Application of hybrid simulation in the representation of human behavior in a manufacturing system

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ABSTRACT

Being one of the efficient analytical tools available to managers, the simulation enables the creation of models that represent complex real systems. Specifically, the Discrete Event Simulation (DES) is widely used in manufacturing. However, the human factor is often represented in the DES models as simple resources and its dynamic behavior is neglected. In this context, Agent-Based Simulation (ABS) offers the opportunity to model human behavior in more detail. To sum up, in this paper a hybrid simulation will be adopted to represent the human factor inserted in an assembly process. Based on the Westinghouse System, the human element is represented in the model by its rhythm of work. After the analysis phase, it was found that the hybrid model simulation provides results with less variability.

KEYWORDS. Human factor, Hybrid simulation, Westinghouse System.

Paper topic (SIM - Simulation)

1. Introduction

The search for flexibility and optimization of cost and time is gradually transforming the manufacturing systems in complex systems. Such systems express a dynamic and non-linear behavior. Moreover, the production planning is significantly affected by this behavior that has the unpredictability as an intrinsic characteristic [EFTHYMIOU et al. 2014]. In this context, the simulation appears as one of the most efficient analytical tools available to managers of complex systems, allowing the creation of models to analyze the performance of such systems [SHANNON 1983; BERTRAND and FRANSOO 2002].

Playing a significant role in assessing the design and operating performance of manufacturing systems, the simulation has proven its effectiveness when applied to many practical problems faced by the manufacturing sector [NEGAHBAN and SMITH 2014]. For example, the Discrete Event Simulation (DES) technique is widely used in the manufacturing area to solve problems involving handling systems and storage of materials, assembly lines, automated cell, production scheduling, inventory analysis and kanban [CHWIF and MEDINA 2015].

Stochastic in nature, DES models are conducted over time from random samples of probability distributions [LAW 1988]. According to Baines et al. (2004), DES models are able to represent the machines in detail. However, the human element is considered a simple resource and its dynamic behavior is often neglected [DIGIESI et al. 2009]. Indeed, it is difficult to perform a more detailed modeling of the human element through DES tools [BAINES and KAY 2002].

Besides the DES, there are other simulation techniques such as Monte Carlo Simulation (MCS), Continuous Simulation (CS), and Agent-Based Simulation (ABS). The ABS – a relatively new simulation technique – has been gaining popularity and application in various fields of scientific knowledge [KASAIE and KELTON 2015]. Written in object-oriented languages, the ABS is a powerful technique for modeling and simulation [BONABEAU 2002; FIORETTI 2013]. According to Macal and North (2010), it is possible to model the dynamics of adaptive complex systems through agent-based modeling. Furthermore, the same authors argue that through agent-based models it is possible to observe the collective effects of the behavior of the agents, either humans or not, and their interactions.

In accordance with Siebers et al. (2010), the combination between DES model and ABS model occurs when a process flow is represented by a DES model and the passive entities of this model are replaced by autonomous entities (agents) with proactive behavior through ABS. It is important to note that the combination of ABS and DES becomes appropriate when one wants to establish behavioral characteristics of a system that reacts according to certain events [BALDWIN et al. 2015]. Being able to be simulated by combining the DES with the ABS, the human factor is one of the elements that influence the behavioral characteristics of diverse manufacturing systems.

Thus, this paper aims to represent human behavior through the application of hybrid simulation. A hybrid simulation can be defined as the union of DES and ABS techniques to build a model that is able to represent appropriately the reality. In this hybrid model, an assembly process will be represented by a work station composed of three workers. The behavior of these three workers will be described through the state diagram of each worker. In addition, with reference to the Westinghouse System [BARNES 1977], it will also be considered in the model the factors that influencing the rhythm of work of each worker.

In the analysis phase two types of experiments will be defined in order to evaluate the representation of human behavior in the simulation. In the first experiment, the human element will not interfere in the process time. In the second one, it will considered the influence of the human factor in the process time.

In conclusion, it is important to emphasize the structure of this paper, which consists of theoretical background, research method, application of the research method, conclusion, acknowledgments, and references.

2. Theoretical background

2.1 Discrete Event Simulation and Agent-Based Simulation: two different approaches

One of the various tools that can be used to assess and to understand an existent or planned production line is the simulation [HARPER and O'LOUGHLIN 1987]. Being a research field in constant evolution, the simulation has contributed to the improvement of manufacturing systems [MOURTZIS et al. 2014]. Indeed, manufacturing is among the areas most benefited by the application of simulation [WILLIAMS 2014].

For Baines et al. (2004), the simulation consists in a building technique of models that describe the behavior of a real system. Additionally, such models may be used to test the performance of a given system on different operating conditions.

The simulation can be classified under different viewpoints. Briefly, discrete and continuous models are the two main approaches in the simulation field. There is also distinction between the types of simulation within these two approaches [ROBINSON 2002]. In this paper, the characteristics that distinguish the different models of discrete and continuous simulation will not be treated. However, in the context of discrete simulation, the Discrete Event Simulation (DES) and Agent-Based Simulation (ABS) techniques will be emphasized.

Used to analyze and to understand the dynamics of manufacturing systems, the DES is one of the techniques with high versatility. This technique allows the evaluation of various operational strategies and system configuration alternatives, supporting decision making. In addition, the frequent use of the DES has increased in recent years due to the expansion of memory and computational power [NEGAHBAN and SMITH 2014].

Generally being stochastic in nature, DES models are conducted over time from the use of random samples of probability distributions [LAW 1988]. In DES models, changes occur at discrete moments, affecting the system state. It is worth emphasizing that the construction of DES models is based on a top-down approach, using flowcharts for example. This approach provides insufficient flexibility with respect to the inclusion of more individual levels of behavior and microdynamics [KASAIE and KELTON 2015]. Ingalls (2008) states that a DES model is basically composed of entities, activities and events, resources, global variables, the random number generator, calendar, system state variables, and statistical collectors.

The ABS is a new simulation technique, which emerged in the late 1990s [ZANKOUL et al. 2015]. The popularity of the ABS technique continues to grow and its application has expanded into various fields, such as the financial, the logistical, the epidemiological and the archaeological ones [KASAIE and KELTON 2015; MACAL and NORTH 2009]. Having the ability to model dynamic behaviors of complex systems in detail, the ABS technique has also been applied with considerable success in the organizations from the industrial area [MORTAZAVI et al. 2015].

Based on the state diagrams, an ABS model consists of possible states of the agent, which are connected by transitions [ZANKOUL et al. 2015]. In a simple way, an ABS model is a system composed of agents and their relationships [BONABEAU 2002]. Being typically responsible for the decisions of a system, the agents are autonomous with communicative and adaptive skills. Groups of individuals can also be modeled as agents. Indeed, the development's essence of useful ABS models are in the identification of the system's agents, the precise definition of the behavior of these agents and the representation of the interactions between them [MACAL and NORTH 2005].

Unlike the top-down approach of the DES models, the ABS models are based on a bottom-up approach. According to Kasaie and Kelton (2015), the bottom-up approach used in the ABS represents a system more realistically, because its several aspects and elements can be considered in the moment of modelling. For Bonabeau (2002), the ABS model is built based on the modeling and simulation of the behavior and interactions of the system's agents. Thus, using this bottom-up approach, the simulation result emerges and is captured.

The combination of the top-down and bottom-up approaches opens space for new types of ABS models [FIORETTI 2012]. In this sense, a specific process flow can be constructed using

DES technique, and the system's entities (agents) with autonomous and proactive behavior can be added through ABS technique, replacing the passive entities of the DES model [SIEBERS et al. 2010]. Therefore, the combination of DES and ABS techniques enables the researcher to simulate system features that are not possible to be simulated in the isolated use of these two techniques [DUBIEL and TSIMHONI 2005].

2.2 Human factor in simulation models

It is evident the human presence in many manufacturing systems; however, depending on the process, this presence can occur in a more accentuated way or not. For Groover (2008), in several manufacturing system, the human element performs some or all of the value-added work realized in parts or products. Besides, Digiesi et al. (2009) argue that in the modern manufacturing systems, human work plays a central role. In this way, being a central theme of modeling and simulation, human behavior is still a traditional challenge for simulation and its application in the military and business area [BRUZZONE et al. 2007].

According to Kasaie and Kelton (2015), identifying and conceptualizing the structure of human behavior and its interactions are common problems in the modeling of complex systems involving the human element. As stated by Brailsford et al. (2012), it is also common the lack of similarity between the results of sophisticated and complex simulation models and the results of real systems. In accordance with the same authors, this lack of similarity occurs because the simulation models do not consider human behavior. For Elkosantini (2015), another problem is the frequent use of deterministic data to represent human behavior in the models. This explains the margin of error between the simulation results and the reality.

In DES models, the inclusion of human performance creates opportunity of knowledge about the impact and the importance of the human factor in the system [BAINES et al. 2004]. Nevertheless, the human element is still regarded as simple resources in DES platforms and its dynamic behavior is often neglected [DIGIESI et al. 2009]. In this scenario, the ABS appears as a natural technique of description and simulation of the system's behavioral entities [BONABEAU 2002].

In agent-based modeling, the system's entities are represented as individuals (agents). Being represented inside a system, the agent can perform various behaviors, such as producing, using, or selling [BONABEAU 2002]. Thus, ABS offers the possibility of capturing human behavior with a high level of detail [BRAILSFORD 2014].

There are many issues involving the worker's behavior. These issues have a greater or lesser effect on the performance of a manufacturing system. For example, from the physical point of view, factors such as noise, heat, and light affect the worker's behavior. Organizational factors, such as labor pattern, incentives, and supervision also affect the worker's behavior. In a more subtle way, the worker's behavior is also influenced by factors such as demographics, attitudes, values, and beliefs of the workforce [BAINES and KAY 2002].

In this paper, the worker's behavior will be addressed based on the Westinghouse System of Rating, which takes into account four factors that can affect the worker’s performance. This type of rhythm evaluation system will be discussed in the next section.

2.3. Westinghouse System of Rating

The rationalization, the cost-cutting, and the productivity increase are essential elements in the time and motion study [MACHLINE et al. 1974]. Introduced by Frederick W. Taylor, the time study is mainly used for the determination of the time-standards of production processes. Complementing this idea, the couple Gilbreth developed the motion study, applying it for the improvement of the work's methods. [BARNES 1977].

The evaluation of rhythm is the one of the most important steps in the time study, and it has a greater degree of difficulty since the time study analyst need to evaluate the worker's speed at executing a process. The act of evaluating the rhythm of a worker may occur on the basis of six types of systems of rating, which are (1) Skill and effort rating (2) Westinghouse System of Rating, (3) Synthetic rating, (4) Objective rating, (5) Physiological evaluation of performance level, and

(6) Performance rating [BARNES 1977]. In this paper, as mentioned earlier, the Westinghouse System of Rating will be considered due to the four factors that influence the rhythm of work of the worker.

The Table 1 shows the four factors considered in Westinghouse System of Rating [BARNES 1977].

Table 1: Westinghouse System of Rating

SKILL			EFFORT		
+0,15	*A1*	*Super skill*	*+0,13*	*A1*	*Excessive*
+0,13	*A2*		*+0,12*	*A2*	
+0,11	*B1*	*Excellent*	*+0,10*	*B1*	*Excellent*
+0,08	*B2*		*+0,08*	*B2*	
+0,06	*C1*	*Good*	*+0,05*	*C1*	*Good*
+0,03	*C2*		*+0,02*	*C2*	
0,00	*D*	*Average*	*0,00*	*D*	*Average*
-0,05	*E1*	*Fair*	*-0,04*	*E1*	*Fair*
-0,10	*E2*		*-0,08*	*E2*	
-0,16	*F1*	*Poor*	*-0,12*	*F1*	*Poor*
-0,22	*F2*		*-0,17*	*F2*	
CONDITIONS			**CONSISTENCY**		
+0,06	*A*	*Ideal*	*+0,04*	*A*	*Perfect*
+0,04	*B*	*Excellent*	*+0,03*	*B*	*Excellent*
+0,02	*C*	*Good*	*+0,01*	*C*	*Good*
0,00	*D*	*Average*	*0,00*	*D*	*Average*
-0,03	*E*	*Fair*	*-0,02*	*E*	*Fair*
-0,07	*F*	*Poor*	*-0,04*	*F*	*Poor*

Source: adapted from Barnes (1977)

Published in 1927, the Westinghouse System of Rating was developed by Westinghouse Company to estimate the worker efficiency based on the factors (1) skill, (2) effort, (3) conditions, and (4) consistency. Mathematically, the equation (1) shows the calculation for the worker's rhythm factor, considering the four factors [BARNES 1977].

$$\boldsymbol{RF = 1 + \sum F} \tag{1}$$

RF represents the rhythm factor of a worker. The number 1 is a constant. Moreover, the expression ∑F represents the sum of the values of the four factors obtained through the table. Finally, it is important to note that afterwards the rhythm factor will be applied to obtain the work time standards [BARNES 1977].

3. Research Method - Modeling and Simulation

Based on quantitative models, the research in production and operations management contemplates the construction of models capable to minimally explain part of the behavior of the real processes, which facilitate the understanding of issues related to decision-making involving these processes [MORABITO NETO and PUREZA 2012].

Being an abstraction of reality, quantitative models are created through Modeling and Simulation method. This allows the researcher the manipulation of variables using or not computational tools. [MARTINS 2012]. According to Bertrand and Fransoo (2002), quantitative models are governed by a set of variables that change themselves during a specific scope.

It is important to mention that there are two specific types of research based on quantitative models. The first one is called quantitative axiomatic research and the second one is called quantitative empirical research. Furthermore, these two types of research are classified into two categories: descriptive and normative research [BERTRAND and FRANSOO 2002; MORABITO NETO and PUREZA 2012].

Mitroff et al. (1974) propose a simple and holistic model that consists of four components. Together, they help building models. These four components are (1) Reality, problem situation, (2) Conceptual Model, (3) Scientific Model, and (4) Solution. The transition between them occurs through the actions of conceptualization, modeling, model solving, implementation, feedback, and validation.

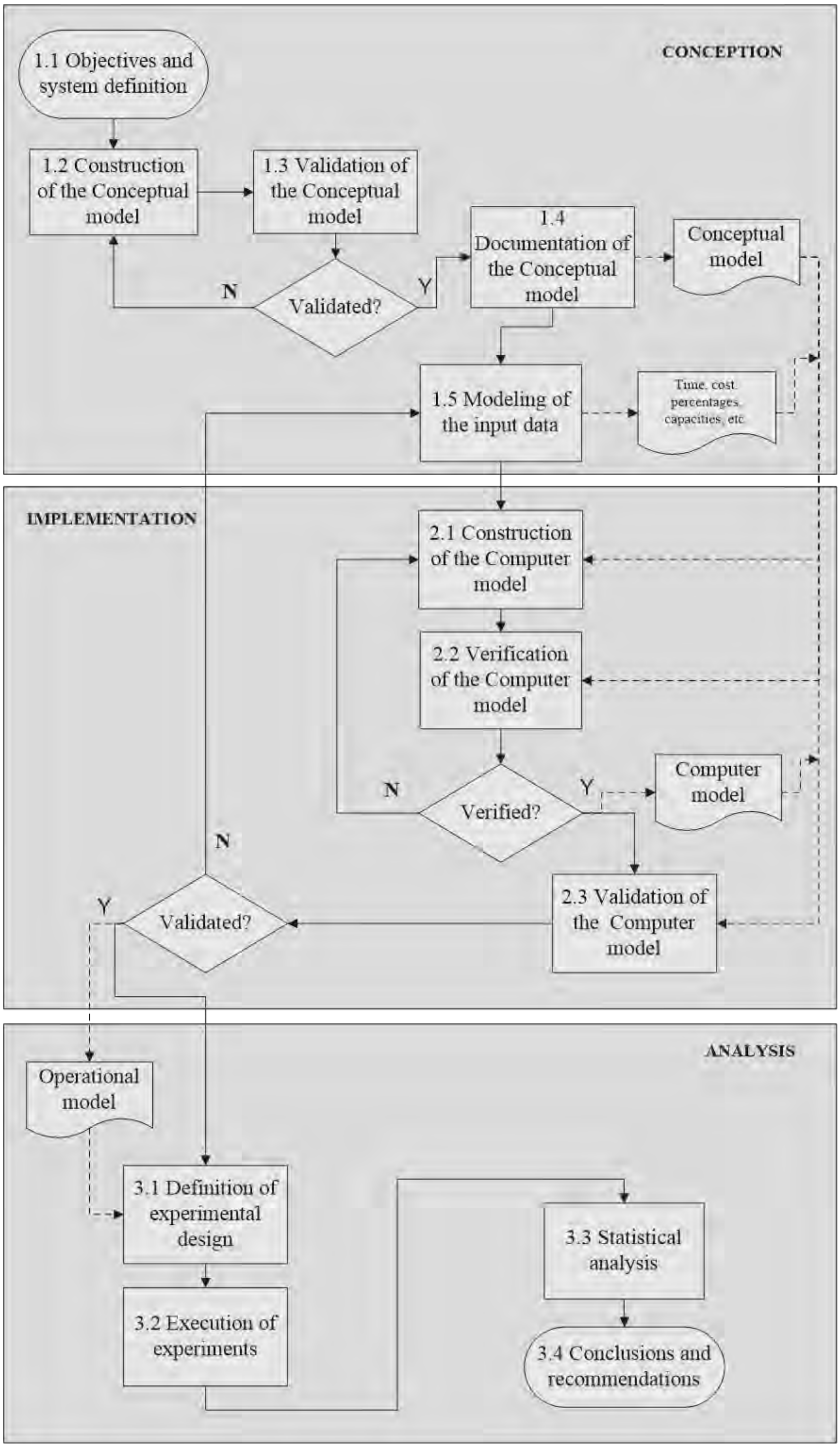

Figure 1: Phases of a simulation project
Source: adapted from Montevechi et al. (2010)

Inspired by the model proposed by Mitroff et al. (1974), several authors have developed models to be applied specifically in simulation projects. One of these models is the one proposed by Montevechi et al. (2010) for simulation project. This model is represented in Figure 1. According to these authors, a simulation project is divided into three phases: (1) conception phase, when the conceptual model is created and validated, (2) implementation phase, when the computer model is created with reference to the conceptual model of the previous phase; in this phase occurs the verification and validation of the computational model, and (3) analysis phase, when analyses are made from the validated computational model.

This paper will apply the model proposed by Montevechi et al. (2010) for the creation of conceptual and computational model. In addition, it also will be adopted the axiomatic descriptive research methodology that is based on the description of the studied system behavior [MORABITO NETO and PUREZA 2012]. This type of methodology focuses on the modeling process [BERTRAND and FRANSOO 2002].

4. Application of the proposed method

4.1 Conception

The first step of the conception phase is the choice of the system or the problem situation. Thus, a process was selected from an assembly line of electronic parts. This process is called TouchUP, and it is composed of three workers. These workers perform the process in discrete time moments. It is worth mentioning the high level of manual activities that this process demands. In conclusion, those are the characteristics captured; they enable the combined application of DES and ABS techniques.

The second step is the construction of the conceptual model. For this purpose, the IDEF-SIM (Integrated Definition Methods - Simulation) technique [LEAL 2008; MONTEVECHI 2010] was used to model the TouchUP process of the assembly line. Figure 2 shows the conceptual model of TouchUP process, which occurs according to a process sheet (PS). As mentioned before, this process is performed by three workers. In the conceptual model, the three workers were respectively named WKR A, WKR B, and WKR C. Finally, the validation of this conceptual model happened face-to-face with experts who know the process.

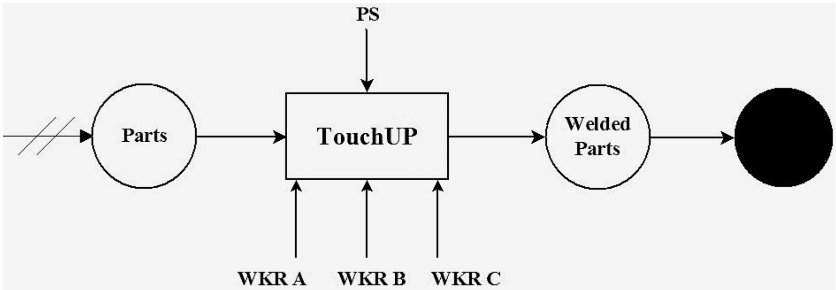

Figure 2: Conceptual model of the assembly process

After validation of the conceptual model, it was made its documentation. Then, the modeling of the input data was initiated. The TouchUP process execution time was collected through filming. Thus, one hundred measurements were done during twenty weeks. The collected data were statistically treated to identify the probability distribution which could best represent the TouchUP process. Thereby, the probability distribution for TouchUp process was Normal (22.41; 184.79).

From Monday to Friday, the three workers start the TouchUP process at 7 hours and 40 minutes (07h40min) and conclude it at 17 hours (17h00min). At 11 hours and 40 minutes (11h40min), the workers have lunch and return to work at 13 hours (13h00min). Therefore, the workers work 40 hours per week. In this context, each worker was represented by a state diagram, considering their working hours and their possible states. Figure 3 shows the state diagram of workers. It is important to mention that the Rhythm Factor cited in the state diagram refers to the Westinghouse System of Rating.

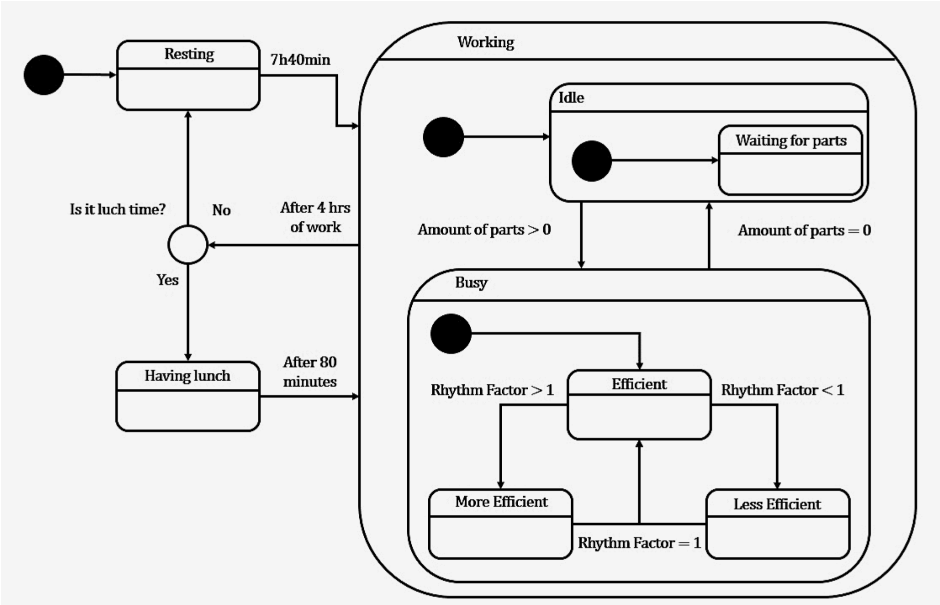

Figure 3: State diagram of each worker

4.2 Implementation

After creating and validating the conceptual model, the construction of the computational model was initiated. At this stage, the Anylogic® software was used to build the computational model. The fact that justifies its choice is that, among the various softwares found on the computer simulation market, it is the only one that allows the creation of hybrid models that integrate the DES and ABS techniques.

Based on the conceptual model shown in Figure 2, the computational model was created. After that, the verification started, i.e., the computational model was compared to the conceptual model to verify their similarity. Figure 4 displays this computational model.

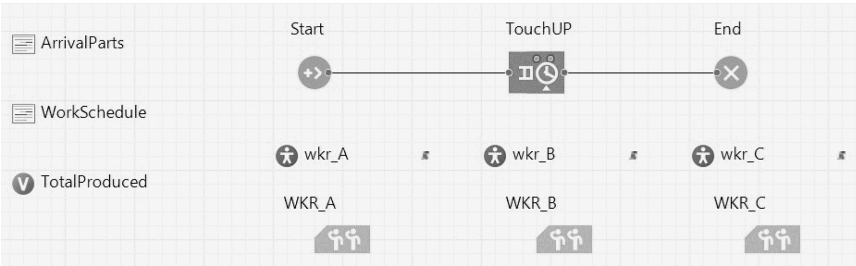

Figure 4: Computational model (DES + ABS)

In the computational model two schedules were considered. The first one is called ArrivalParts, representing the rate of arriving parts per hour. The second one was WorkSchedule, which defines the entry and exit times of the workers. It was also added to the model the variable TotalProduced, which shows the number of parts produced by the workers during a week.

The agents wkr_A, wkr_B, and wkr_C represent the three workers in the TouchUP process. The Anylogic® allows the creation of state diagrams; therefore, it was created a state diagram for each worker based on the Figure 3. At this point it is important to emphasize the inclusion of the four factors of the Westinghouse System that influence the workers' rhythm. Moreover, the factor conditions receives the value zero in the computational model because all workers have the same working conditions. Finally, the equation (1) is represented in the model by the variable Rhythm Factor. This variable will influence the TouchUP process time.

The results of the computational model need to be compared with the real data to achieve the model validation. [ELKOSANTINI 2015; SARGENT 2013]. Thus, the computational model validation will occur by comparing the results from the computational model and from the real system. Here, it is important to point out that two computational models will be validated for further analysis. The first model receives the name Model DES. The second one is called Model HYB. The Model DES is a purely DES model where the human element is not considered. As for the Model HYB, it represents a hybrid model (DES + ABS) that takes into account the human factor.

Thus, after the collection of thirty replicates, the sample containing the data from the Model DES was compared with the sample from the real data. This comparison occurred by the 2-Sample t test. This test verifies if the means of the samples are statistically equal. Hence, the null hypothesis (H0) is that the means of the samples are not different, and the alternative hypothesis (H1) is that the means of the samples are different. The result of the test was a P value equal to 0.330. This means that the sample mean of the real data is not significantly different from the sample mean of the Model DES data. Therefore, the Model DES was validated.

The same process was applied to validate the Model HYB. Thus, after the collection of thirty replications, the 2-Sample t test was applied to check whether the means of the samples are statistically equal. Consequently, the null hypothesis (H0) is that the means of the samples are not different. The alternative hypothesis (H1) is that the means of the samples are different. The result of hypothesis testing 2-Sample t was a P value equal to 0.562. This means that the sample mean that represents the real data is not significantly different from the sample mean of the Model HYB data. In conclusion, the Model HYB was validated.

4.3. Analysis

Since the computational models were validated, the phase of definition of experimental design was then started. Thereby, to evaluate the representation of human behavior in the results of the hybrid simulation model, two experiments were defined. The first experiment is called Exp. DES, and the name of the second is Exp. HYB. It is important to note that there is no presence of the human factor in Exp. DES. However, the Exp. HYB takes into account the representation of human behavior.

In Exp. DES it was applied the Normality Test which was used to verify the normality of the data from the Exp. DES. The result of the test was a P value equal to 0.877. This shows that the data from the Exp. DES are normal. After application of the Normality Test, it was performed the 2 Variances test to determine whether the variances between the data from the Exp. DES and the real data were different. The result was a P value equal to 0.290, indicating that the sample variance of the Exp. DES data is not significantly different from the sample variance of the data that represent the real data.

The Normality Test was also applied in the Exp. HYB. The result of this test was P value equal to 0.891. Hence, it is concluded that the data from the sample of the Exp. HYB are normal. Next, it was performed the 2 Variances test and the result was a P value of 0.820. This means that the sample variance of the data of the Exp. HYB is not significantly different from the sample variance of the real data.

After the normality and variance tests, two comparisons were done to verify the variability between the samples. The first comparison was performed between the Real Data sample and the Exp. DES sample. Figure 5 shows the result of this comparison.

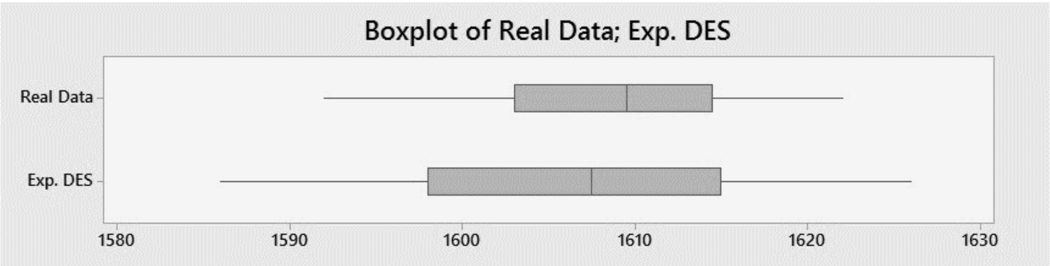

Figure 5: Comparison between Real Data sample and Exp. DES sample

The second comparison was done between the Real Data sample and the Exp. HYB sample. Figure 6 displays graphically the result of this comparison.

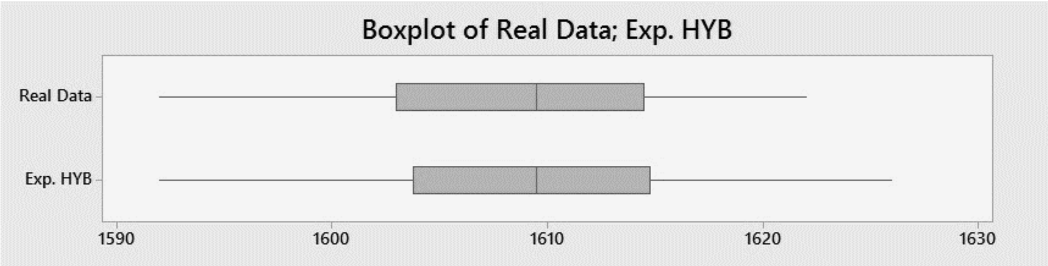

Figure 6: Comparison between samples Real Data and Exp. HYB

Based on statistical tests, it is concluded that the results of the Exp. DES and the Exp. HYB have a normal distribution, and the variance of each experiment is statistically equal to the variance of the real data. Nevertheless, the variability of the Exp. DES is greater than the variability of the Exp. HYB. In other words, the hybrid model (DES + ABS) has a lowest data variability.

5. Conclusion

The combination of the DES and ABS techniques provides to the researcher the opportunity to model the human element inserted in a manufacturing process. This occurs when the manufacturing process under study is first modeled by DES, and after the human factor of this process is modeled through the ABS. Thus, the passive entities of the DES model are replaced by autonomous and proactive agents.

The hybrid model presented in this paper contains three agents. Each of these agents is described by nine states, four parameters and one variable. The four parameters represent the four factors from the Westinghouse System. These factors directly affect the variable that represents the rhythm of work. Finally, the rhythm of work variable affects the execution time of the TouchUP process in every simulated day.

During the development of the hybrid model, the state diagram played a key role for the agent's representation in the system. The logic is in the state diagram, guiding the behavior of agents in the computational model.

Based on statistical analysis, it is concluded that the combination of DES and ABS techniques reduces the variability of the data from the computational model. This reduction of the computational model data variability provides an approximation of the real system studied. Therefore, the hybrid model has the ability to better represent the reality.

Finally, for future work it is suggested the inclusion of other factors in the computational model that influence human behavior, such as motivational, social and psychological factors. Another suggestion is to simulate similar processes and compare the variability of their results. In addition, the states of agent can be improved and applied in other contexts in the manufacturing sector.

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