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A METHOD PROPOSAL FOR CONDUCTING SIMULATION PROJECTS IN INDUSTRY 4.0: A CYBER-PHYSICAL SYSTEM IN AN AERONAUTICAL INDUSTRY

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ABSTRACT

In Industry 4.0, computer simulation has been changing its application. Simulation models focused on specific analysis give space to models with automation degree and they are integrated with different systems. This integration favors the constant model updating based on variations in the real system, enabling faster decision making. In this way, simulation models are part of cyber-physical systems since they represent a virtual version of the real process. In this context, the present work proposed a method adapted from Montevechi et al. (2010) to carry out simulation projects according to Industry 4.0 principles. Finally, the proposed method was applied in a supply material process in an aeronautical industry, validating it and showing how the simulation works in the Industry 4.0.

1 INTRODUCTION

It is necessary to go beyond the computer model building to achieve an efficient simulation project (Sturrock 2014). A structured method is essential for its development and success (Law 2009). The methods present steps and sequences that guide the modeler to develop a good project, establishing logical flows (Montevechi et al. 2015). The literature presents several methods for the simulation project. However, they differ in some stages and detail levels.

In this sense, Montevechi et al. (2015) analyzed the main simulation books and papers published in the Winter Simulation Conference (WSC), gathering the methods that detail and explain the steps to follow in a Discrete Event Simulation (DES) project. In their study, the authors show that the methods proposed by Montevechi et al. (2010) and Balci (2012) are the most detailed and have more activities. In addition, the method of Montevechi et al. (2010) is the only one that divides the simulation into three major phases: Conception, Implementation, and Analysis.

In summary, the first phase, called “Conception”, comprises the stages of problem formulation, conceptual model building, conceptual model validation and documentation, and input data modeling. In the problem formulation, the process must be well defined, and the actions must be specified (Balci 2012). The second step is the conceptual model building: an abstraction using a process mapping technique, regardless of the computer software (Balci 2012, Montevechi et al. 2010, Brooks and Robinson 2001). Next, the conceptual model validation consists of determining that the premises of the conceptual model are consistent with the premises of the real system, giving support to the simulation model (Sargent 2013). After, documentation must be performed. Montevechi et al. (2010) state that many techniques can be used in the documentation step; however, opting for one focused on simulation is ideal. The last stage is the input data modeling. Time, cost, percentage, capacities, etc., are input data. They may vary according to the project goal (Banks et al. 2010, Montevechi et al. 2010).

The second major phase is called "Implementation" and covers: computer model building, computer model verification, and computer model validation. The computer model building must be carried out in a familiar software for the modeler. Afterward, it is necessary to verify the computer model, ensuring that its programming corresponds to the conceptual model (Sargent 2013). The last stage of this phase is the computer model validation. Validation can be performed through hypothesis tests, confidence intervals, data comparison charts, etc. These methods are performed with the output data from the real system and the simulated system (Sargent 2013). If the model is non-observable, Sargent (2013) suggests techniques such as animation, comparison with other models, face-to-face validation, and internal validation.

The last phase is called "Analysis". This phase comprises experiment planning and analysis, data analysis, and conclusions. In the experiment planning and analysis, possible scenarios are elaborated. Design of Experiments (DoE) and statistical tests may be used (Montgomery 2012). In the next step, the results of the scenarios are analyzed, obtaining conclusions, and answering the problem defined in the first stage.

Despite being a reliable and efficient method in simulation models, it refers to traditional simulation projects, which aim at specific analyzes and improvements in a system. With the Industry 4.0 evolution, it is noted that the simulation projects have been changing. In this sense, the use of the tool has also been transforming, and methods that enable simulation applications are missing. According to Uriarte et al. (2018), in the Industry 4.0, simulation models tend to be integrated with information and management systems, adaptive into the real process and capable of assisting in decision making. Therefore, simulation models are part of cyber-physical systems since they represent a virtual version of the real process.

Based on the simulation in the modern industry, the paper aims to explore the tool as part of a cyber-physical system to support decision making. Thereby, we adapted the method conducted by Montevechi et al. (2010). We proposed new steps, aiming to adapt it for simulation in cyber-physical environments. As a result, the article proposes a framework for performing simulation projects, integrating DES with systems and data from the real process, and support decision making constantly. Finally, to validate the changes in the method, we used it to build a simulation model in a real process. The object of the study is a supply material process in an aeronautical industry. The plant has a large built area (around 107000 ft^2), allowing the operator of supply materials to choose one of the numerous possible routes to replenish the stocks. The scenario suggests unnecessary movements and transports and, therefore, the simulation aims to optimize decision making regarding the most efficient route in the real process, turning into a cyber-physical system. The rest of the paper is as follows: section 2 gives the background on this work (simulation, industry 4.0, and cyber-physics system). The proposed method is described in section 3. Section 4 is dedicated to the method application and discussions. Section 6 concerns the conclusion and future work.

2 LITERATURE REVIEW

2.1 Simulation

Banks (1998) defines simulation as the process of imitating real systems, creating inferences about its characteristics. According to the author, the tool can describe and analyze the behavior of systems and answer questions about them. Law and Kelton (2000) already considered, in the early 2000s, that simulation can provide decision-makers with a broad view of the real system. Also, the authors affirm that simulation can forecast the results before making changes in the real environment. Moreover, since new manufacturing systems have been developing, simulation allows the analysis of different data and variables that are impossible or impracticable for the human mind (Barlas and Heavey 2016).

Simulation has been consolidated in many sectors in the last decades, contributing to cost reduction, product development, an increase in the product, and service quality. However, in recent years, simulation has been used in projects with a defined scope of activity and time. This fact must change in the modern industry. In this sense, traditional modeling and simulation must change to support intelligent manufacturing. Industry 4.0 requires the manufacturing system modeling and other systems through the concept of virtual industry and artificial intelligence to control the process, which includes autonomous operating systems adjustment (self-organization) (Rodič 2017).

Negahban and Smith (2014) state that the systems and industry evolution demands more attention to the simulation integrated with higher levels of management systems. Integration increases the engagement of interested parties regarding the use of the tool. Despite the view that simulation will become an even more important tool, being a key technology in the Industry of the future (Uriarte et al. 2018), Skoogh et al. (2012) point out that many companies have failed to take advantage of its benefits. Therefore, simulation has to change. In Industry 4.0, it requires participation between researchers and industry, enabling using different technologies, tools, and concepts (Rodič 2017).

2.2 Industry 4.0 and Cyber-physical Systems

The term Industry 4.0 was proposed by the German government in 2011 and represents the evolution of industry for the fourth industrial revolution (Rodič 2017). Rüttimann and Stöckli (2016) report that the first three industrial revolutions refer to scientific and innovative events. The first was marked by the steam engine, while the second by the use of electricity as a basis for the production lines. The third revolution is associated with computer systems and information technologies. However, the fourth industrial revolution represents a revolution in how companies will recognize and deal with technological challenges. In addition, Industry 4.0 intends to integrate and virtualize industrial systems, aiming at completely automated, integrated, and connected production (Rüttimann and Stöckli 2016, Uriarte et al. 2018). According to Rodič (2017), in the organizational scope, integration includes all business divisions and the value-added chain inserted in digitalization.

The three relevant characteristics of Industry 4.0 are the ability to deal with complex systems, capacity for innovation, and flexibility. The term “Virtualization” becomes one of the main concepts in Industry 4.0 and refers to a virtual copy of the physical system, turning into a cyber-physical system (Uriarte et al. 2018).

Cyber-physical systems are mechanisms where the physical and virtual environments are closely connected, and both interact to share and exchange information. The processes are connected and enable communication through data inputs and outputs. The interaction between the physical environment and a digital model response takes place through algorithms and computer processing. Moreover, the cyber-physical system may monitor the real system and assist in decision making in cooperation with humans, machines, and sensors (Zhong et al. 2017).

For Industry 4.0, simulation plays an essential role in the real processes virtualization (Rodič 2017). There is no doubt that industries considered intelligent will be highly automated. However, intelligent manufacturing is not related to the degree of shop floor automation, but rather to its autonomy, evolution, simulation, and optimization. The industry's "intelligence" level will be determined by the virtualization degree of the physical space (Kusiak 2018).

2.3 Simulation as part of a cyber-physical system

Nowadays, simulation projects present an increasing trend involving several integrated areas for decision making. In contrast, in the past, simulation was used in precise analyzes with limited scope and periods. Moreover, specific and complex models need to be replaced by controlled and user-friendly interfaces and integrated with several operating systems (Rodič 2017). Therefore, it is noted that simulation models start to act as virtual copies of real systems. Thereby, simulation is a crucial tool in Industry 4.0, facilitating the evolution of solutions and improvements in a complex and dynamic environment (Uriarte et al. 2018).

Kritzinger et al. (2018) state that the fourth industrial revolution brought a fast environment where simulation has become an indispensable methodology. The tool acts preventively by answering questions with unlimited scenarios, anticipating solutions, and analyzing the system behavior through questions arising in the modeling. For Turner et al. (2016), the real innovation related to intelligent manufacturing is the constant collection and analysis of data from the real system for decision making through scenarios evaluated by simulation.

3 PROPOSED METHOD

As mentioned in the Introduction, Montevechi et al. (2010) presented a method to carry out DES projects. However, we proposed some changes in the method to adapt it to Industry 4.0. In this context, Uriarte et al. (2018) point out that simulation is not only a tool for specific and isolated analyzes, but it is to connect and integrate with several data and sources to support decision making. Furthermore, simulation models that require a simulation expert tend to be replaced by user-friendly models (Rodič 2017). Finally, Uriarte et al. (2018) highlight some characteristics that the simulation models should present in the modern industry: (i) Connection and integration of the simulation model with information and management systems, (ii) Model adaptation in near or real-time according to changes in the physical system, (iii) Connection with analysis and optimization tools, (iv) Assistance in decision making. Figure 1 presents the proposed method, aiming at conducting simulation projects in Industry 4.0. The steps that have been modified and/or added will be explained in the next sections.

3.1 Conception

This phase is a conceptual stage, nothing was changed in these steps.

3.2 Implementation

Regarding the second phase, we created two steps that assist in the integration of the simulation model and the real system: *Model Update Data and Desired Responses Definition* and *Interface Structuring with the Real Process*. Therefore, communication between the physical and digital systems takes place through the process data.

3.2.1 Model Update Data and Desired Responses Definition

This step aims to integrate the simulation model and the real system. The model is modified over time based on changes in the real process. These changes allow the simulation to be used as a continuous decision-making tool. However, before establishing communication between both parties, two main issues must be defined: *what information does the computer model need to be a virtual copy?* and *what information does the real process need after running the simulation?*

The cyber-physical system replicates the real process using a simulation model. It is connected to the physical world and it behaviors according to changes in the real systems, accessing and processing data automatically (Xu and Li 2018). The connected systems enable communication through data inputs and outputs, which allow interaction between the physical environment and virtual response using algorithms and computer processing (Zhong et al. 2017). However, if the data are not available for the update, the modeler should use tools to replace them, such as forecast and/or historical data.

3.2.2 Interface Structuring with the Real Process

The interface that makes a connection between the real process and the virtual world (simulation model) was structured after defining the necessary inputs and outputs. It may be implemented in different ways, depending on the simulation software and the real system connection. Skoogh et al. (2012) point out that simulation software has been including communication tools that are integrated with external sources, reducing intermediate systems usage. However, direct connections may be difficult due to data processing before updating them in the simulation model. This difficulty contributes to the use of intermediate systems and interfaces (Barlas and Heavey 2016). Sometimes, it is necessary to use intermediate interfaces because there is a wide variety of data sources, and they must be filtered and analyzed beforehand (Skoogh et al. 2012). The interface should be building considering the data fitting.

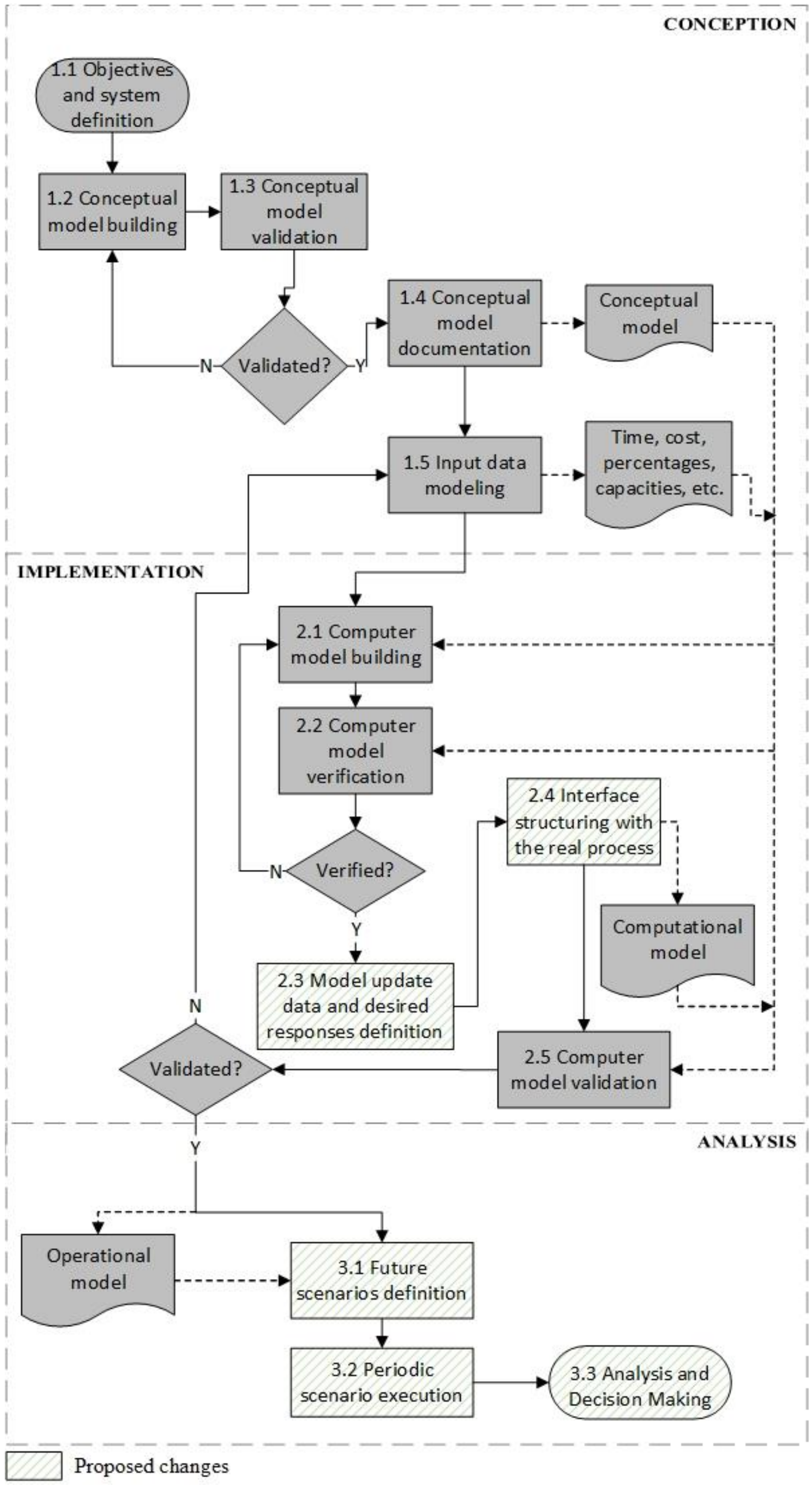

Figure 1: Modeling and Simulation method in Industry 4.0. (Adapted from Montevechi et al. (2010).)

3.3 Analysis

Some changes were made in this stage. We created three new steps, replacing the proposals by Montevechi et al. (2010): *Future scenarios definition, Periodic scenario executions,* and *Analysis and decision making*.

3.3.1 Future Scenarios Definition

The scenarios to be tested must be defined. Barlas and Heavey (2016) point out that the development and evolution of real systems require evaluations and analyses of different data and variables. In this way, the scenarios simulation can analyze different variables from the perspective of predefined responses, aiming at better decisions of the real system. There are several ways to build scenarios. The modeler may use the trial and error method ("best guess") where the experimenter tests random changes in the model. A second way is to use DoE, where the variables are tested together, showing their influence on the responses. It is still possible to use optimization via simulation software. In this case, the modeler must define the test variables, objective function, constraints, and response variables (Montgomery 2012).

3.3.2 Periodic Scenario Executions

In Industry 4.0, periodic model execution becomes essential. Tao et al. (2018) state that the virtual environment must be integrated and synchronized with the physical system. Therefore, the simulation model must be executed in a predetermined time-periods to represent the real process. The model may adapt if there are any variations in the physical system, aiming to predict and optimize decisions (Rodič, 2017). The model adaptation should be done through parameter updating, such as batch size, process time, and number of workers in the workstations. Regarding the interval time between model executions, the modeler must choose a break time which does not harm the decision-making. Consequently, it is necessary to consider the process characteristics to define the time between model updates. For example, if the production is planned every day, the decision-maker should update the model every day; if the production is planned every week, the model should be updated once a week.

3.3.3 Analysis and Decision Making

The analysis and decision making must be carried out at the end of each simulation round and on time. Thus, changes in the real system can be made. Therefore, when starting a new cycle in the real system, decision-makers know how the process will behave in the next minutes, hours, or days (depends on the horizon defined in step 3.3.2).

4 METHOD APPLICATION

This section aims to apply the proposed method in a real process to verify its validity. Thereby, all the steps involved in Figure 1 will be described and presented.

4.1 Object of the Study

The process is a supply of parts from an aeronautical industry in Brazil. The process consists of four production lines located at different points, and each one has independent demands. Each line has an intermediate stock (Kanban station) which must be replenished periodically. For the replenishment, the operator chooses the Kanban station sequence to supply (route). However, the choice is related to the employee's experience, and we do not guarantee that it is the most efficient. Through simulation as a continuous decision tool, the goal is to reduce waste related to the movement and transport of materials, making a lean process. Since it is a manual process, there are connections between the virtual model and the real system through the Enterprise Resource Planning (ERP) data.

4.2 Conception Phase

4.2.1 Objectives and System Definition

The project aims to evaluate the best route for replenishing materials through simulation as a daily tool to aid decision making, acting as part of a cyber-physical system. Thus, we built a DES model and an interface between the simulation model and the real process, making the virtual model a reflection of the real system. Therefore, decision making is possible based on the model results, interfering in the real process again.

4.2.2 Conceptual Model Building

Chwif and Medina (2015) state that, based on an abstraction of the real process, the modeler should use an appropriate technique for representing simulation models. The conceptual model presents the sequence of activities, the responsible staff, and rules in the logic. For conceptual modeling, we used the IDEF-SIM technique (Montevechi et al. 2010), which uses logical elements present in other techniques, adapting them for the simulation. Pereira et al. (2015) say that the symbols used in IDEF-SIM are a direct translation of the conceptual model for programming in simulation software. The technique features components such as entities, locations, resources, functions, controls, logical rules, and transports.

The process is divided into two stages: (1) Receiving and storage and (2) Supplying Kanban. The first part includes the material arrivals at the factory until the allocation in the main inventory. The second part shows the material ordering until the replenishment. The replenishment of the Kanban stations is the main study question since all the analyses will be done based on this stage. Figure 2 presents the conceptual model of the process.

4.2.3 Conceptual Model Validation

According to Sargent (2013), the conceptual model validation ensures that the theories and inferences of the model are correct. The author suggests using face-to-face, structured walkthrough, and trace techniques. The conceptual model was tested with two of them. First, we use validation through the structured walkthrough technique: the model was presented to two researchers who know the modeling process. After some evaluations and changes proposed by the evaluators, the model was validated, and the final version was reached. Then, the model was submitted to the Face-to-Face technique, where a process specialist (operation manager) evaluated the conceptual model, based on knowledge about the real system. Trace technique was not necessary because it was done indirectly using other techniques.

4.2.4 Conceptual Model Documentation

The IDEF-SIM technique also contributes to the model documentation favoring its understanding (Montevechi et al. 2010). We carried out the documentation using this technique (Figure 2).

4.2.5 Input Data Modeling

First, the modeler must define which input data is relevant. Thereby, three input parameters are essential: *Picking Cycle Time (PCT)*, *Supply Cycle Time (SCT)*, and *Operator Travel Speed (OTS)*. We have considered SCT as deterministic. The data modeling process is divided into three stages: (1) Data Collection, (2) Data Processing, and (3) Inference (Chwif and Medina 2015). Data were collected through sampling, analyzed using descriptive statistics, and fitted into a probabilistic model. The times were associated with normal distributions (95% confidence level). For PCT, we have a normal distribution of N(176.10, 26.77) seconds, and for OTS, we have a normal distribution of N(1.10, 0.26) m/s.

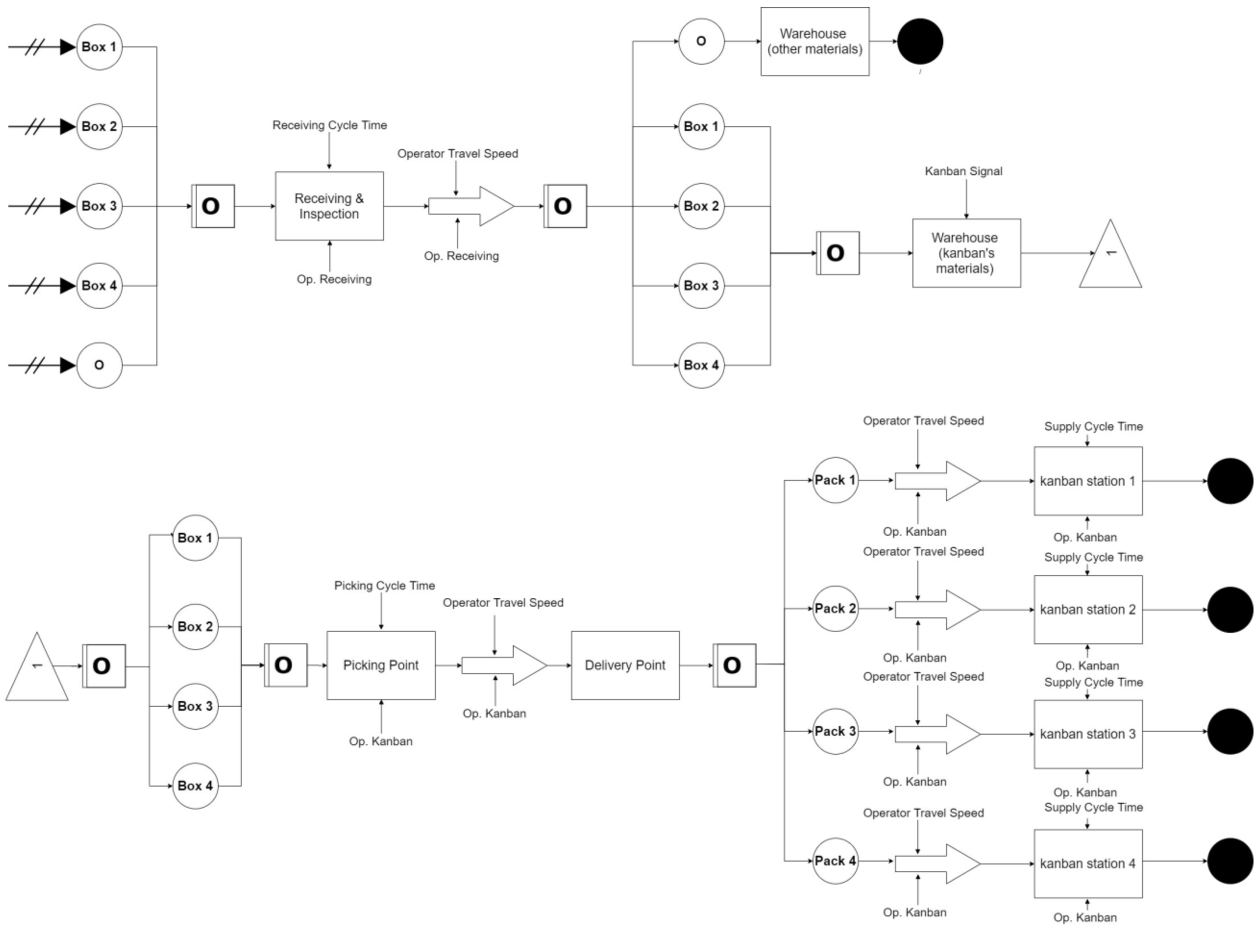

Figure 2: Conceptual model.

4.3 Implementation

4.3.1 Computer Model Building

The high graphic resolution of the computer model, the high detail level, and the low abstraction level are essentials points for the simulation adequacy in Industry 4.0 (Rodič 2017). Considering the need to build models that increasingly explore graphic and visual resources, we used the FlexSim® software. We chose it due to the user-friendly programming (object-oriented) that requires little or no use of codes and the possibility of building 3D models, extending to Virtual Reality. Figure 3 presents the 3D computer model.

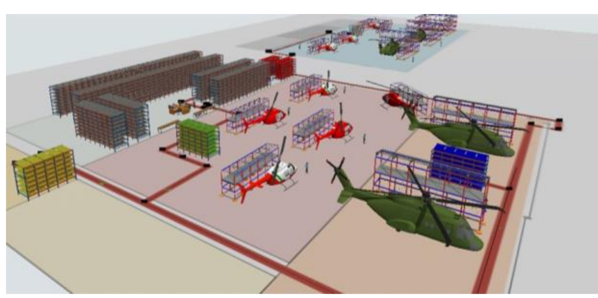

Figure 3: 3D view of the computer model in FlexSim®.

4.3.2 Computer Model Verification

Model verification is the analysis of the computer model according to the logic imposed by the conceptual model (Chwif and Medina 2015). Sargent (2013) indicates that, in cases where the computer model was built from simulation software, the verification should focus on the model's functions analysis, such as simulation logic, times, and activity flows. Thereby, the computer model verification was performed using two techniques suggested by Chwif and Medina (2015): (1) Modular implementation, which is based on the construction and testing of the model in parts, and (2) Graphical animation, where it seeks to identify and correct errors through model visual monitoring. Therefore, during computer model programming, the software allowed simulations in some parts of the model. This process was essential to find errors in logic and functions. Also, by monitoring the simulation in the 3D view, we carried out some scenarios to test all logics.

4.3.3 Model Update Data and Desired Responses Definition

The material demand at each Kanban station is the crucial factor for changes in the real process. Thus, we choose this parameter as a model update data. In this way, the simulation model was programmed to periodically receive a list of the materials consumed at the different Kanban stations according to the real process. The answer to the real process is the most efficient supply route. We have considered the distance traveled by the supply operator and the number of materials supplied during the period. We chose these parameters because the managers consider the volume supplied in the period as essential for measuring operational performance. Moreover, we should reduce as much as possible the unnecessary or excessive people's movement and the transport of materials (Lean principles). Finally, more efficient routes benefit valuable time, allowing increase tasks that add value.

4.3.4 Interface Structuring with the Real Process

For the integration interface, we chose a Control and Management Dashboard built in Excel®. Several other studies use intermediate systems to allow integration between the simulation model and the real world (Rodič and Kanduc 2015, Barlas and Heavy 2016, Rodič 2017). Initially, the dashboard works as a database, importing the materials' demand for a report coming from the ERP system. Then, it allows the update and simulation of the virtual model with the actual operation data. Finally, the dashboard allows obtaining the results from the simulation, enabling decision making. Figure 4 shows the dashboard.

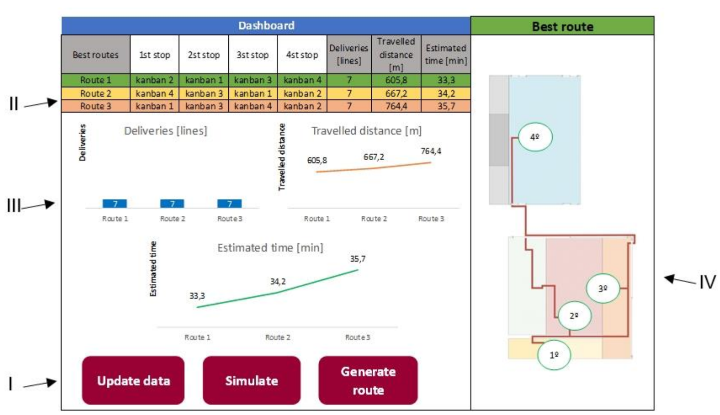

Figure 4: Interface dashboard between the real process and the simulation model.

Figure 4 also highlights the main features of the dashboard, in which: (I) are the dashboard control buttons (they allow the user to interact with the system); (II) are the route panel (after exporting the simulation results, the dashboard presents the three best routes); (III) are the comparison charts (the dashboard displays the route comparison charts); (IV) is the route map (it indicates the supply order of the Kanban stations for the operator).

Figure 5 illustrates the data and information flow in the proposed system. Data from the real system is the input of the simulation model and the decision-maker (operator or operation manager) acts in the real system based on the simulation results.

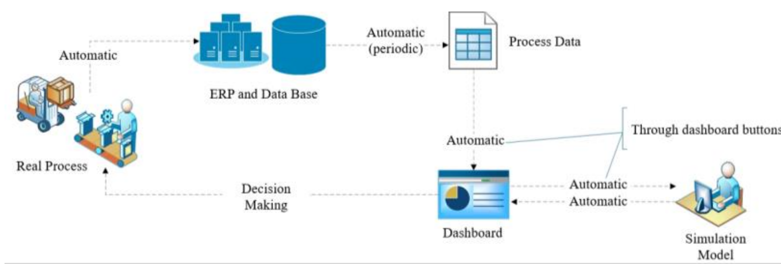

Figure 5: Data and information flow between the real system and the simulation model.

4.3.5 Computer Model Validation

For the computer model validation, we opted for the Formal Quantitative procedure where statistical tools help to determine operational validity (Chwif and Medina 2015). The parameter chosen was the Unit Supply Time (UST). To obtain the UST, the total time of each supply round was divided by the total number of supplied materials. Thereby, we chose the variance ANOVA test to compare the real system data with the results of the model's replicates. The simulation model was programmed to run 17 replicates in each round, to provide the accuracy of one minute and the 95% confidence level (Chwif and Medina 2015). The ANOVA test shows that it was not possible to prove significant differences between the real and simulated data (p-value = 0.584) with a 95% confidence level, validating the model (Montgomery and Runger 2012).

4.4 Analysis

4.4.1 Future Scenarios Definition

For the scenario's definition, we used the optimization via simulation approach. The scenarios were defined to test the possible supply routes and obtain the ideal route based on traveled distance and the material replenishment. The model tests all possible routes and the optimizer seeks to minimize the distance and maximize the number of supply parts. After carrying out the experiments, the software classifies each of the routes in a ranking where the optimum presents the best result combining the response variables. In this way, the results are recorded in a database and imported to the control and management dashboard. In addition, other scenarios may be tested according to decision-making needs.

4.4.2 Periodic Scenario Executions

The simulation model needs to be updated periodically, according to the system characteristics. Thus, the material supply process is carried out during the entire working day and, when a supply route is completed, the process starts again with a new decision making. Consequently, at the end of each route, the operator must make a new decision for the next replenishment. For this new route, the simulation model will be updated and executed, assisting in decision making.

4.4.3 Analysis and Decision Making

The analysis and decision making are carried out at the end of each round of the material supply. When starting a new replenishment, the operator has access to the most efficient route. We note that the proposed method helped as a basis for the development of the simulation project as part of a cyber-physical system. This method was presented to several simulation experts during the stages of this research and we can ensure its validity. We obtained a robust method and adapted to the new requirements of the simulation by creating steps related to the integration of the simulation model and the real system.

5 CONCLUSIONS

With the Industry 4.0 advancement, we need to adapt tools and concepts already established to apply in the current processes and operations. In a scenario where competitiveness and complexity are fast increasing, there is a need to use integrated systems and tools to help decision making more efficient and assertive. In this context, the present work was developed, aiming at the use of simulation in the modern industry, integrating it with information systems and operations decisions. To develop simulation projects in this area, a method was proposed, based on Montevechi et al. (2010), in order to adapt the steps to a cyber-physical system (Industry 4.0 principle). These systems are intended to represent the real environment and assist in decision making continuously. The proposed method was applied in a material supply process for an aeronautical industry. As a result, in addition to the method validation, we obtained a virtual system that is influenced by the real process, and it can optimize decision making. Finally, we highlight the ability of the simulation to adapt to new trends and needs, showing itself as a robust technique and compatible with the modern industry. For future work, we suggest new applications of the method to verify its viability in other industrial scenarios and sectors, such as services and healthcare.

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