to the simulation model, which models the respective materials and information flows. Thus, the purpose of this paper is to present such tool being used to test scenarios that, contrarily to the traditional simulation approach, incorporate disruptions in an interactive way, meaning that users may fire such events at any desired simulation time and with different parameters. Thus, the tool is used to assess the impact of disruptions in the performance of the system. The conclusions of this paper highlight the benefits that can be obtained with the proposed interactive approach, as it allows a virtualization of the real system to be obtained and, at the same time, use the simulation model to assess what would be the impact of certain disruptions.

Keywords: Simulation; Supply Chain; Big Data, Industry 4.0

1. Introduction

The integration of the physical world and its virtual copy in cyberspace, through Cyber-Physical Systems (CPS), and the Internet of Things (IoT) are some of the pillars of Industry 4.0. By implementing these concepts, the smart factory will be a reality [1], [2]. To achieve it, several fields of knowledge can contribute, e.g., Robotics, Materials, Information Systems, Informatics and Simulation [2], [3].

Kagermann et al. [2] stressed the use of simulation to analyze the behavior of complex systems such as Supply Chains (SCs), hence allowing to improvement industrial processes. The authors also noted the importance of using Big Data in conjunction with simulation solutions, as it allows data from several sources to be considered in the model.

Vieira et al. [4] reviewed simulation studies closely related with the concept of Industry 4.0, in order to identify the boiling research directions for simulation, which are aligned with the industrial revolutionary movement. According to the authors, such studies include the use of Big Data technologies applied to SC problems, due to the possibility of capturing the detail of processes that Big Data allows, along with the ability to consider the uncertain nature of SC systems that simulation offers.

In light of this, Zhong et al. [5] outlined the current movements on the application of Big Data for Supply Chain Management. According to the authors, the increasing volume of data in the several SC sectors is a challenge which requires tools to make full use of the data, with Big Data emerging as a discipline capable of providing solutions for analysis, knowledge extraction, and advanced decision-making.

According to Tiwari et al. [6], the use of analytics in SCs, including simulation methods, is not new. However, the advent of Big Data presents itself as an opportunity for its use in conjunction with such analytics methods (e.g. simulation). In particular, the authors stress the importance of such duo in

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predictive and prescriptive analytics, with simulation being used in the former to predict future events and in the later to enhance alternative decision-making testing.

As the cited works suggest, and to the best of the authors' knowledge, a gap can be identified in literature, which concerns the existence of Big Data structures to store and integrate data from several sources, with the end goal of providing such data to a SC simulation model. Such solution is currently being developed by the authors. It consists of a Big Data Warehouse (BDW) structure that stores and provides integrated real industrial data. Since Big Data concepts and tools are being used to integrate, process and provide huge volumes of data to the simulation model, this can be interpreted as a Big Data context. See [7] for details regarding the development of the BDW structure. Thereafter, this data can be provide to a SC simulation model that was developed in SIMIO [8], [9].

Thus, and using the developed tool, the purpose of this paper is to present an alternative approach to test the impact of risk scenarios in SCs, which consists in interactively using the simulation model. In other words, the simulation model is used to reproduce a copy of the real system using the data stored in the BDW and, during runtime, events can be triggered, which may result in different impacts. Thus, this paper presents such approach and demonstrates its use, by testing certain scenarios.

When establishing the aspects for which simulation required further contributes, Robinson [10] already portrayed some of the uses for which simulation can be to, in order to comply with the Industry 4.0 research and innovation agenda. In particular, the ability for users to interact with a simulation while it runs may enhance the stakeholders' interest in the model and thus improve the benefits retrieved from it. Such feature is henceforth referred to as interactive simulation.

This paper is structures as follows. Section 2 describes the system considered in this paper. Section 3 addresses the fundamentals of the development of the simulation model. Section 4 illustrates and discusses the obtained results and section 5 discusses the conclusions and outlines future research directions.

2. System Description

This project is being developed at a plant of the Bosch Group, which produces electronic components for cars. Around 7 000 different types of materials are actively being supplied by roughly 500 different suppliers, located in more than 30 countries, especially from Europe and Asia, with Germany (209 suppliers) and Netherlands (10 suppliers) having more suppliers from Europe, and Malasya (16 suppliers), Taiwan (13 suppliers), China (12 suppliers), Hong Kong (11 suppliers) and Singapore (7 suppliers) having more shipments from Asia.

This section describes the SC system that was considered for this research. In this regard, Fig. 1 illustrates a summary of the main material and information flows that occur in such system.

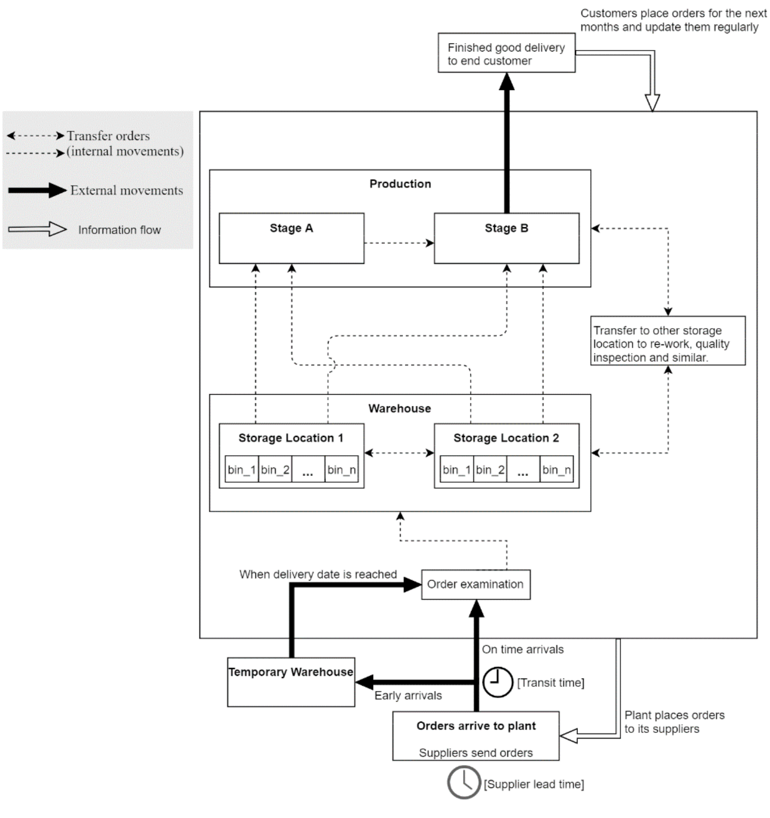

Fig. 1: Summary of material and information flows of the SC system.

To fulfill its customers' orders for finished goods, the plant divides its production in two stages: A and B. In stage A, components of the finished goods are produced using raw materials. Later, such products are sent to stage B, where the final production of the finished goods occurs, using raw materials and other components produced in stage A.

The plant follows a Just in Time (JIT) philosophy, which consists in demand-driven production, aiming to reduce overall wastes with inventory levels and other aspects [11], [12]. Whilst JIT may result in such benefits, it also may result in high vulnerabilities [13], if the available materials are not enough to cover eventual disruptions. Therefore, to mitigate these possibilities, organizations tend to adopt safety stock strategies, which is also a complex task, as low values may result in stockouts and high values may cause excessive costs due to overstock. As such, manufacturing plants, its suppliers and customers must work in an integrated environment, in order to efficiently manage the entire chain.

In light of the above and as Fig. 1 illustrates, eventually, orders are placed to suppliers and monitored, so that when the right time comes, they can be sent to the plant, in order to arrive in the scheduled date, hence reducing the need to create material buffers. While, in fact, most of these arrivals occur at the scheduled date, some suppliers provide the orders before the scheduled date. When these situations occur, the plant stores such orders in the Temporary Warehouse, which is managed by suppliers, so that the plant does not incur in excessive costs with these orders. In its turn, when suppliers are delayed, the plant may schedule special freights, which are considerably costlier, albeit much faster. In fact, whilst early arrivals results in high warehousing costs for suppliers, late arrivals may result in material shortages, potentially leading to production stoppages.

When materials arrive to the plant, the contents are may be examined to assess their quality (the movements depicted in Fig. 1 represent the main ones that occur in the plant, albeit there exists many other movements, mostly for quality inspection, re-work and similar tasks) and, afterwards, are stored in the warehouse, which is divided in two main locations. Both locations store raw materials, however, location 1 stores mostly electronic components, while bulkier materials are mostly stored in location 2.

3. Simulation Model

This section briefly describes the simulation model, focusing on describing how users can interact with it during runtime. See [14] for details regarding the approach that was followed to allow the simulation model to also be used for prediction.

The simulation model was developed in SIMIO and runs in a world-map view provided by Google Earth, where entities represent both internal and external logistic movements, i.e., orders to suppliers - and the respective material arrival - and material transfers that occur within the plant (e.g., store materials in the warehouse and send them to production). These movements comprise the types that occur in any SC.

Furthermore, entities travel throughout the model without links between objects, as the only object of the model is the one that represents the plant itself. Such objects are illustrated in Fig. 2.

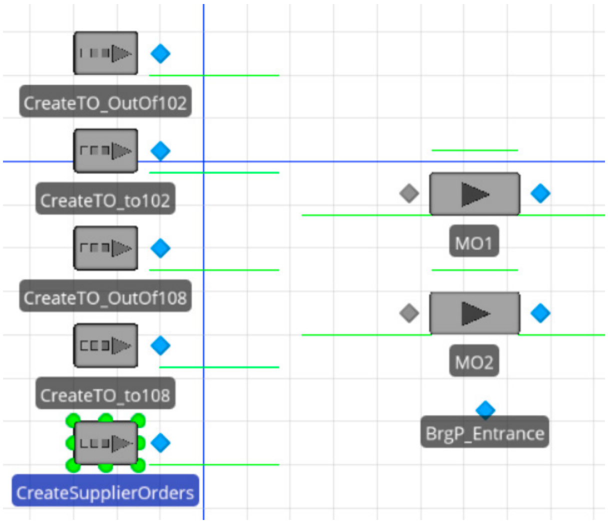

Fig. 2: SIMIO blocks that comprise the only physical object of the model.

The objects depicted on the left of the figure are Source objects and are responsible for creating entities, which represent either internal material movements or orders to suppliers. Thereafter, using several processes, the movements of entities are modelled using processes and using the Free Space feature that SIMIO offers, which allows entities to freely move in an orthogonal tridimensional space. Eventually, production orders occur, which sends entities to the MO1 and MO2 Servers depicted in the above figure.

SIMIO allows the user to place buttons, which when clicked trigger specific events. In their turn, those events trigger the execution of processes, which specify actions that happen when the mentioned events are triggered. The great advantage of these buttons is that they allow the user to fire them at the desired simulation time and any number of times. Fig. 3 shows the process that is executed when a button is clicked, with the purpose of halting the production of the plant during a specified time, resuming it afterwards.

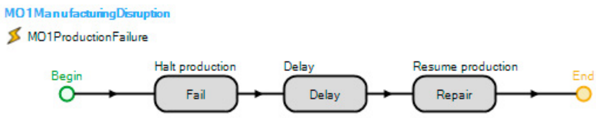

Fig. 3: Process executed to stop the production during a given interval and resume it afterwards.

When the button is clicked, the Fail "Halt production" step stops the Servers used to model the production of the plant or any specified Server, depending on the options set by the user. Thereafter, the Delay step holds the process during a specified disruption time, before resuming the production of the halted Servers.

This section provided some basic understanding of how the simulation model works. Next section provides an example application of the tool being used to assess the impact of production stoppages on the performance of the plant.

4. Analysis of Results

In this section, it will be discussed how the model can be used interactively, i.e., instead of the traditional approach consisting in incorporating risks based on distributions, the disruptive events here considered are triggered by actions of the user. Thus, in this section, events that halt the production of the plant during a given time period are considered. Therefore, the following three scenarios are considered:

1. Running the model using the data provided by the BDW, without considering any disruption, i.e., producing a mimic of the real system;
2. Running the model using the data provided by the BDW and considering a disruption in the plant that lasts 3 days;
3. Running the model using the data provided by the BDW and considering a disruption in the plant that lasts 5 days.

Furthermore, the following Key Performance Indicators were considered for this research:

- Production utilization;
- Stock level.

Fig. 4 shows the obtained results for the production utilization of the plant, for the three considered scenarios.

Fig. 4: Utilized production capacity units (1) without any disruption event, (2) with a disruptive event lasting 1 day (3), and 5 days (top); and the percentage difference of the utilized capacity units for both disruption scenarios (bottom).

As the figure shows, the disruption events were fired on the 9th of December, as it was around this date that the production was higher. As can be seen, the disruption lasts for 1 and 5 days, respectively and, when the plant recovers from the disruption, it takes approximately half a day to recover to regular production in the scenario in which the event lasted 1 day, and approximately 3 days in the scenario where the event lasted 5 days. However, it should be noted that these results do not consider setup times, thus the production is immediately resumed to its maximum capacity after recovering from the disruption in the plant. The percentage differences can be seen in the same figure, at the bottom. In its turn, Fig. 5 shows the stock level for the considered scenarios.

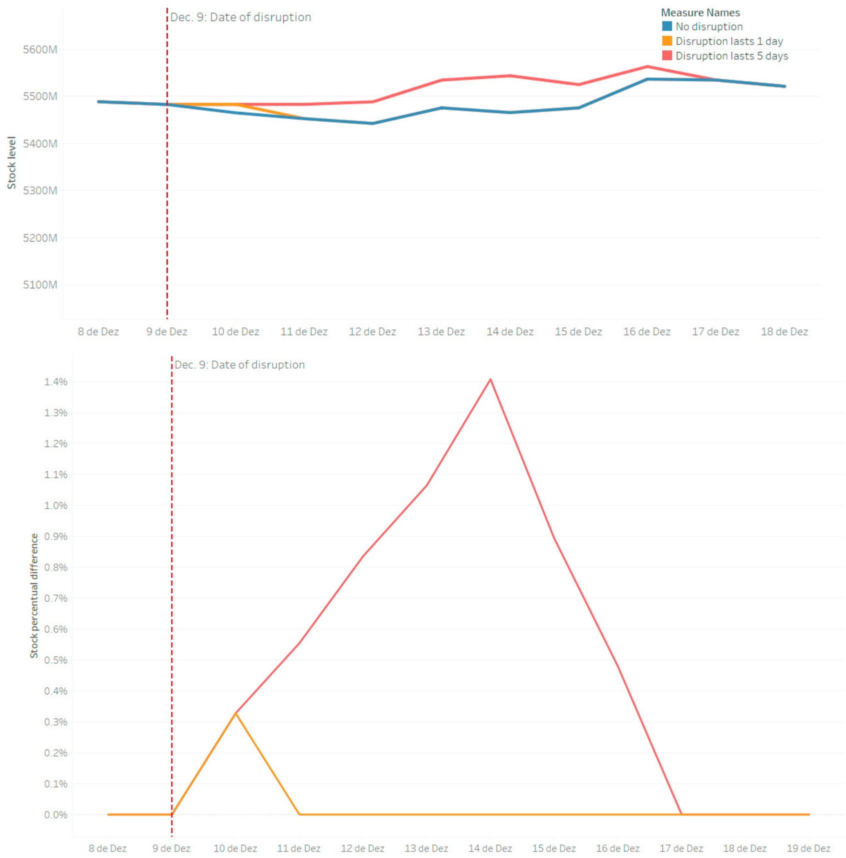

Fig. 5: Stock level (1) without any disruption event, (2) with a disruptive event lasting 1 day, (3) and 5 days (top); and percentage difference of the stock level for both disruption scenarios (bottom).

As can be seen, as soon as the disruptive event is triggered the stock stops being consumed and increases up to 0.35% and 1.4% when the disruptions last 1 and 5 days, respectively. After the respective disruptions, the production which was resumed to its maximum capacity, starts regularly consuming the materials in stock. Thus, since the production was resumed to its maximum capacity (see Fig. 4), the stock level of the scenarios that considered disruptions (see Fig. 5), reach the same level as the scenario that did not consider any disruption after 2 and 8 days, respectively for the scenarios that disrupted the production during 2 and 5 days, respectively.

5. Conclusions

Industry 4.0 establishes many research and innovation goals, which require the utilization of several fields of knowledge. Allgined with this movement, recent studies have outligned the need for SC simulation models and Big Data concepts and technologies to be applied to enhance risk mitiation. In light of this, this paper proposed an approach to use such tool, which, instead of typical simulation approaches, allows users to fire disruptions in rintime and, thus, assess their impact in the overall performance of the system.

The results presented and discussed in this paper portray the benefits of the proposed tool for decision-makers in SCs. However, while the tool can be used for purposes that are typical of a simulation solution, e.g. visualize complex systems and test alternative scenarios, in this paper it was used to test scenarios that considered production stoppages fired by users during runtime, in na interactive way. Such approach is usefull as it allows to mix the benefits of using the real data to produce a virtual representation of the real system and, at the same time, include uncertainty.

The area of application of this research also heightens the importance of risk mitigation approaches, as it is a SC of the automotive electronics industry. In fact, these SCs are typically characterized by having single sourced materials, with suppliers typically providing multiple materials, thereby exposing the entire SC to risks.

While this paper succeeded in using interactive simulation to assess the impact of disruptions in the performance of a manufacturing plant, such disruptions only comprised production stoppages. Thus, this research can be enhanced by considering other types of disruptions, e.g., assessing the impact of suppliers disrupted in a given geographic location. Furthermore, being a comprehensive project that requires data of several departments, efforts must still be made towards collecting the required data that is still missing, as well as allowing the BDW to operate in real-time, i.e., to automatically extract, clean and store data in the BDW.

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