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Are Simulation Tools Ready For Big Data? Computational Experiments with Supply Chain Models Developed in Simio

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Abstract

The need and potential benefits for the combined use of Simulation and Big Data in Supply Chains (SCs) has been widely recognized. Having worked on such project, some simulation experiments of the modelled SC system were conducted in SIMIO. Different circumstances were tested, including running the model based on the stored data, on statistical distributions and considering risk situations. Thus, this paper aimed to evaluate such experiments, to evaluate the performance of simulations in these contexts. After analyzing the obtained results, it was found that whilst running the model based on the real data required considerable amounts of computer memory, running the model based on statistical distributions reduced such values, albeit required considerable higher time to run a single replication. In all the tested experiments, the simulation took considerable time to run and was not smooth, which can reduce the stakeholders' interest in the developed tool, despite its benefits for the decision-making process. For future researches, it would be beneficial to test other simulation tools and other strategies and compare those results to the ones provided in this paper.

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

1. Introduction

Over the years, a vast literature of simulation studies targeting Supply Chain (SC) problems has been published in multiple sources [1]. As the cited authors note, most of these studies use the traditional approach, which consists of using statistical distributions to model the many business processes associated to these SC networks, failing to use real data in their simulation models. The authors also noted that such approach could increase the stakeholders' involvement in simulation projects, as well as to increase the level of detail and realism provided by simulations. To provide real data to simulation models, structures such as Data Warehouses (DWs) can be used, which allow data originated from multiple sources to be stored and integrated in a single structure.

Despite this reduced use of structures like DWs that provide real data to simulation models, in the recent Industry 4.0 agenda there has been a strong appeal for the complementation of Big Data technologies in SC simulation models [2], [3]. In fact, the benefits that have been reported for the use of structures like DWs can be heightened with the use of Big Data concepts and technologies, combined with the advantages that simulation may offer to SC problems.

In Big Data environments, data is generated at increasingly higher volumes and velocities and with multiple formats [2], [3]. Due to the availability of these vast volumes of data, traditional tools, such as DWs, are no longer capable of dealing with today's world of Big Data environments. Thus, it becomes mandatory to adopt other concepts and technologies that are capable of storing, integrating and processing data, so that added value can be retrieved.

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It is in this context that a project is being developed, which consists in developing a Decision Support System (DSS) comprised of a Big Data structure, namely a Big Data Warehouse (BDW) [4], [5], and a SC simulation model. The former stores data from several SC business processes and integrates it, hence allowing the data to be processed and provided to simulation models. In its turn, the latter receives real data from the BDW and reproduces the corresponding material and information flows that occurred, allowing several purposes to be achieved, e.g., prediction, virtualization of the real system, test risk scenarios, analysis of complex problems and others.

In [6], the process of the requirements elicitations for the development of the BDW was described, which also included the description of the development steps for said structure. The study culminated with an illustration of interactive dashboards than can be created using the integrated data stored in said structure. Regarding the simulation model, see [7] for details regarding its development and its application to test risk scenarios.

Thus, and with the acquired experience of working in SC simulation models in Big Data contexts, the purpose of this paper is to provide aspects related with the performance of SIMIO while conducting such experiments. To achieve this goal, the experiments that were conducted in this project, including those presented in [7], will be used.

This paper is organized as follows. Section 2 analyzes literature related with Industry 4.0, with emphasis on the one that stresses the need to combine Simulation and Big Data to enhance the decision-making process in SCs. Section 3 discusses the materials and methods adopted for this research. Section 4 presents and discusses the obtained results. Section 5 discusses the main conclusions obtained from this research.

2. Related Work

Since its beginnings, industry underwent several paradigms shifts, which are labelled as industrial revolutions [8]. Ultimately, industry will enter its fourth era and hence the term “industry 4.0”. The term originated from the German expression “industrie 4.0”, which became known in 2011, when an association of the same name promoted an idea aiming to enhance the competitiveness of the German manufacturing industry. In its turn, the German government supported this idea, by announcing that industrie 4.0 would be part of its “High-Tech Strategy 2020 for Germany” initiative, aiming at technological innovation leadership [9]. Thereafter, the term was adopted in Europe as “industry 4.0” [8]. Other zones of the globe also adopted their own projects, focusing on technological innovation, e.g. United States and China. Notwithstanding, the German program is the one with more capital investment [10].

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 [8], [9]. Thus, Industry 4.0 can be considered an agenda, and, to achieve it, some of the mandatory steps are: a paradigm shift from centralized to decentralized, semantics between machines, modularity, interoperability between systems and information virtualization [8].

According to Lasi et al. [8], there are some triggers for the rise of Industry 4.0 that can be identified, namely the need for a decrease in development and innovation periods and the need for the “batch size one”, i.e., the chase for product customization. Ensuring this demands higher resource efficiency, flexibility and decentralization. On the other hand, the authors also stressed some of the expected technology advancements. Firstly, the increase in use of mechanization and automation in several industrial processes. Secondly, advancements in the digitalization are also expected, since large amounts of data are being retrieved from manufacturing tools and can support functions of control and analysis that need to be explored. Lastly, the authors also emphasize the role of miniaturization, since increasingly powerful computers are being installed on fewer space with the expansion of embedded and ubiquitous computing.

In Industry 4.0, six principles can be distinguished, regarding its development and deployment. The first is the interoperability among systems, people and information, since these interchange data with different formats, through the IoT and Internet of Services (IoS). These should enable real-time decision-making, consisting in the second principle. The gathering and analysis of data should focus not only on internal processes, but also on external. The third principle regards with virtualization of information. CPS must be able to virtualize a copy of the real world and monitor objects existing in the surrounding environment. Thus, information of surroundings is easily reachable. CPS should also be able to work independently – fourth principle – paving the way for more flexible systems, albeit conflicting goals should still be delegated to higher hierarchical levels. Lastly, the fifth and sixth principles respectively concern with being able to rapidly react to customer demand changes, by efficiently connecting people with production devices using IoS, whilst being able to rapidly change the production accordingly to new market needs [11].

The goal of Industry 4.0 is, thus, to improve industrial processes, as is emphasized by Kagermann et al. [9]. Such improvement may involve several methods, with the authors stressing the use of simulation to analyze the behavior of complex systems such as SCs. Simulation is even mentioned in one of the example applications provided by the authors, to analyze crisis scenarios in SCs. The authors also noted the importance of using Big Data in conjunction with such solutions, as it allows data from several data sources to be considered in the model.

Vieira et al. [12] 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.

Zhong et al. [2] outlined the current movements on the application of Big Data for Supply Chain Management

(SCM). 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. [3], 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 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. As such solution is currently being developed by the authors, several simulation experiments have been conducted with it, from which some interesting insights were obtained. As such, this paper provides them and discusses them.

3. Materials and Methods

In this section, the materials and methods used for this research are presented. In light of this, first subsection describes the SC system that was modelled in the SC simulation model that was developed in SIMIO [13], [14]. Next, second subsection describes the framework adopted in this work, while the last subsection describes the experiments that were conducted, as well as the elements that were registered for each one.

3.1. System Description

This subsection briefly describes the SC at hand, which comprises an automotive electronics manufacturer, of the Bosch Group, and its suppliers from all around the world. In this system, around 7 000 different types of materials are actively being supplied by roughly 500 different suppliers, located in more than 30 countries. Moreover, Germany, Netherlands, Switzerland, Spain, China, Taiwan and Malasya are the countries that supply more types of materials. Most of the suppliers are from Europe and Asia, with Germany (209 suppliers) and Netherlands (10 suppliers) having more suppliers and shipments 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. Fig. 1 shows the location of all suppliers (top), suppliers from Europe (bottom left) and from Portugal (bottom right).

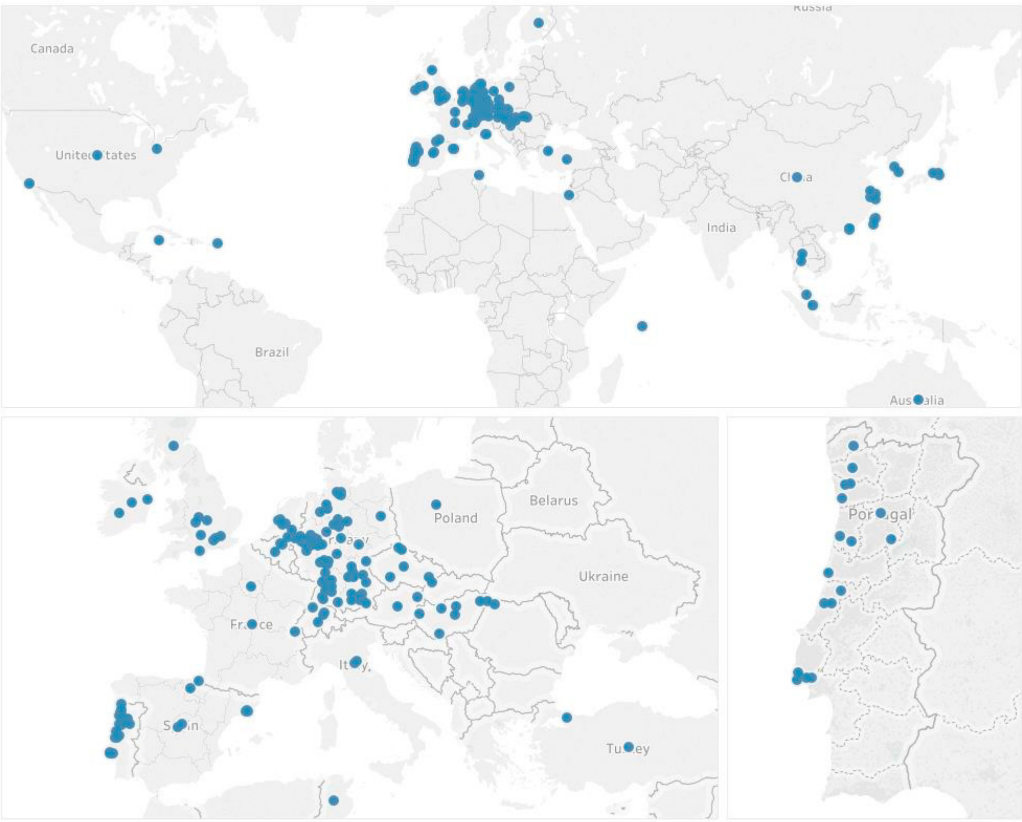

Fig. 1: Location of all suppliers: world (top), Europe (bottom left) and Portugal (bottom right).

Car manufacturers need to comply with very strict security norms for their products, while still providing high levels of product customization, required by increasingly demanding end customers [15], [16]. At the same time, an ordinary car is comprised of multiple materials supplied by single sources, exposing manufacturers to specific suppliers, thereby posing a disruption danger for the entire SC [17]. Hence, entities interoperating in these SCs need to comply between them, in order not to jeopardize the entire chain [18].

3.2. Framework

This subsection briefly describes the framework that was followed in this work. In light of this, Fig. 2 depicts the elements that comprise such framework.

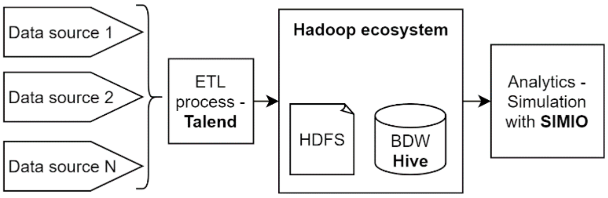

Fig. 2: Framework followed for this work.

As the figure shows, the first development step consists in developing Extract, Transform, Load (ETL) jobs which extract data from the considered sources, corrects identified data problems and loads the data to the **Hadoop** ecosystem, namely to the Hadoop Distributed File System (HDFS). The Talend software was used for this task. Thereafter, additional jobs are used to create and populate the **BDW** tables which are stored in Hive. Finally, it is possible to provide the stored data to analytics tools and, in this project, the main objective was to use simulation. Thus, for the development of this simulation model, the **SIMIO** software was used.

3.3. Conducted Experiments

To obtain the results for this research, a set of experiments were conducted using the SIMIO SC simulation model. For each experiment, several elements were registered and compared. In this regard, the following experiments were conducted:

- **Experiment 1:** Model runs considering all movements of all materials;
- **Experiment 2:** Model runs considering only the movements to productions, i.e., materials that were used to produce finished goods;
- **Experiment 3:** Model runs based on statistical distributions;
- **Experiment 4:** Model runs based on the data provided by the BDW and based on statistical distributions;
- **Experiment 5:** Model runs considering disruptions only in the manufacturing plant;
- **Experiment 6:** Model runs considering disruptions of suppliers;
- **Experiment 7:** Model runs considering variability of suppliers;
- **Experiment 8:** Model runs considering variability of customers.

Experiment 1 considered all material movements, i.e., it contains those that occurred within the plant and are particularly useful to (1) account the available materials in a dynamic plant where materials may have to go through rework, quality inspection and others; (2) and to provide information regarding the contents of the plant's warehouse. Hence, experiment 2 simplified this by one considering the materials that enter the plant and those that are sent to production, in order to produce finished goods that are required by customers, in a plant that follows a pull strategy.

In experiment 3, the model runs based on statistical distributions (that are previously determined using the data stored in the BDW), with only specific context data (of the BDW) being used, e.g., suppliers' country and suppliers for each material. In its turn, experiment 4 runs first based on the data stored in the BDW and, afterwards, based on statistical distributions during 3 additional years.

Finally, whilst experiments 1 to 4 aimed to mimic the behaviour of the real system, using the data stored in the BDW or statistical distributions, experiments 5 to 8 considered different types of disruptions or variability from either ends of the SC, i.e., suppliers or customers. Table 1 shows the simulation time and number of replications run for each conducted experiment.

For each experiment, the number of created entities, the number of simulation instructions that were executed, the total computer memory required, the elapsed time to (run, load and save) and the total volume of data that was used, both in number of rows and in gigabytes (GBs), will be collected and analyzed. Such discussion is provided in next section.

Table 1: Parameters of simulation experiments.

Experiment	Simulation time	Number of replications
1	1 year	1
2	1 year	1
3	1 year	1
4	4 years	1
5	1 year	1
6	1 year	1
7	1 year	10
8	1 year	10

Finally, the experiments were conducted on a desktop computer with 64 bits Windows Server 2016, Intel® Core™ i7-6950X CPU and 64 GB memory, using 64 bits SIMIO simulation software.

4. Results and Discussion

In this section, the results obtained for each conducted simulation experiment will be provided and discussed. In light of this, Table 2 shows the number of created entities, executed instructions and memory required that was registered for each conducted experiment.

Table 2: Number of created entities, executed instructions and memory required per experiment.

Experiment	Created Entities	Executed Instructions	Memory Required	Total Rows of Data	Volume of Data
1	~3.9 M	~ 300 M	20 GB	~ 8 M	~3 GB
2	~2 M	~ 150 M	16 GB	~ 3 M	~ 1 GB
3	~2 M	~ 150 M	0.64 GB	~ 0.013 M	~ 0.001 GB
4	~8 M	~800 M	16 GB	~ 3 M	~ 1 GB
5	~2 M	~150 M	16 GB	~ 3 M	~ 1 GB
6	~2 M	~150 M	16 GB	~ 3 M	~ 1 GB
7	~2 M	~150 M	16 GB	~ 3 M	~ 1 GB
8	~3.9 M	~150 M	16 GB	~ 3 M	~ 1 GB

M=1 000 000 entities / GB = Gigabytes

As can be seen, the experiment that was used the highest volume of data was experiment 1. A fortiori, this also culminated in the highest number of data rows and volume of data, executed instructions computer memory required to run this experiment. In its turn, it can also be seen that the volume of data that was used for experiment 2 was the same volume used for the experiments that considered disruptions and variability, i.e., experiments 5 to 8. Experiment 8 considered a high number of entities due to the increased customers' orders that were simulated in this experiment.

The volume of data that was used in these experiments certainly raises the question of whether the context considered in this project can be considered a Big Data one. In this regard, two aspects must be emphasized. First, while working on this project, which consisted in working within an organizational environment, several data issues were found. Such data issues, on one hand, consisted of data that could not be used, due to missing values, errors and other aspects. On the other hand, it also consisted of data sources that could not be obtained for several reasons, e.g., sensitive data sectorized in different Departments, culminating in the impossibility of its use. The issues with organizational data have been analyzed by previously research [19], [20]. As such, data issues have a strong impact on the volume of data managed by researches of this type, whether to increase or decrease it.

Nevertheless, the second aspect that must be emphasized is related to the Big Data concepts and technologies that were employed in the project. See [6] and [7] for further details. In fact, as Madden [21] suggested, there is no widely accepted threshold for a Big Data context. Thus, often, this value is defined as the volume that exceeds the capacity of traditional tools to process the data, which was the case with this research. Furthermore, the data issues that were observed and the volume of data that was extracted and stored in the BDW testify the importance of employing such concepts and technologies, as the data is expected to exponentially increase in volume, velocity and variety, especially when Industry 4.0 completely materializes, allowing data to be automatically extracted, transformed and loaded to storage structures, as per a Big Data context.

The values presented in Table 2 for the computer memory required of each experiment were gathered while the model was not running. Thus, the provided values are related with the fact that SIMIO, before starting a simulation run, loads the data it will need to the memory of the computer, which can increase even further during simulation run time, as Fig. 3 illustrates.

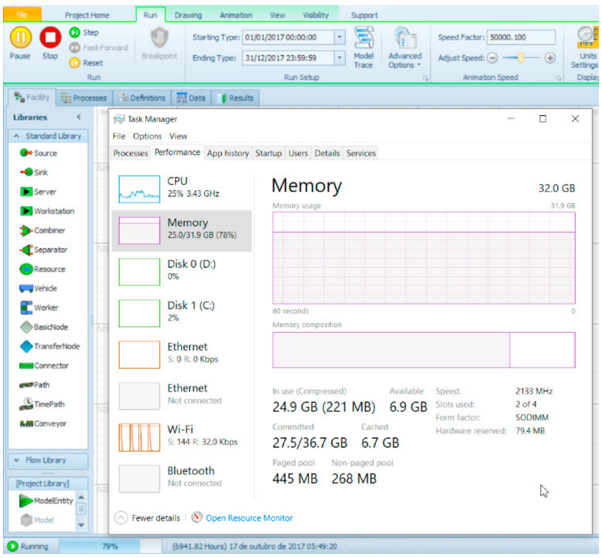

Fig. 3: Example of the simulation model during run time.

Whilst SIMIO allows data to be retrieved in runtime, which could potentially reduce the values presented in Table 2, such approach made the simulation run much slower, due to security reasons when establishing connection between the simulation model and the Big Data cluster of the organization. As such, the data is imported to the model, so that SIMIO does not need to import any data during runtime. To provide additional insights for the comparison of the conducted experiments, Table 3 shows the elapsed time to run, load and save each one.

Table 3: Elapsed time to run, load and save the models.

Experiment	Running	Loading	Saving
1	~20	~10	~2
2	~6	~10	~2
3	~180	<1	<1
4	~600	<1	<1
5	~6	~10	~2
6	~6	~10	~2
7	~10	~10	~2
8	~15	~10	~2
Units in minutes			

Table 3 shows that, when comparing the approaches of using data of the BDW and using statistical distributions, some additional conclusions can be withdrawn. The first is that the former approach requires higher computer memory. Longo and Mirabelli [22] also reported the high computational resources required to run simulations of SC systems, especially when considering transactional data. Indeed, running the model using this approach required at least 16 GB of computer memory (see Table 2). On the other hand, the latter approach (experiments 3 and 4) decreased the required memory, albeit the elapsed time to run a single simulation replication considerably increased from 6 minutes (experiment 2) to 180 minutes (experiment 3), when running 1 year based on statistical distributions. Interestingly, when both approaches were combined (experiment 4), i.e., running based on 1 year of data of the BDW, followed by 3 years based on statistical distributions, the elapsed time to run 1 replication increased to roughly 600 minutes (10 hours).

Notwithstanding, to use the distributions approach in a complex and huge-scale process such as this one, still required running the model using the data stored in the BDW, in order to make the model coherent. For instance, when an order is placed to a supplier, it is necessary to get the associated supplier's country, to place the order to that geographic location; the same applies for material's characteristics, e.g.: standard price, shelf life, safety stock.

5. Conclusions

Simulation and Big Data are two knowledge areas that can be combined to create solid DSSs to enhance decision-making process in SC systems. Such DSS is currently being developed at a manufacturer plant of the automotive electronics industry of the Bosch Group. Being pioneers in developing such artifact, the authors used this paper to provide some results of simulation experiments that were conducted, hoping to serve as a milestone for future researches in the same domain.

The experiments presented and discussed in this paper provide insights regarding the required computer memory, elapsed time to run, save and load the model, volume of data that was managed and other aspects. In fact, and regarding the volume of data used for this research, it is arguable if it can be considered a Big Data context. While the reasons for this volume were discussed in the paper, it is also interesting to note that, despite such volume, considerable computer memory and the time to run, load and save the model were required.

The simulation run in all experiments was not smooth, making the interaction with the model hard. This is something that could not be provided to the reader with the provided experiments' results and other illustrated elements and was observed despite the features of the computer that was used. All in all, while the developed tool provides considerable benefits for decision-makers in SCs, this could constitute an inhibitor for stakeholders' interest in the developed artifact.

The above discussed aspects related to the computer memory, that was required for the experiments, are directly related with the strategy of importing the data of the BDW to the simulation model. However, such strategy had to be used, as establishing connections with the Big Data cluster during run time considerably worsened the smoothness of the simulation run. Therefore, this could not be explored in this research, however, it remains one interesting strategy that could be explored by future researches in the same field, as it could considerably decrease the computer memory used by the experiments, allowing the smoothness to be increased. To do this, it needs to be ensured that the simulation model may establish communication with the Big Data cluster, without any considerably delays.

Despite the discussion that this paper provided, it must be noted that the insights and conclusions conveyed by it are directly related with the simulation tool that was used, i.e., SIMIO. Notwithstanding, a strong conviction remains that similar conclusions would be obtained with other tools.

Regarding future work directions, efforts must be made towards allowing the BDW to be refreshed in real-time, as the volume of data referred in this paper refers to a first instance of the BDW, which comprises data of a single year. To achieve this, other Big Data concepts can be applied to allow the real-time interoperability between systems that are exchanging data, e.g., between SAP and the BDW. Still related with this research, efforts can also be made towards evaluating if other simulation tools or other strategies (e.g., not importing all the data to the simulation model) will considerable change the insights and conclusions shared in this paper.

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