SIMULATION OF AN AUTOMOTIVE SUPPLY CHAIN IN SIMIO: DATA MODEL VALIDATION

António AC Vieira[a], Luís MS Dias[a], Maribel Y Santos[b], Guilherme AB Pereira[a] and José A Oliveira[a]

[a]Department of Production and Systems, ALGORITMI Research centre, University of Minho
[b]Department of Information Systems, ALGORITMI Research centre, University of Minho

[a]{antonio.vieira, lsd, gui, zan}@dps.uminho.pt
[b]maribel@dsi.uminho.pt

ABSTRACT
This paper presents a simulation model of the supply chain of a company of the automotive industry. The purpose of this paper is to use the presented model to validate the considered set of variables that we think are relevant to the problem. This approach was important as it allowed to consider a set of variables that could have been ignored if a different approach had been followed. It should be stressed that, due to privacy concerns, real data was not used, but rather random distributions assigned by the modeler. Notwithstanding, by recognizing that, for the data used, the outputs are in accordance to what happens in the real system, the authors concluded that the set of variables can be considered as validated. Yet, it is still necessary to further complement the model with additional available variables that were not included at this stage, due to its complexity, e.g., customer demand variability, uncertainty associated to suppliers' and impact of external events, such as transportation delays.

Keywords: Big Data (BD), real-time, discrete-event simulation, logistics, supply chain, industry 4.0.

1 INTRODUCTION
As defined by Levi et al. (2003), Supply Chains (SC) are complex and dynamic networks, comprised by entities, such as suppliers and customers, wherein material and information exchanges occur, driven by demand and supply interactions between these entities. Several activities take place in SC, e.g., manufacture products, transport of raw materials from supplier to manufacturers, etc. Ultimately, the goal of each entity in these networks may be seen as the ability to fulfil their customers' orders, at a minimum cost, whilst improving their competitiveness. In other words, to efficiently manage raw materials receipt and timely schedule deliveries at the right time, place and quantities.

In light of this, companies need to carefully manage their role in the SC. To ensure this, Supply Chain Management (SCM) plays a relevant role. According to Levi e al. (2003), some relevant factors to efficiently manage the role of a company in a SC include the need to deliver products according to customer's requirements and reducing total costs with inventory and transportation costs associated with the delivery of goods. On the other hand, their dynamic nature also contributes to the increasing complexity of such networks, since the relationships between involved entities and other aspects such as customer demand, supplier capacity and others may abruptly change. Furthermore, risks are inherent to SC, since uncertain events and variability may lead to SC disruptions, affecting all involved entities' performance.

Usually, uncertain events that affect the performance of a SC can be started from either the customer or the supplier end. For instance, customers' demand variability may originate situations in which production is insufficient, leading to orders unfulfillment, or overstock situations. Another example is given by products that are in end-of-series phase, because they may need to be scrapped, leading to further unnecessary costs. Lastly, unpredictable and rare external events, such as transportation delays, accidents, or even natural disasters (e.g., earthquakes, floods, etc.) may jeopardize the performance of the SC.

In fact, a proper assessment of consequences of certain events in a global SC is not easy to determine, due to the complexity associated to these networks. Thus, rather than being preemptive, involved agents are left with reactive responses, due to the lack of such tools.

These slow actions can, in their turn, lead to further negative impacts to a company and to other companies with relationships with the affected company. Such an example could be witnessed in the infamous earthquake that occurred in March 2011, which damaged the Tohoku Pacific Coastline, causing severe damage factories in that zone of the globe, also affecting other companies around the globe, including zones not affected by the earthquake (Matsuo 2015, Park et al. 2013).

It is in this context that the need to properly assess the performance of a company inserted in a SC of the automotive industry sector emerged. The purpose is to develop a real-time simulation model capable of assessing relevant metrics, while being fed with real data from a Big Data Warehouse (BDW). The goal is to use the simulator as a tool capable of extracting additional knowledge from the BDW, apart from traditional Big Data Analytics (BDA) approaches. This way, managers are capable of using these tools to properly assess the performance of their SC and even to test different scenarios, in real-time, among many other advantages, arising from the combined benefits of these two techniques: Simulation and Big Data.

In light of this, the purpose of the present paper is to document the work conducted to develop a discrete-event simulation model, representing the SC of the company at hand. The simulation model is not yet finished. Thus, this paper presents a version of the model that was developed to validate the data model necessary for this project, i.e., the variables that are more relevant to address this problem. The current version of the simulation model was developed in Simio (Vieira et al. 2014, Dias et al. 2016, Vieira et al. 2015).

In light of the exposed, next section of this paper contributes with a literature review of related past works existing in literature. Section 3 describes some of the main variables that were included in the model, as well as the mechanics associated to the problem. Thereafter, section 4 focuses on describing how this simulation model was developed in Simio. In its turn, section 5 discusses some of the results analysis that is possible to do at this phase. Lastly, the conclusions section finishes by presenting the main contributions of work conducted until this phase, while also highlighting some future work directions for the next phases of this project.

2 LITERATURE REVIEW

Assessing risks associated to SC is a recent and boiling research topic, which is dedicated to developing proactive mechanisms to mitigate risks throughout the entire SC (Ponis and Ntalla 2016). To thoroughly address this problem, companies should extract knowledge from their stored data, through BDA techniques (Hofmann 2017), which are aligned with the industry 4.0 movement. However, Kache et al. (2017) consider that, despite the advantages of BDA, it is still in its early steps, regarding its application in SC management.

In light of the above, Tiwari et al. (2018) characterized the available BDA techniques and provided a comprehensive review of BDA applications in SC contexts, between the years 2010 and 2016. Sanders (2016) examined how leading companies use BDA to extract knowledge and improve the performance of their SCs. The author also proposed a framework for the use of BDA, based on lessons learned from experience. In their turn, Zhong et al. (2016) summarized some of the most successful implementing cases of Big Data solutions, by analyzing several cases throughout the world. The authors also analyzed the possible impacts of BDA on the decision-making process in the performance of SC. Chen et al. (2015) examined how the use of BDA can contribute to the added-value in a SC. Lastly, Zhong et al. (2016) reviewed currently used BDA technologies, while also identifying some challenges, opportunities and future perspectives for BDA. More recently, Santos et al. (2017) presented a BDA architecture, under an industry 4.0 perspective, in a company of the Bosch Group. The presented architecture collects, analyzes and visualizes data related to quality complains and internal defect costs.

Despite the reviewed studies, to the best of the author's knowledge, less attention has been paid to BDA techniques focused in logistics problems related to the automotive industry. A fortiori, there is also a lack of proposed BDW with the same scope and of simulation models that use data provided by these systems to properly assess the performance of a SC. In fact, from the examples found in literature, few are oriented towards SC management and no solution oriented towards SC problems of the automotive industry was found. This idea is also corroborated by Ivanov (2017). In fact, even discrete-event simulation models of SC problems are rarely approached, as suggested by Kagermann et al. (2013), which identity this as one of the most important fields requiring the use of simulation approaches, allowing companies to comply with the industry 4.0 agenda. According to the authors, due to the high levels of uncertainty and variability of SC, simulation is one of the most effective technique to address these problems.

3 SIMULATION MODEL

The first subsection of this section focuses on describing the main relevant variables associated to the problem in analysis. In its turn, the last subsection focuses on explaining how the described system was modelled in Simio.

3.1 Relevant Variables

Car manufacturers must comply with very strict security norms for their products, while still providing high levels of product customization, required by their customers (Simchi-Levi et al. 2015, Masoud and Mason 2016). On the other hand, a single car is comprised by roughly 5 000 parts, thus factories coexisting in these SC need to cooperate, in order not to jeopardize the entire chain (Kırılmaz and Erol 2017). Due to this, companies in these SC tend to apply Just in Time philosophies which consist in scheduling the materials' arrival to when they will be required and avoiding as much as possible stocking them, otherwise the costs with stock would be unbearable. Thus, safety stock, or safety time is used, which consists in buffers of materials to be used in production.

Typically, one of the main characteristics of automotive SCs is that materials are supplied by a single supplier, exposing manufacturers to the possibility of materials' disruption (Thun and Hoenig 2011). Furthermore, most first-tier suppliers purchase the same materials from the same suppliers. Because of this, when these non-first-tier suppliers fail to fulfill orders, several other plants are affected. This problem is prolonged in time, since usually suppliers take too much time to recover from these failures (Matsuo 2015).

To efficiently manage the entire SC, companies must cooperate. One of the ways of doing this is by forecasting sales and sharing information between them. This allows companies to schedule long-term orders.

When customers' orders arrive, the bill of materials explodes the needs associated to the required finished goods and the respective orders are sent to the suppliers of these materials. In their turn, suppliers must repeat these steps, in order to collect their raw materials from their suppliers. Depending on the situation, when the final customer changes its orders, it may be possible for companies to contact their suppliers and change their orders. It should also be noted that the quantity to be shipped from a supplier to the plant must be negotiated and, in some cases, there are constrains, e.g. minimum order quantity. Along with the quantity of the required material, a delivery time may also be associated, indicating when the material needs to arrive to the plant, in order not to arrive too late, neither too soon, which could cause additional unnecessary stock costs.

When materials are ready to be sent, a regular transporter is assigned. Yet, if by some reason, the regular transport cannot deliver the materials in the scheduled time, a special transport, or freight, must be assigned. Yet, these special freights have considerable costs. When materials arrive to the plant, they are stocked for a brief period of time, since everything was planned so that their production could start after their arrival.

To give a small perspective on the scale of values in analysis, on the company in question, just in 2017, more than 5 000 different raw materials were supplied by 400 different suppliers, spread across the globe. Most of these suppliers are located in Asia, thus, many times, the sea transport is used, which considerably increases the transport duration. Their activity resulted in more than 200 000 material receipts, comprised by different materials and quantities.

The description of the problem at hand, provided in this subsection, contributed with an overall overview and also with some variables that must be considered by the simulation model. The next subsection describes how this model was developed.

3.2 Modeling

The main steps conducted to develop the current simulation model is here addressed. The model was developed in Simio, a recent object-oriented tool. The first step consisted in developing the main object of the model, which is the factory of the company in question. The Simio standard objects used to achieve this can be seen in Figure 1.

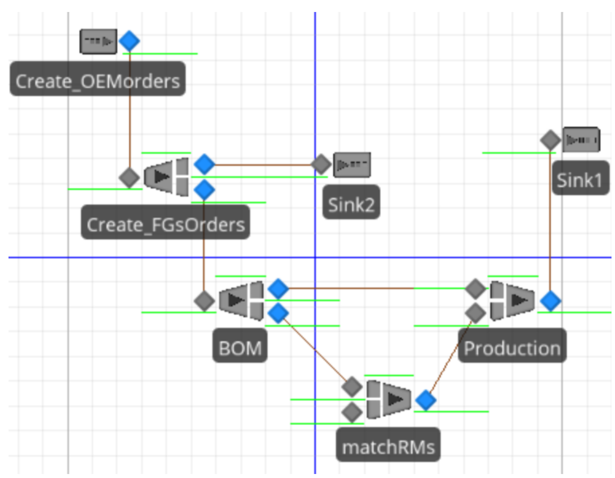

Figure 1: Simio standard objects used to model the behavior of the system.

The flow of entities in this simulation model starts at the "Create_OEMorders", which is responsible for creating customers' orders, which can be comprised of several finished goods. Because of this, the next object creates a new entity for each finished good ordered, representing this information. Thereafter, for each finished good order, it is necessary to explode its BOM (Bill Of Materials), in order to create orders for the respective raw materials. For each exploded raw material, a new entity is created which is sent to the "matchRMs", in order to wait for the arrival of the ordered material. At the same time, an additional entity is created, which represents the raw materials. These are transferred to the suppliers' location and are kept there until the correct time to send the orders arrives. It should be noted that this transfer of material between the suppliers and the plant is modeled as Free Space, which is a Simio feature which allows users to model entity flows without the need to use any type of connector between different objects (see Figure 4). When the raw materials are ready to be sent to the plant, they can either be sent via normal transport, or via special freight, in case it is determined that the material will not arrive in time to initiate production at the scheduled time, therefore jeopardizing the fulfillment of a customer's order. Lastly, the materials arrive at the plant via the "matchRMs" (see Figure 1). When they enter this object they execute a process, as is illustrated in Figure 2. The process is depicted in Figure 3.

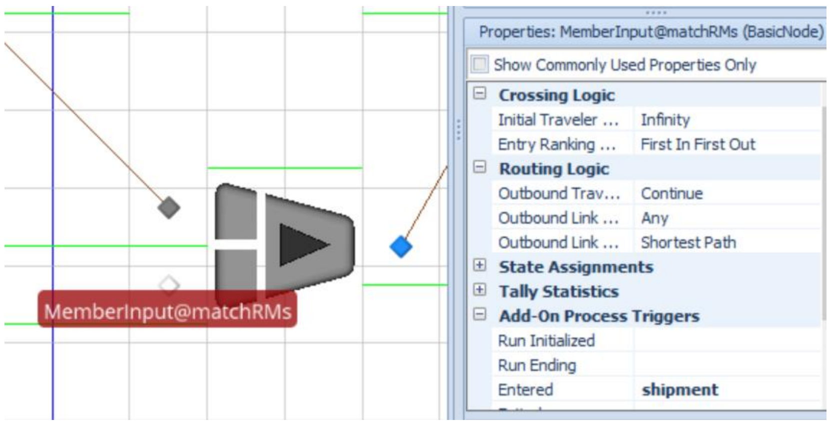

Figure 2: Properties of one of the standard Simio objects used in the simulation model.

It should be stressed that this is just an example of a process used in this model. Simio allows users to create several processes and execute them at any physical location of the model, as shown in Figure 2. This gives the user increasing model flexibility since it allows to mix different simulation modelling approaches, objects and processes, in this case.

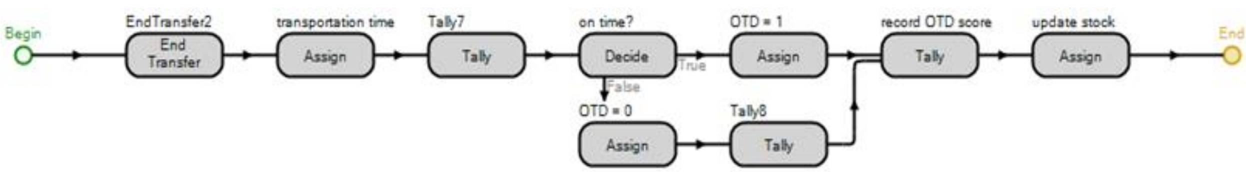

Figure 3: Process used to model the arrival of raw materials to the plant.

The process represented in the above figure starts by communicating to another process in execution that the entity executing this process has been transferred from Free Space to the input node of the "matchRMs" object (see Figure 2). Thereafter, the process saves the transportation time of this order and assesses if the part arrived according with the planned schedule, or if it was a delay. Lastly, the process finishes by updating the stock levels with this arrival.

After the arrival of the materials, these are matched with the entities that represent these orders and they are afterwards stored until the time for them to initiate the production arrives. At this point, the entities can proceed to the "Production" object, in order to produce the corresponding finished good and deliver it to the customers.

Figure 4 shows a 3D view of the model in execution. In the figure, it is possible to see, at the center, an object which represents the plant in question. The yellow triangles spread across the model represent orders that were already sent to the corresponding suppliers' location, but that were still not sent to the plant, since they are still in production. On the other hand, several small truck objects can be seen throughout the model, which represent orders that have already been shipped to the plant. Furthermore, these represent normal transports. In its turn, in the figure, special freights are represented with the symbol of an airplane. In the figure, it is possible to see two special freights arriving to the plant.

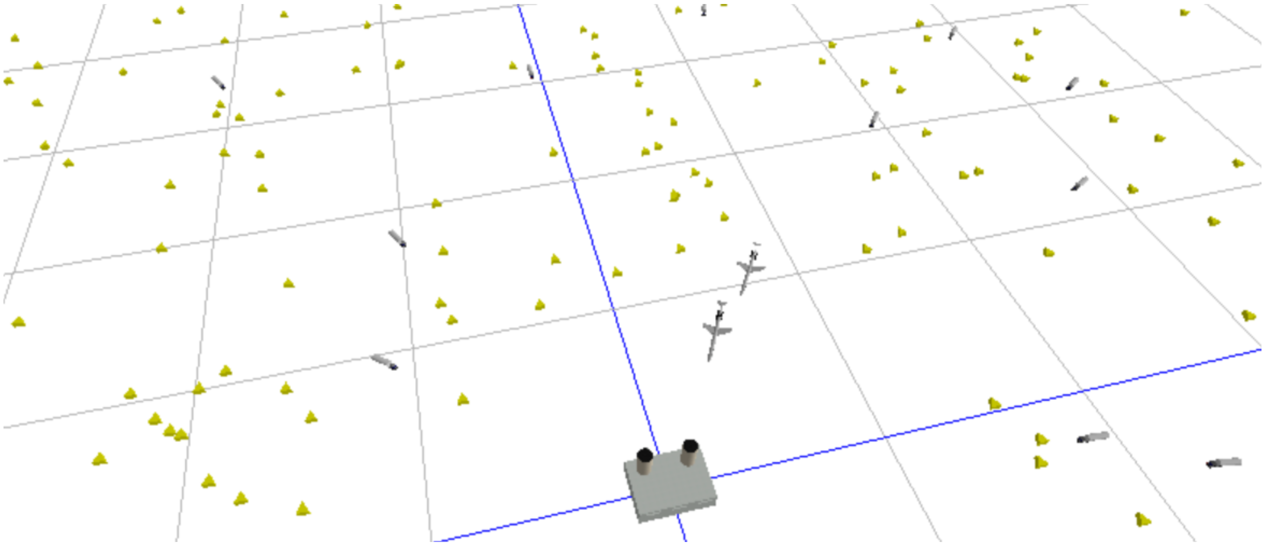

Figure 4: 3D view of the simulation model while running.

4 PRELIMINARY RESULTS

This section presents some preliminary results analysis that is already possible to perform with the developed simulation model. Whilst the model is not completely finished, while developing such model, it was possible to identify the need for certain variables, which is important, especially when tackling such complex problems, such as the dynamics of an automotive SC. Therefore, this approach allowed validating the data model used until this phase by conducting simulation experiments and assessing their adequacy to the problem at hand.

The first thing that should be noted is that the results presented in this section are not real, since, for security reasons, it was not possible to show the obtained results. Thus, the authors assigned random distribution values for the considered variables. Therefore, the purpose of this section is not to analyze the specific obtained results, but rather to analyze if the results make sense for the tested scenarios and thus validate the applied data model.

Several performance indicators and properties were implemented in the simulation model in order to assess the impact of the later on the former by running different simulation experiments. In this sense, the following Key Performance Indicators (KPI) were considered:

- Stock levels
- Percentage of suppliers' on-time deliveries
- Percentage of special freights
- Percentage of delayed orders

Furthermore, 4 different scenarios were tested. The results obtained for these 4 scenarios are presented in

Table 1. For these scenarios, 6 months of simulation time was used, with 15 days of warm-up period and 5 replications.

Table 1: Simulation results obtained for the 4 considered scenarios.

	Stock	On-time deliveries	Freights	Delayed deliveries
Scenario 1	85%	97%	0%	0%
Scenario 2	92%	98%	0%	0%
Scenario 3	85%	100%	52%	0%
Scenario 4	88%	100%	58%	0,2%

In the first 2 scenarios, special freights were not considered, as the corresponding KPI indicates (0% of transports were special freights). This resulted in a percentage of suppliers' on-time deliveries of 97%. The 3% of orders that did not arrive on the scheduled date can be explained by the variability on the supplier side of the SC, e.g., a transportation delay occurred, or some disruption on the second-tier suppliers. On this light and to further increase the percentage of on-time deliveries, in scenario 2 suppliers send their orders up to 3 days before the scheduled date. Yet, as the results indicate, the percentage of on-time deliveries only increased 1%, whilst the stock levels increased 7%, from 85% to 92%, thus, the solution seems to be to include special freights, which is considered by scenarios 3 and 4.

In Scenario 3 orders are sent on the scheduled date and special freights are considered. As the results indicate, the simulated plant achieved a percentage of on-time deliveries of 100%, whilst maintaining the stock levels in 85%. This indicates that the simulation model mimics the real systems, since in this type of SC, managers must carefully ponder between storage costs and costs with special freights. In scenario 4 the number of customers' orders was increased, in order to assess its impact on the established KPI. By analyzing the results of this scenario, it is possible to see that the stock levels increased as expected, as well as the percentage of special freights. Apart from these, some delayed orders were registered (0.2%), as result of increasing the customers' orders intensity.

5 CONCLUSIONS

The efficiently managing of complex Supply Chain (SC) networks is a very complex task. Modelling such systems with simulation can be very useful in order to test different scenarios, quantify different performance measures, thus contributing to a more preemptive approach, rather than a reactive one. In fact, addressing SC problems is one of the purposes of the industry 4.0 movement. Moreover, also aligned with this new movement, Big Data Analytics (BDA) allows managers to extract knowledge from their stored Big Data (BD) sets. It is in the light of this that this project is being conducted in a company of the automotive industry. The work consists in developing a discrete-event simulation model supported by a Big Data Warehouse (BDW) system that stores the available data, oriented towards specific logistic problems. Thereafter, the BDW can support the developed simulation model with data, which, in its turn, is able to provide extra knowledge, aiding in the decision-making process.

In this regard, this paper presented a version of the developed simulation model, which was developed in Simio. For privacy reasons, it was not possible to show real data from the case study company. Rather, random distributions values assigned by the modeler were used, in order to validate the variables used in this model. As the results presented in section 4 suggest, the response of the output results, for the tested scenarios, are in accordance with what is expected and with what happens in the real system in analysis. Due to this, the authors concluded that the set of variables used in this model is validated. It should be noted that the authors were not interested in the concrete values, but rather, in the response of outputs to the different tested scenarios. This approach was important because it allowed to consider variables that otherwise could not have been included, or forgotten. The obtained results indicate that, despite still being incomplete, it was possible to model the most important processes associated to the problem at hand with the considered variables.

For the next development steps regarding the development of the simulation model, it is important to include other variables that were identified but not yet implemented, such as: production capacities; customer demand variability; suppliers' constraints, such as minimum and maximum order quantity; impact of external events, for instance, transportation delays or natural disasters; costs associated with production line stoppages; costs with overstock; materials' shelf life; consider different storage units; consider measures and volume occupation on the warehouse; customers' orders forecast; consider customer order change and, based on this possibility, react by changing orders with suppliers, if possible, in order not to incur in unnecessary order costs; and consider secondary suppliers for a given material, despite these being rarely used in these type of SC.

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REFERENCES

Chen, D. Q., Preston, D. S. & Swink, M. 2015. How the use of big data analytics affects value creation in supply chain management. Journal of Management Information Systems, 32, 4-39.

Dias, L. M. S., Vieira, A. A. C., Pereira, G. A. B. & Oliveira, J. A. 2016. Discrete Simulation Software Ranking – a Top list of the Worldwide most Popular and Used Tools. Proceedings of the 2016 Winter Simulation Conference.

Hofmann, E. 2017. Big data and supply chain decisions: the impact of volume, variety and velocity properties on the bullwhip effect. International Journal of Production Research, 55, 5108-5126.

Ivanov, D. 2017. Simulation-based single vs. dual sourcing analysis in the supply chain with consideration of capacity disruptions, big data and

demand patterns. International Journal of Integrated Supply Management, 11, 24-43.
Kache, F. & Seuring, S. 2017. Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. International Journal of Operations & Production Management, 37, 10-36.
Kagermann, H., Helbig, J., Hellinger, A. & Wahlster, W. 2013. Recommendations for implementing the strategic initiative INDUSTRIE 4.0: securing the future of German manufacturing industry; final report of the Industrie 4.0 working group, Forschungsunion.
Kirilmaz, O. & Erol, S. 2017. A Proactive approach to supply chain risk management: Shifting orders among suppliers to mitigate the supply side risks. Journal of Purchasing and Supply Management, 23, 54-65.
Levi, D. S., Kaminsky, P. & Levi, E. S. 2003. Designing and managing the supply chain: Concepts, strategies, and case studies, McGraw-Hill.
Masoud, S. A. & Mason, S. J. 2016. Integrated cost optimization in a two-stage, automotive supply chain. Computers & Operations Research, 67, 1-11.
Matsuo, H. 2015. Implications of the Tohoku earthquake for Toyota׳ s coordination mechanism: Supply chain disruption of automotive semiconductors. International Journal of Production Economics, 161, 217-227.
Park, Y., Hong, P. & Roh, J. J. 2013. Supply chain lessons from the catastrophic natural disaster in Japan. Business Horizons, 56, 75-85.
Ponis, S. T. & Ntalla, A. C. 2016. Supply chain risk management frameworks and models: a review. International Journal of Supply Chain Management, 5, 1-11.
Sanders, N. R. 2016. How to use big data to drive your supply chain. California Management Review, 58, 26-48.
Santos, M. Y., E Sá, J. O., Andrade, C., Lima, F. V., Costa, E., Costa, C., Martinho, B. & Galvão, J. 2017. A Big Data system supporting Bosch Braga Industry 4.0 strategy. International Journal of Information Management, 37, 750-760.
Simchi-Levi, D., Schmidt, W., Wei, Y., Zhang, P. Y., Combs, K., Ge, Y., Gusikhin, O., Sanders, M. & Zhang, D. 2015. Identifying risks and mitigating disruptions in the automotive supply chain. Interfaces, 45, 375-390.
Thun, J.-H. & Hoenig, D. 2011. An empirical analysis of supply chain risk management in the German automotive industry. International journal of production economics, 131, 242-249.
Tiwari, S., Wee, H. & Daryanto, Y. 2018. Big data analytics in supply chain management between 2010 and 2016: Insights to industries. Computers & Industrial Engineering, 115, 319-330.
Vieira, A., Dias, L., Pereira, G. & Oliveira, J. 2014. Comparison of Simio and Arena simulation tools. ISC. University of Skovde, Skovde, Sweden.
Vieira, A., Dias, L. S., Pereira, G. A. B., Oliveira, J. A., Carvalho, M. S. & P., M. 2015. Using Simio to Automatically Create 3D Warehouses and Compare Different Storage Strategies. Faculty of Mechanical Engineering Transactions, 43, 335-343.
Zhong, R. Y., Newman, S. T., Huang, G. Q. & Lan, S. 2016. Big Data for supply chain management in the service and manufacturing sectors: Challenges, opportunities, and future perspectives. Computers & Industrial Engineering, 101, 572-591.

AUTHOR BIOGRAPHIES

ANTÓNIO A C VIEIRA was born in 1989 in Vila Nova de Famalicão, Portugal. He graduated in Informatics Engineering in the University of Minho. He holds a MSc degree in Systems Engineering at the University of Minho. He is making his doctoral studies in Advanced Engineering Systems for Industry at the University of Minho, in partnership with Bosch Car Multimedia Braga. His main research interests are Modelling and Simulation, Programming Languages and Big Data Analysis. He is Invited Assistant Professor at the University of Minho. His email address is antonio.vieira@dps.uminho.pt.

LUÍS M S DIAS was born in 1970 in Vila Nova de Foz Côa, Portugal. He graduated in Computer Science and Systems Engineering in the University of Minho, Portugal. He holds an MSc degree in Informatics Engineering and a PhD degree in Production and Systems Engineering from the University of Minho, Portugal. His main research interests are Simulation, Systems Performance, Operational Research and Systems Visual Modeling. He is Auxiliar Professor at the University of Minho. His email address is lsd@dps.uminho.pt.

MARIBEL Y SANTOS
Maribel Yasmina Santos is an Associate Professor at the Department of Information Systems and Researcher of the ALGORITMI Research Centre, University of Minho (UMinho), in Portugal. She received the Aggregated title (Habilitation) in Information Systems and Technologies (IST) from UMinho in 2012 and a PhD in Information Systems and Technologies from UMinho in 2001. She was Secretary-General of the Association of Geographic Information Laboratories for Europe (AGILE) from May 2013 to June 2015. Her research interests include Business Intelligence and Analytics, Big Data and (Big) Data Warehousing.

GUILHERME A B PEREIRA was born in 1961 in Porto, Portugal. He graduated in Industrial Engineering and Management in the University of Minho, Portugal. He holds an MSc degree in Operational Research and a PhD degree in Manufacturing and Mechanical Engineering from the University of Birmingham, UK. His main research interests are Operational Research and Simulation. Currently he is Pro-Rector of the University of Minho. He is Associate Professor at the University of Minho. His email address is gui@dps.uminho.pt.

JOSÉ A OLIVEIRA was born 1966 in Matosinhos, Portugal. He studied Mechanical Engineering at the University of Porto, Portugal. He graduated with a Ph.D. in Production and Systems Engineering at University of Minho, Portugal. His main research interests are Optimization with Heuristic Methods in Systems Engineering. He is Auxiliar Professor at the University of Minho. His email address is zan@dps.uminho.pt.