ANALYSIS OF THE INSERTION OF HUMAN CHARACTERISTICS THROUGH HYBRID SIMULATION

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ABSTRACT

Modeling and simulating human behavior are still a traditional challenge in the field of simulation because of the complex principles that govern human actions. Nevertheless, Agent-Based Simulation (ABS) has brought a new perspective of modeling and simulation. This new simulation approach offers the opportunity to model human behavior in more detail. In addition, ABS can be combined with Discrete Event Simulation (DES). From this combination emerges hybrid models that are able to depict real systems with a higher level of detail. Therefore, this paper aims to analyze the insertion of human characteristics inherent to operators present in an assembly line through hybrid simulation. In methodological terms, this paper uses the modeling and simulation methodology to build the hybrid model. The results of the hybrid model show that the addition of human characteristics in a simulation model increases the variability of the output data.

KEYWORDS. Hybrid simulation, Human characteristics, Assembly line.

Paper topic (SIM - Simulation)

1. Introduction

Despite the progress of technology, human beings still play a key role in modern production systems. Hence, researches involving the human element in production systems are being developed in simulation area to realistically represent the human factor and its behavior. However, [Bruzzone et al. 2007] admit that human behavior is still a traditional challenge for the simulation area itself and its application in the business areas.

Regardless of the automation level, the performance of many manufacturing systems is affected by human behavior [Brailsford 2014]. Indeed, human labor is an essential element in modern manufacturing systems and, therefore, it must be reliably expressed in the modeling process of such systems [Digiesi et al. 2009]. [Baines et al. 2005] recognize that increasing the reliability of a simulation model is related to the act of representing the human factor more realistically within this model.

For [Kasaie and Kelton 2015], identifying and conceptualizing the structure of human behaviors and interactions is a common problem in modeling complex systems involving human element. In Discrete Event Simulation (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]. However, DES tools often neglect the dynamic behavior of the human beings [Digiesi et al. 2009].

Agent-Based Simulation (ABS), also called Agent-Based Modeling and Simulation (ABMS), is a relatively new simulation approach that provides the modeler an opportune method to represent behavioral elements. According to [Bonabeau 2002], it is more usual to describe and to simulate a system composed by ‘‘behavioral’’ entities through ABS.

It is possible to combine ABS approach with DES approach. From this combination hybrid models emerge, being able to depict real systems with a higher level of detail. [Dubiel and Tsimhoni 2005] argue that this combination enables the researcher to simulate system characteristics that would not be possible to simulate using one of these two techniques separately.

Hybrid modeling is one of the research challenges in ABS area. The challenge is to link consistently two models with distinct logics that use modeling tools that also have distinct characteristics [Macal 2016]. Therefore, based on the importance of human beings to production systems and the challenge of combining two different simulation approaches, this paper aims to analyze the insertion of human characteristics inherent to operators present in an assembly line through hybrid simulation.

In hybrid model, an assembly line will be represented by ten workstations composed of fourteen operators. The behavior of these workers will be described through a state diagram. Furthermore, based on the Westinghouse System of Rating [Barnes 1977], the factors effort and consistency will affect the behavior of each operator.

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 factors will not interfere in the process time. In the second one, it will be considered the influence of the human factors in the process time.

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

2. The combination of two distinct simulation approaches

Discrete Event Simulation (DES) is one of the simulation approaches that supports decision makers. Through DES, it becomes possible to study and analyze complex systems [Banks et al. 2005]. With DES, it is possible to deal with stochastic uncertainties and to have an understanding about the process that is present in the system [Macal and North 2005]. Thus, according to [Siebers et al. 2010], it is appropriate to use DES in problems that involve simulations of queues or networks of complex queues. In these cases, the processes can be well defined and their uncertainties can be represented by means of stochastic distributions.

In most production systems, the human element is one important component. In the literature there are researches addressing the human element from the perspective of DES. For example, [Brailsford and Schmidt 2003] created a DES model for diabetic retinopathy screening based on human characteristics. In the manufacturing sector, another research to be cited is that of [Vilela 2015], which deals with the variation of the human work rhythm through a more detailed modeling of the input data.

With the emergence of ABS, the insertion of the human element into simulation projects gained a new perspective. According to [Macal and North 2013], ABS approach provided the opportunity to model individual behaviors more easily. Thus, several limitations related to traditional approaches can be overcome through an agent-based model [Stummer et al. 2015].

There are several definitions about what ABS is. In this context, [Macal 2016] offers four alternative definitions for ABS in increasing order of complexity based on agent properties. The first definition is the Individual ABS that considers that agents have prescribed behaviors and they are represented in the model individually. In this paper, this definition for ABS will be adopted.

The main difference between DES and ABS models is in the modeling approach. According to [Kasaie and Kelton 2015], the DES adopts a top-down modeling approach to represent the processes of a system. This type of approach affords a low flexibility in incorporating individual levels of behavior. As for ABS, it follows a bottom-up modeling approach that allows modeling diverse aspects of a system and its elements with high flexibility. This fact makes ABS a flexible and powerful tool for modeling systems that contain behavioral elements.

It is possible to combine ABS and DES approaches. In accordance with [Fioretti 2012], integrating top-down and bottom-up approaches opens space for new types of ABS models. [Siebers et al. 2010] state that a hybrid model occurs when a process flow is represented by a DES model and the passive entities of this model are replaced by autonomous agents with proactive behavior through ABS.

There is no consensus in the academic field about the precise definition of the term agent. Despite this non-agreement, there are points in common between the agent definitions [Macal and North, 2005]. The agents are autonomous elements that are self-organized by specific rules of decision-making [Mortazavi et al. 2015]. For [Brailsford 2014], agents are individuals present in ABS models that act independently. These agents may have the ability to learn from the past and to adapt their reactions and behaviors into a future scenario. Moreover, agents may also have the ability to communicate with one another and with their own environment.

Representing the human factors in a productive system through agents increases the possibility of including characteristics related to human behavior in more detail. Despite this advantage, it is a challenge to define which human characteristics will be considered in the model due to their complexity.

In manufacturing field, there are many issues involving the operators' behavior. For example, in agreement with [Baines and Kay 2002], physical factors such as noise, heat, and light affect the operator's behavior; organizational factors such as labor pattern, incentives, and supervision also affect the operator's behavior.

It is true that human factors are complex. Such complexity manifests itself through human decisions, behaviors and actions. Identifying the factors that interfere with human choices is difficult. However, this difficulty does not prevent the use of theories about the possible factors that influence the actions of the human element within a given environment.

Based on Westinghouse System of Rating [Barnes 1977], this paper will represent the operators' behavior considering the factors of effort and work consistency. This is because operators, in the real context, do not have the autonomy to change the skill and condition factors in a short time. In conclusion, the choice of Westinghouse System of Rating is related to the opportunity to explore effort and consistency values that estimate the performance of an operator.

3. Research Method

In the literature, several approaches serve as tools to create conceptual and computational models. One of these approaches is the one proposed by [Montevechi et al. 2010] which is divided into three major phases: (1) conception phase, when the conceptual model is created and validated, (2) implementation phase, when the computer model is created according 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. Figure 1 shows more details about the phases.

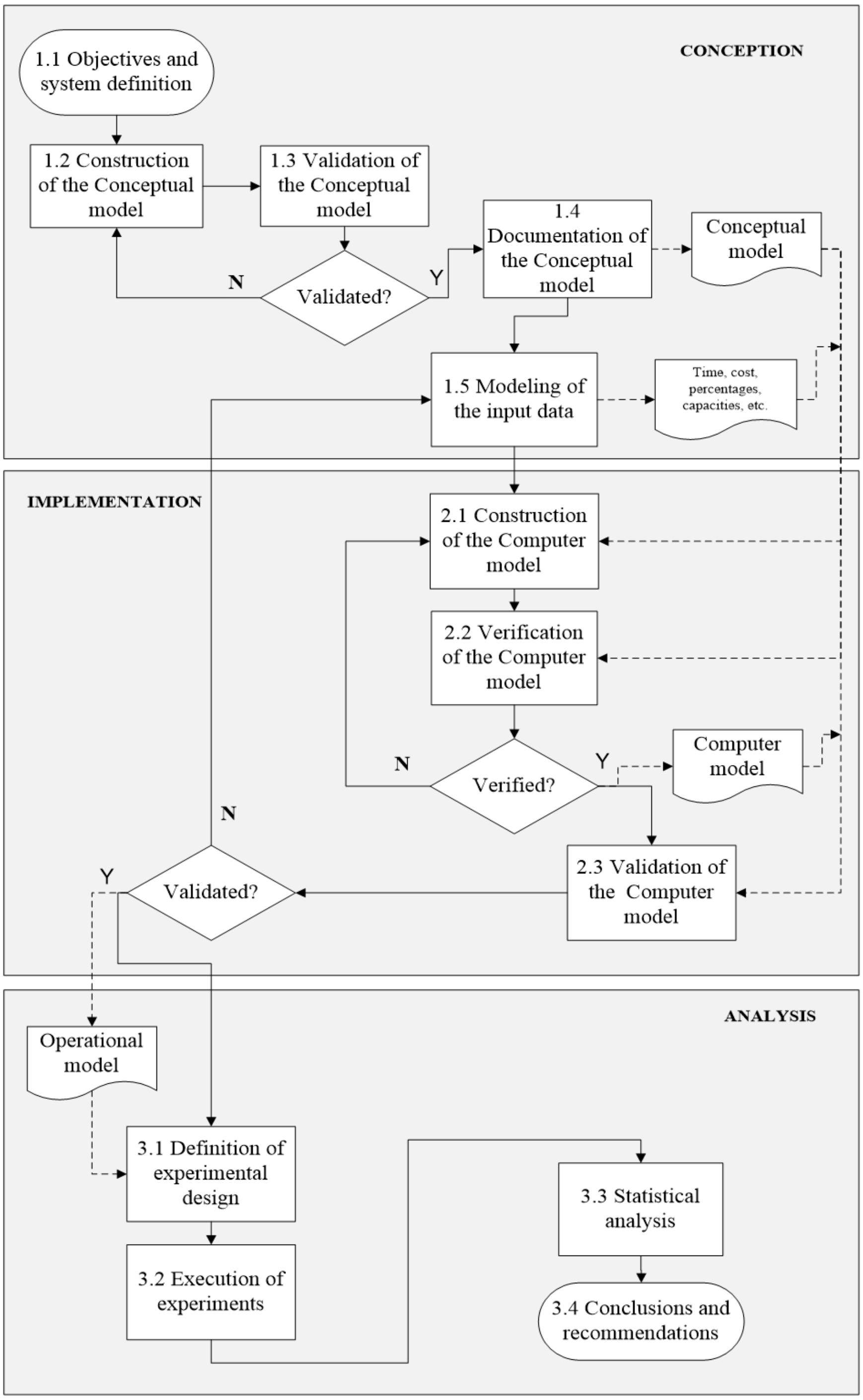

Figure 1: Phases of a simulation project
Source: [Montevechi et al. 2010]

In addition to the approach proposed by [Montevechi et al. 2010], this paper also adopts the ODD Protocol modeling tool. The ODD Protocol is essentially a tool for facilitating the writing and reading of Agent-Based Simulation models [Grimm et al. 2010]. This tool is divided into three large blocks as shown in Figure 2.

Overview	1. Purpose
	2. Entities, state variables, and scales
	3. Process overview and scheduling
Design concepts	4. Design concepts
Details	5. Initialization
	6. Input data
	7. Submodels

Figure 2: Phases of a simulation project
Source: [Grimm et al. 2010]

The sequence of steps proposed by [Montevechi et al. 2010] and the ODD Protocol developed by [Grimm et al. 2010] are the two methodological tools that will be applied in this paper.

4. Results

4.1 Conception

The purpose of this paper is to analyze the representation of the human factor presented in a manufacturing line using ABS combined with DES. In this sense, an assembly line of printed circuit boards was chosen for this analysis. This assembly line is composed of ten workstations and fourteen operators as shown in Figure 3.

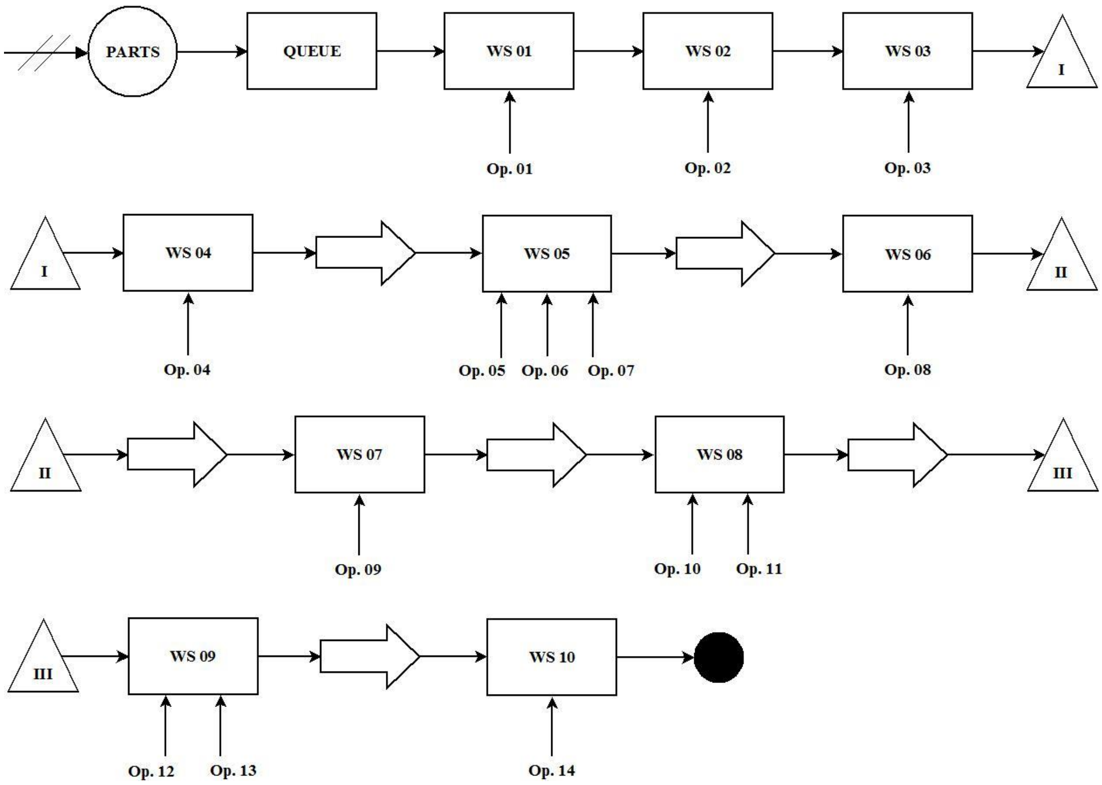

Figure 3: Conceptual model of assembly line.
Source: adapted from [Vilela 2015]

The construction of the conceptual model used in this paper is based on the work developed by [Vilela 2015]. This conceptual model was constructed using the Integrated Definition Methods - Simulation (IDEF-SIM) [Leal 2008] and validated through Face Validity [Sargent 2013].

With the conceptual model built and validated, the agent-based conceptual model was created through the ODD Protocol tool. The purpose of the agent-based conceptual model is to represent the operator through his rhythm of work, taking into account the factors effort and consistency. Table 1 shows the values of these two factors.

Table 1: Westinghouse System of Rating

EFFORT		
+0,13	*A1*	*Excessive*
+0,12	*A2*	
+0,10	*B1*	*Excellent*
+0,08	*B2*	
+0,05	*C1*	*Good*
+0,02	*C2*	
0,00	*D*	*Average*
-0,04	*E1*	*Fair*
-0,08	*E2*	
-0,12	*F1*	*Poor*
-0,17	*F2*	
CONSISTENCY		
+0,04	*A*	*Perfect*
+0,03	*B*	*Excellent*
+0,01	*C*	*Good*
0,00	*D*	*Average*
-0,02	*E*	*Fair*
-0,04	*F*	*Poor*

Source: [Barnes 1977]

The process overview and scheduling of the agent is represented by means of a state diagram shown in Figure 4.

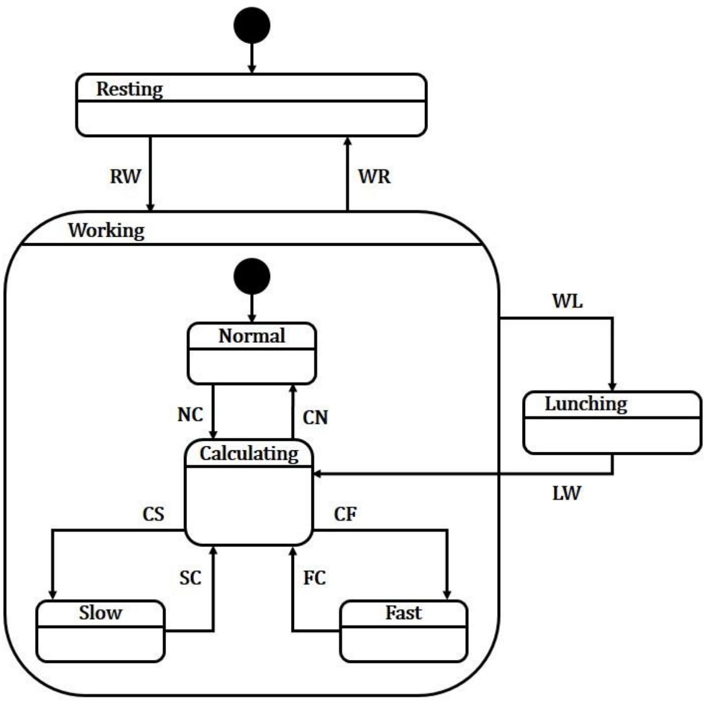

Figure 4: State diagram of each agent.

Each operator works for 4 hours in the morning and 4 hours in the afternoon. Thus, operators perform their tasks for 8 hours daily from Monday to Friday [Vilela 2015]. Based on this information, the first state is called "Resting": this state represents the hours of rest of the operators that are fifteen hours. The second state is the "Lunching": this state represents an employee's daily lunch hour. The third state is called "Working": the agent remains in this state during eight hours per day.

Within the "Working" state, there are four more states. Three of these states represent the rhythm of the agent. For example, at each random hour of work, the agent goes to the "Calculating" state to change its rhythm of work. If rhythm is equal to one, the agent remains at its normal rhythm of work in the next random hour by going to the "Normal" state. If rhythm is above one, the agent will increase its rhythm of work in the next random hour by going to the "Fast" state. If rhythm is below one, the agent will decrease its rhythm of work in the next random hour by going to the "Slow" state. It is important to note that the rhythm to be adopted by each agent is not deterministic, since the value of the rhythm is stochastically determined based on the values in the Table 1.

At the data collection stage, the random phenomenon collected was the process time of each assembly line workstation. In this collection stage, stopwatches and camcorders were used as resources [Vilela 2015]. For each workstation, 100 data were selected. Therefore, in total there are 1,000 data.

From these data, it was possible to find the probability distributions that represent each one of the workstations of the assembly line. Table 2 shows the workstations and their respective probability distributions.

Table 2 - Workstations and their probability distributions

Workstations	Probability distributions	Workstations	Probability distributions
WS 01	Normal (11.18, 70.14)	WS 06	Normal (11.79, 77.20)
WS 02	Normal (8.29, 61.33)	WS 07	Normal (2.68, 39.66)
WS 03	Normal (5.18, 50.97)	WS 08	Normal (15.07, 178.54)
WS 04	Normal (4.41, 86.02)	WS 09	Normal (7.77, 93.95)
WS 05	Normal (31.05, 215.16)	WS 10	Triangular (16, 19, 17)

4.2 Implementation

Based on the validated conceptual model and the probability distributions of each process, the Hybrid Simulation Model (HSM) was constructed using AnyLogic® software. Figure 5 shows the first part of the HSM.

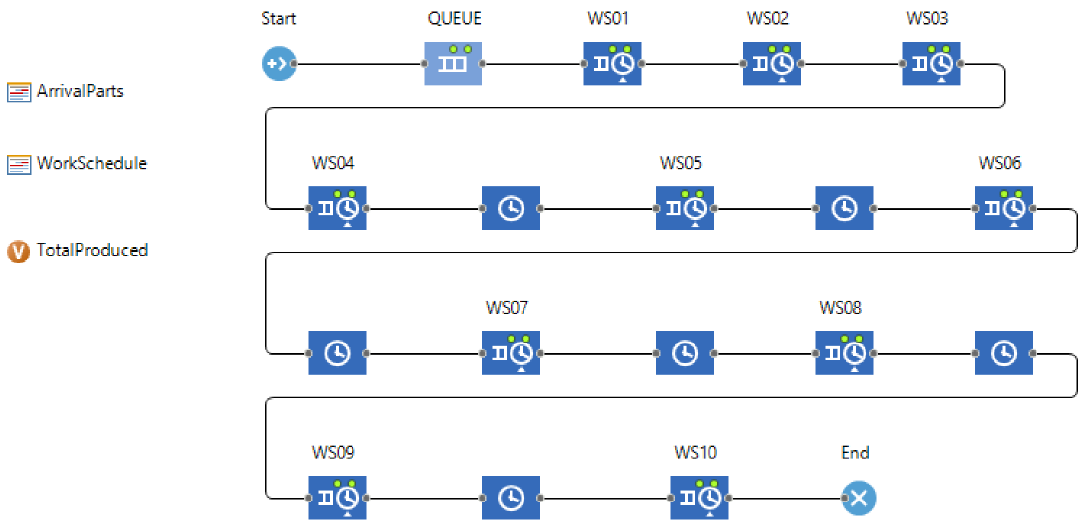

Figure 5 - The first part of the HSM

In the first part of the HSM, two schedules and one variable were considered. The “ArrivalParts” schedule represents the rate of arriving parts per hour. The “WorkSchedule”

schedule defines the entry and exit times of the operators. The “TotalProduced” variable shows the number of parts produced by the operators.

In the second part of the HSM are the fourteen operators of the assembly line. The agents that are connected to the resource pools and the workstations represent the fourteen operators. Figure 6 shows the second part of the HSM.

Figure 6 - The second part of the HSM

The third and last part of the HSM is shown in Figure 7, which represents the state diagram of the agent and its variable, parameters and schedules.

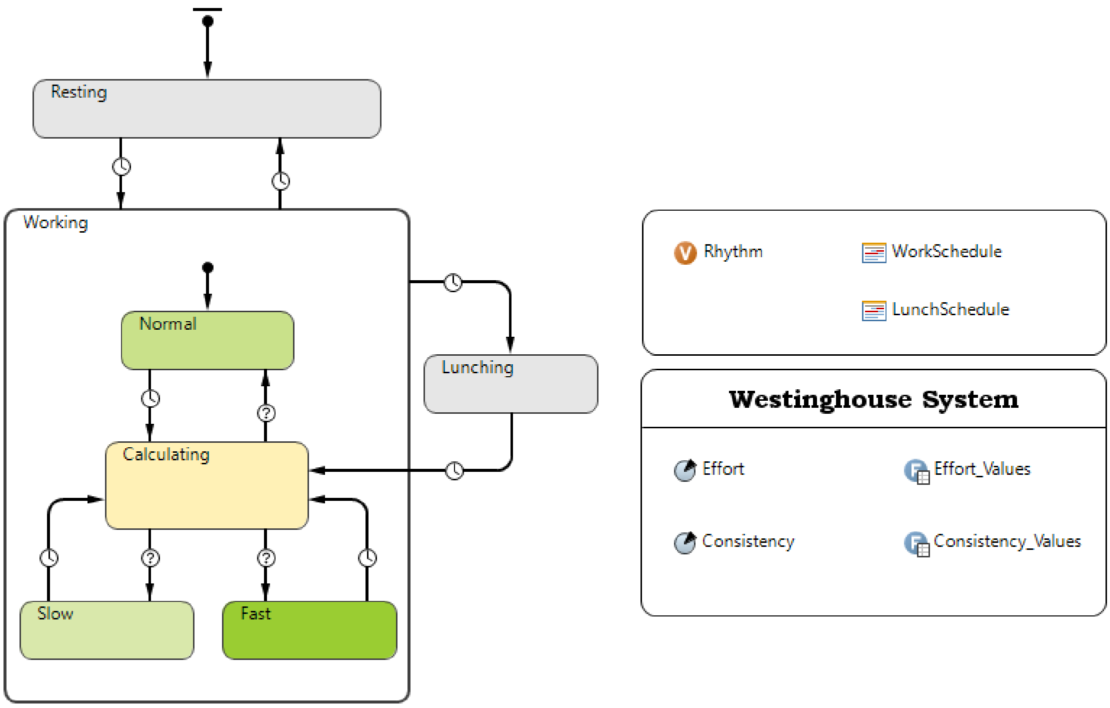

Figure 7 - The third part of the HSM

Based on the variables and parameters that influence the logic of the transitions that connect the seven states, the agent changes its rhythm of work during the simulation. The "Rhythm" variable interferes with the probability distribution of the workstation where the agent is. The value of the "Rhythm" variable is calculated when the agent changes its rhythm state.

Once the computational model is constructed, the second step of the implementation phase is the verification of the computational models. The HSM was verified by comparing its logic with the validated conceptual model logic. After this comparison, the debugger built model that Anylogic® software offers to find structural and logical errors was performed. .

After verification, the HSM went to the third step of the implementation phase, which is the validation of the computational model. Within the context of an objective approach proposed by Sargent (2013), the data generated by HSM were compared with the real data through statistical tests.

The statistical tests used in this paper were Normality Test, Outlier Test, and Two-Sample t for Mean. It is important to say that the level of significance (α) adopted was 0.05. The results of these statistical tests are in Table 3.

Table 3 - Results of statistical tests

STATISTICAL TESTS	Null hypothesis	Alternative hypothesis	P-VALUE
Normality Test	Data follow a normal distribution	Data do not follow a normal distribution	0.89
Outlier Test	All values in the sample are from the same, normally distributed population.	One of the values in the sample is not from the same, normally distributed population.	0.78
Two-Sample t for Mean	The sample mean of the Real Data is not different from the sample mean of the HSM data	The sample mean of the Real Data is different from the sample mean of the HSM data	0.93

The results of the statistical tests prove that the data generated by HSM is close to the real data. Thus, there is no evidence to reject the null hypotheses of the tests. In conclusion, the HSM is validated.

4.3. Analysis

After the conception and implementation phases, the analysis phase began. In this phase, the defined experiment consisted of comparing the results from HSM and Discrete Simulation Model (DSM) with Real Data. In DSM, operators are represented as simple production resources and their dynamic behavior will not be considered. The intention of this experiment is to verify if there are significantly differences between the results from the two simulation models.

Before performing the experiment, DSM was constructed using AnyLogic® software. Then, DSM was also verified by comparing its logic with the validated conceptual model logic. DSM validation occurs through three statistical tests. Therefore, adopting 0.05 of level of significance (α), the following statistical tests were applied to DSM: Normality Test, Outlier Test, and Two-Sample t for Mean. Table 4 shows the results of statistical tests.

Table 4 - Results of statistical tests

STATISTICAL TESTS	Null hypothesis	Alternative hypothesis	P-VALUE
Normality Test	Data follow a normal distribution	Data do not follow a normal distribution	0.42
Outlier Test	All values in the sample are from the same, normally distributed population.	One of the values in the sample is not from the same, normally distributed population.	0.73
Two-Sample t for Mean	The sample mean of the Real Data is not different from the sample mean of the HSM data	The sample mean of the Real Data is different from the sample mean of the HSM data	0.66

Since both models were validated, the execution of the experiment started. With reference to the thirty real data on the assembly line production, thirty replications were performed from the HSM and the DSM. In order to analyze the insertion of human characteristics inherent to operators in HSM, a boxplot was performed to examine the center and spread of all samples data.

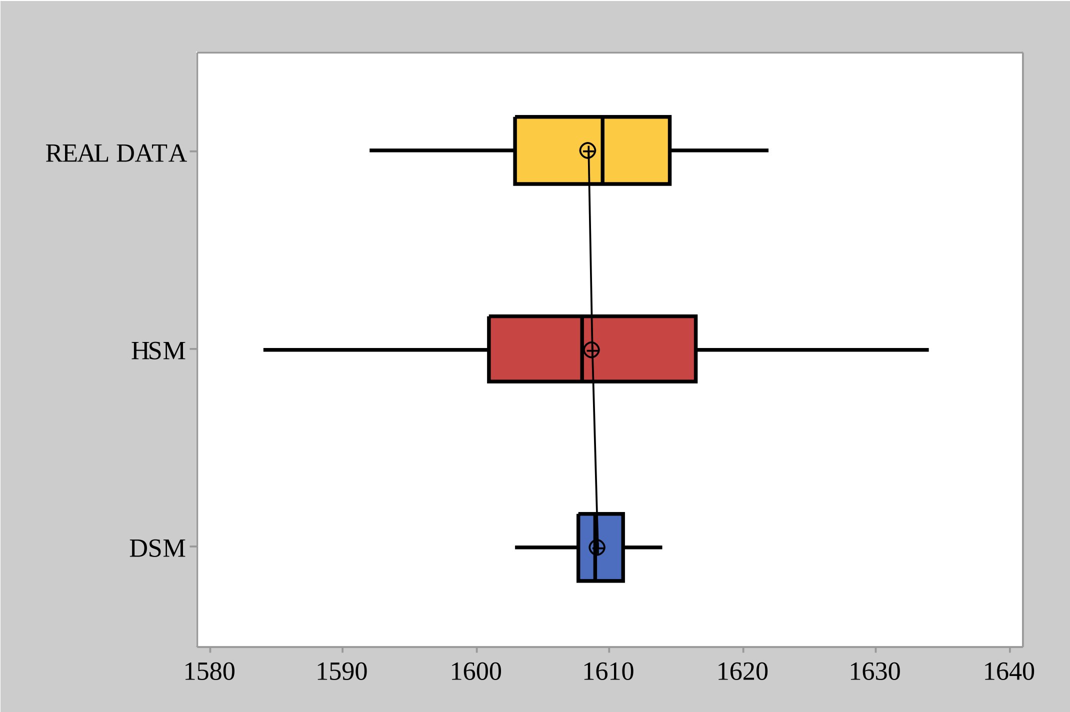

Figure 8 - Comparison between Real Data, HSM, and DSM

The comparison between the samples demonstrates that the variability of the model's results is different. In the DSM, the results have the lowest variability. This fact is due to the non-insertion of the work rhythm of the operators in the model and the small standard deviation of the probability distributions of each workstations. However, in the HSM, the insertion of the work rhythm increased the variability of the results.

5. Conclusion

The high degree of manual labor and the occurrence of changes at different moments of time are inherent characteristics of the chosen manufacturing system. In this context, it was possible to combine the concepts that encompass the human work rhythm, the Discrete Event Simulation (DES) and the Agent-Based Simulation (ABS). The combination of ABS with DES occurred when the agents were added to the model. In this case, the state diagram developed based on the ODD Protocol was essential to build the logic of agents.

Despite the difficulty in detecting and describing the logical structures that govern human behavior, the modeling of the fourteen operators inserted in the assembly line was based on the Westinghouse System of Rating. This concept focuses on the change in the work rhythm of each operator, considering the values of the factors of effort and consistency. Thus, in the hybrid model, the work rhythm of the operators changed at each random hour during the simulation based on the values of the Westinghouse System of Rating.

Based on the statistical tests, the sample mean of the models are not statistically different from the sample mean of the real data. There is a considerable difference in the variation of the HSM data with the variation of the DSM data. This difference demonstrates that the variability of the model's results increases when human characteristics are added.

Finally, for future work it is suggested the inclusion of other factors in the computational model that influence human actions. Besides, human characteristics involving decision-making processes can also be considered to improve the behavior of the agents. Another suggestion is to model and simulate similar assembly line and compare the variability of the model's results.

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