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HYBRID SIMULATION OF PRODUCTION PROCESS OF *PUPUNHA* PALM

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ABSTRACT

This work simulated some alternatives of dynamic allocation of additional human resources in a company that produces various products from *Pupunha* palm. Its goal was to increase the average amount of trays produced per day in this line through a hybrid application of discrete event and agent-based simulation. Two different decision-making forms were proposed to find out which workstation should have received an additional operator. The first proposal was made on the level of occupancy of the operators, while the second one was made on the queue size. The computational model was operationally validated by comparing its results with the actual production data of the company. Twelve scenarios were analyzed using the established financial index. Based on the occupancy rate, the ratio improved on the average 27.68%, with an additional operator, while applying the second criterion this improvement was 117.41%.

1 INTRODUCTION

Constantly, companies are seeking improvements in their own processes, so they can increase their productivity and, therefore, their profits. Within this need, the simulation is a tool that replicates the real system and it is used to analyze and improve the procedures intended to be simulated and evaluated (Montevechi et al. 2007). This technique has been increasingly used by organizations of various sectors and segments such as manufacturing, logistics, and services, among others (Sandenayake et al. 2008).

Considering the development of a simulation model, it is necessary to analyze what one modeler wants to simulate, so it will coincide with the real system. This model should be developed keeping in mind the goals or some specific applications, and the validation of the model has to relate with them. It can be very expensive and take a long time to achieve a validation fully reliable. Therefore, tests and experiments are performed until they reach a sufficient level of confidence (Sargent 2011).

According to Montevechi et al. (2012), the discrete event simulation (DES) has been one of the most widely applied techniques that analyze the complex problems in the industrial environment, as it allows the creation of multiple scenarios and its results lead the organization to a better decision-making. Before any application and implementation, the simulation aims to understand the whole behavior and performance of the real system, thereby reducing the unnecessary costs and making it a great advantage.

Although the discrete event simulation is quite comprehensive, some systems are very complex, and hence, the traditional tools have not been sufficient to analyze them (North and Macal 2007). Considering this aspect of analyzing some systems and according to Bonabeau (2002), the agent-based modeling and simulation (ABMS) is a technique recently applied to capture the emergent phenomena, which are results from the interaction of independent entities. The interaction of independent organisms by definition cannot be reduced to parts of the system because of the interaction among them. As stated by Sanchez and Lucas (2002), the agents also interact with their local environment through the simple internal rules for the decision-making, the movement and the action processes. The overall behavior of the simulated system is the result of a dense interaction between the relatively simple behaviors of the agents.

The objective of this study was the proposal of some decision making alternatives to support the dynamic allocation of additional resources i.e. the operators, that could increase the average amount of daily *Pupunha* palm trays produced in a specific line, through the use of hybrid simulation (DES + ABMS). The hybrid simulation was able to cover the discrete and behavioral aspects of this work. These proposals were made to a company that produces a variety of products derived from the *Pupunha* palm. To fulfill the objective of this work, two forms of the decision-making process were analyzed. The first manner showed which workstation should have received an additional employee in accordance to the level of occupancy, while the second alternative took into consideration the size of the queue.

This work is divided into these seven parts: theoretical foundation of the main topics, research methodology, modeling and simulation method application, results, conclusion, acknowledgements and references.

2 THEORETICAL FOUNDATION

2.1 The Company

By the end of the 90s, Brazil was considered the worlds' leading producer, exporter and consumer of the heart of the palm. However, the indiscriminate extraction of *Euterpe edulis* palm (*Juçara* palm) resulted in the shortage of the *Juçara* palm, and that shortage aroused the interest of commercial cultivation of *Pupunha* palm without spikes for industrial production. Those types of technically managed cultivation of *Pupunha* palm (*Bactris gasipaes Kunth*) gained importance in the Brazilian economic scenario due to their characteristics when compared to other species of palms, such as earliness, rusticity and vigor. The increased demand and good profitability of the *Pupunha* palm drew the attention of farmers, thus justifying the choice of the company for this work.

This company has in its production of *Pupunha* palm a mix of the following types: *Tolete*, Chopped, Lasagna, Spaghetti, and Carpaccio trays. The modeling and simulation of their production line involve the manufacture of the new products such as *Banda*, Round Sliced and *Tolete* jars. The establishment of the company originated its own activity, cultivation and extraction of *Pupunha* palm. In 2013, it started a project in which the concern was beyond cultivation and secured the quality of the product.

2.2 Discrete Event Simulation

Simulation has been, for many decades, one of the most popular techniques to support the decision making process (Luban 2005). According to Albright and Winston (2007), the discrete event simulation (DES) is defined as a representation of an item or event, whose main objective is to simulate a system through a computer model. This computer model supports the decision-making process, the make up of experiments, and the analysis of the alternatives before implementing them in the real system. The simulation model must be verified and validated through various tests, evaluations and comparisons with the real system being studied (Sargent 2011).

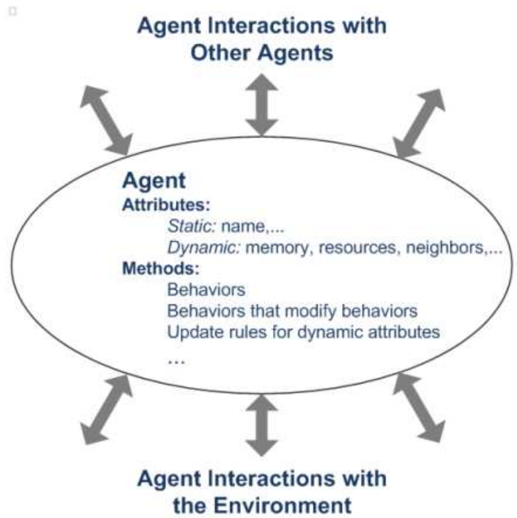
Several authors report the advantages of simulation, including, being: (a) the analysis of complex manufacturing systems combined with more effective cost; (b) the benefit of the design of realistic models to represent important features of the system, and to perform complex interactions among the different variables; (c) the simulation models are able to directly address the measures of performances used in the real system; (d) and finally the visual output assists in the development and the validation of the computational model (O'Kane, Spenceley and Taylor 2000; Banks et al. 2005).

2.3 Agent-based Simulation

The agent-based modeling and simulation (ABMS) has its historical roots in the study of complex adaptive systems (CAS), which were originally motivated by researches on adaptation and emergence of biological systems. In addition to learning over time to respond effectively to the new situations, one of the key features of a complex adaptive system is its ability to adapt to a changing environment (North and Macal 2007).

For Bonabeau (2002), the ABMS is more an attitude than a technology. This perception aims to describe a system from the perspective of its constituent units. Colier and Ozik (2013) stated that the ABMS is a method for calculating the potential consequences, at the system level, of groups of individuals' behavior. It also allows modelers to specify the rules of individual behavior for each agent; it describes the circumstances or the topology in which the individuals act; and, then, it executes the rules to determine possible outcomes at the system level.

According to Macal and North (2013), for the practical purposes of modeling, it is considered that the agents have certain properties and attributes (Figure 1), such as: (i) Modularity, where the agent has its limits easily determined either if something (state element of the model) is part of the agents, it is not part of them or it has a common feature among them; (ii) Autonomy, i.e. agents can act independently in their environment and interact with other agents according to the situations of interest that arise from the model; (iii) Sociability, wherein the agent interacts with other agents to conquer space, to recognize another agent, and to communicate, among other examples; (iv) Conditionality, where the agents' status varies over time.



Source: Macal and North (2013).

Figure 1: A typical agent.

When the ABMS is applied to the human systems, Bonabeau (2002) summarizes that the interactions between the agents are complex, nonlinear, discontinuous or discrete, the spaces of the agents are crucial and the agents' positions are not fixed. Since the population is heterogeneous, so are its interactions and the agents show some complex behaviors like learning and adaptation.

2.4 Related Researches

The hybrid modeling and simulation has been presented in a few and more recent articles. Hao and Shen (2008) mention that the hybrid approach was used to implement the simulation of the system of material handling, by combining a discrete event and an agent-based modeling. Using the AnyLogic™ software, agent-based models were built for a number of components (mobile or fixed) in a discrete event model of a simplified pulled production line with a kanban system (Hao and Shen 2008).

Wang et al. (2013) used two dynamic systems, named DES and ABM (agent-based modeling) to describe the model of a car supply chain from two manufacturers. The software used was also the Anylogic™, whereby the model of simulation of this entire chain was examined. To prove the effectiveness of this model were used the inventory of results, the inventory of distributors' cost, and the customer satisfaction.

According to Suh (2014), the agent-based simulation (ABS) provides freedom in the description of a large number of suppliers, warehouses, distributors and customers at the level of a physical person. It complements the traditional discrete event simulation, in which those tasks are more difficult to be performed. Another similar examples of this supply chain models can be seen in Endrerud, Liyanage and Keseric (2014), Onggo (2014), Flynn et al. (2014), Graunke et al. (2014) and Long and Zhang (2014).

3 RESEARCH METHODOLOGY

Bertrand and Fransoo (2002) cite that the research methodology of modeling and simulation is based on the quantitative models and on the assumption that one can build objective models. These models explain the behaviors of the real operational processes, or they capture a part of the problems of the decision-making process faced by managers during these procedures.

This work used a sequence of phases in a simulation project proposed by Montevechi et al. (2010). According to it, a simulation project is divided into three phases, and each one has a model itself: the conception phase (conceptual model), the implementation phase (computer model), and the analysis phase (operational model).

The conception, which is the first phase, presents its main task as the choice of a process mapping technique, because this decision is usually left out and in which an adequate importance is not given in simulation projects, which may result in a great risk of unnecessary rework. The conceptual model aids the data collection, thus indicating the information to be collected and speeding up the computational model development. This phase is extremely significant, but often it does not receive the necessary attention from modelers**.** In this phase are also defined the purpose or application, the scope, and the level of detail that will be adopted (Pereira et al. 2013) in the model. When the conceptual model is verified and validated, the modeler should move to the implementation phase.

During this phase, the modeler (professional, manager, supervisor, etc) should choose a software, and then transform the conceptual model into a computational one, which also needs to be verified and validated (Pereira et al. 2013). In the last phase, the computer model should be submitted to the variations and several experiments, which will result in the creations of new scenarios and replicas, so that the responses can be analyzed and compared with the actual system (Montevechi et al. 2007). This phase is very important for managers and analysts, because at this moment the various analyses begin to obtain consistent results, and to lead to a better decision.

4 APPLICATION OF THE MODELING AND SIMULATION METHOD

According to the sequence of steps described in the research methodology, the first stage of the work was the conception phase, where the conceptual model of the *Pupunha* palm production system was developed. The model supported the data collection, as it indicated the points wherein the data should be collected, which facilitated the construction of the computational model. The mapping technique used in this phase is called IDEF-SIM and it was implemented on the software DIA™ and detailed as follows.

The process begins with the arrival of "Palmetto *in natura*" (i.e. fresh palm) entity, in a daily amount of 1,000 units**.** In this system there are: 11 different locations (Thinning 02 and 03, Cut, Sanitation, Cooling, Chopping, Packing, Salting Wait, Filling, Cooking, and Quarantine); six resources (Operators Op1 to Op6); and 15 other entities (Palmetto, Whole *Tolete,* Whole Heart, *Tolete*, *Banda,* Round Slice, Heart, trays of *Tolete*, Chopped, Lasagna, Spaghetti, Carpaccio and jars of *Banda*, *Tolete* and Round Slice).

After the process begins, the "Palmetto *in natura*" (i.e. fresh palm) entity follows through the first cut, Thinning 02, and uses operators Op1 and Op2 as resources, resulting in a new entity, Palmetto. This goes to the second and third cuts, Thinning 03 and Cut, respectively, following two new entities Whole *Tolete* and Whole Heart. The first, Whole *Tolete*, goes to the Cut location with the use of operator Op5, and it will result in another two new entities named *Banda* and *Tolete*. The second (Whole Heart), also moves to its respective location, the Cut, using the Op6, and it will produce Round Slice and Heart entities. *Banda* and Round Slice entities follow to the Salting wait location. The Heart entity, a batch of 200 units, goes to the locations Sanitation and Cooling, where Op6 prepares it for another location, Chopping. Here, the Op4 cuts the heart entity in four new ones (16.64% Chopped, 27.91% Lasagna, 38.63% Spaghetti and 16.81% Carpaccio). These new entities follow to Packing (operator Op6) in lots of four units, which will result in the new products called Chopped, Lasagna, Spaghetti and Carpaccio trays.

The *Tolete* entity, a batch of 800 units, passes through the Sanitation and Cooling locations, using the operator Op5. After that, 20% of it goes to Salting wait and 80% for Packing (Op5), which originates the new entity *Tolete* tray with four units each. The 20% of *Tolete* entity continues to the Filling location (operators Op4 and Op5). This location prepares the jars of *Banda* (200 units), *Tolete* (20 units) and Round Slice (100 units) products (new entities). These products end their process in lots of 70 jars, in Cooking, Cooling and Quarantine locations.

After the construction of the conceptual model, the same is validated through the Face-to-Face technique by presenting it to the company's consultant. The data were acquired through the filming and the chrono analysis, by marking the lead-time manufacturing process. The times of each location are presented in the table 1. The values fixed by the consultant show nearly automatic behavior, and, thus, it was decided by the authors to use the standard time.

Table 1: Location times for the simulation.

Location	Time
Thinning 02	Normal (52.004; 6.264) seconds
Thinning 03	Normal (24.454; 2.806) seconds
Cut	Normal (27.033; 2.773) seconds
Tolete Cut	Normal (14.525; 1.516) seconds
Heart Cut	Normal (14.525; 1.516) seconds
Sanitation	30 minutes
Salting	20 minutes
Drying	15 minutes
Chopping	30 seconds
Packing	Normal (65.303; 2.937) seconds
Tolete Packing	Normal (50.849; 2.483) seconds

Filling	3 minutes
Cooling	30 minutes
Quarantine	13 days

Then, the computer model was constructed by the authors using the software AnyLogic® 7.0.3. The use of this software enabled the use of the hybrid model (which means discrete events and agent-based). The validation of the computational model was performed through the two-sample-t statistical technique on the software Minitab 16®, by comparing the actual data of number of trays produced per day with the simulated data, and, then, its assessment, with a confidence level of 95%, if they are statistically different.

Later, a financial index was used, compared to a daily profit and explained by the equation (1). This index will serve as a comparison indicator to evaluate the financial viability of the scenarios.

$$\sum_{i=1}^{n} SPu - \sum_{i=1}^{n} VCu - O * 3795.68 \tag{1}$$

Where n is the number of produced trays; SPu is the selling price of a unit; VCu is the variable cost of a unit and O is the amount of additional operators.

The value of $ 3,795.68 corresponds to the expense of 62 days for each additional operator, and it is proportional to the simulation period. The values of the sales revenues and the variable costs are expressed in table 2.

Table 2: Sales revenues and variable costs for each type of tray.

Tray	SPu	VCu
Carpaccio	3.33	1.16
Tolete	6.40	4.06
Spaghetti	3.33	1.16
Lasagna	3.33	1.16
Chopped	3.33	1.28

4.1 Decision Process

The contribution of ABMS is simulating the decision-making process of a hypothetical manager who will supervise the occupancy level of the operators, as well as the queue size in each workstation. The manager's decision, according to the operators' occupancy level, is represented by a flowchart in the figure 2. The operators, who are available, are represented by OpX, where X goes from 1 to 6.

The other logical decision, considering the size of intermediate inventory, is shown by the flowchart in figure 3.

Note that the process makes a cyclical check every 10 minutes to verify the occupancy level or the size of the intermediate inventory for each OpX. This verification interval will be changed to one hour if and when there is at least the need for one additional operator.

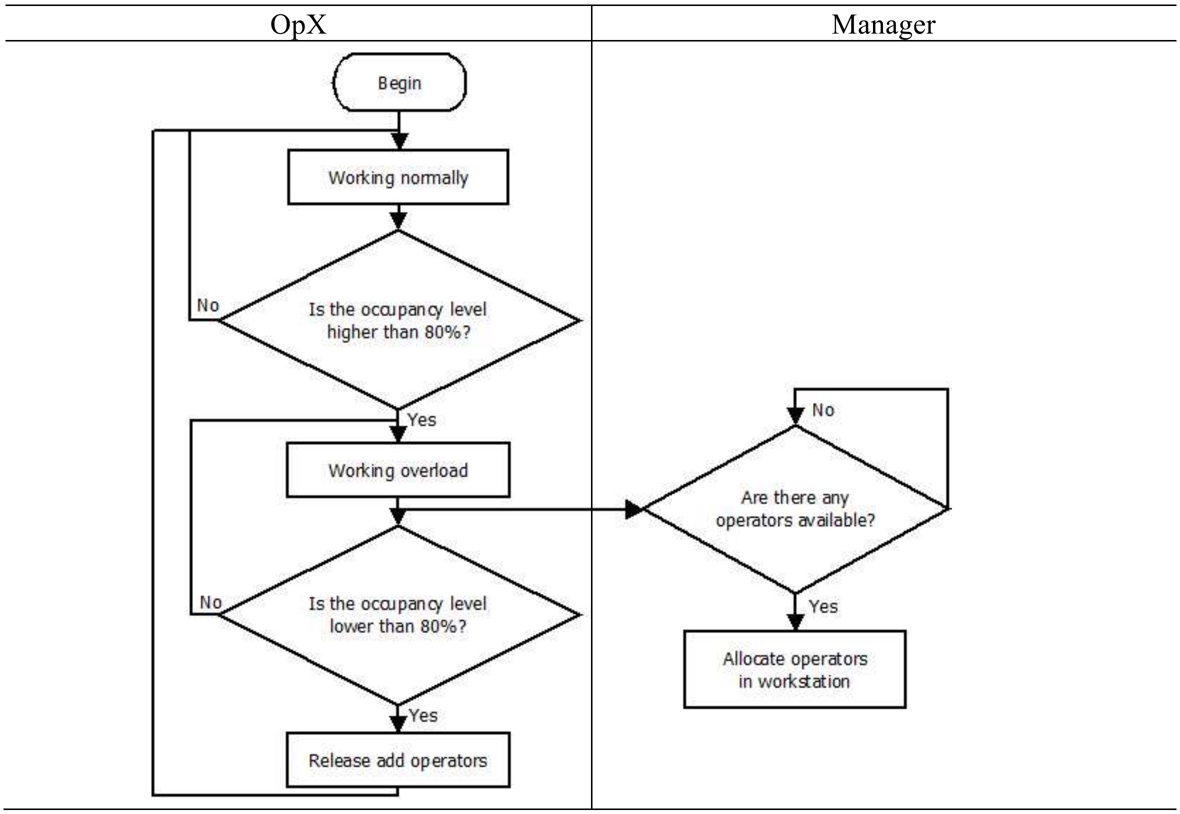


Figure 2: Decision process for the operators' occupancy level.

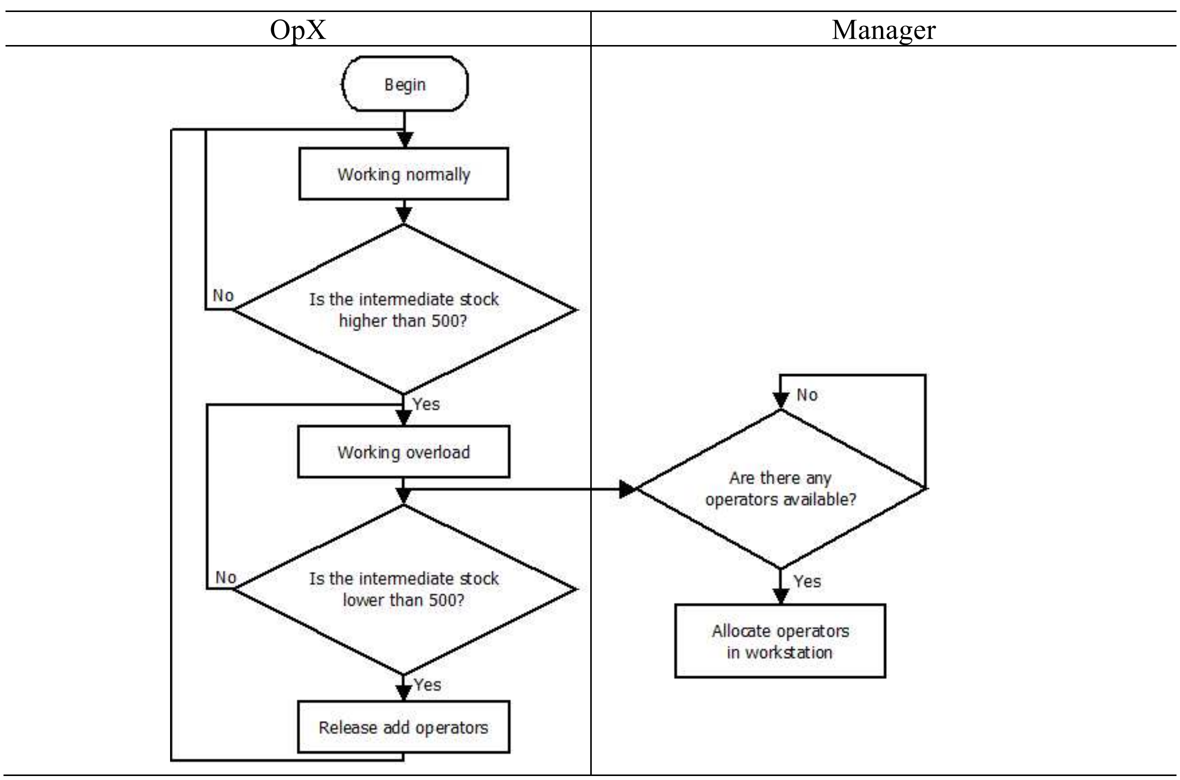


Figure 3: Decision process for intermediate inventory size.

5 RESULTS

The first hypothesis evaluated was observing if the model could be validated, that is, whether there was a statistical match between the simulation model and the actual data. The P-value of the two-sample-t test was equal to 0.968. Thus, with a confidence level of 95%, the model was considered valid.

5.1 General Result

Then, 12 simulation experiments were performed in each decision-making process, based on the occupancy levels and the intermediate inventory sizes, and considering 0, 1, 2, 3, 4 and 5 additional operators. Fifty replicates were executed for each experiment. Figures 5.1 and 5.2 show the boxplot graphics of the resulted financial index.

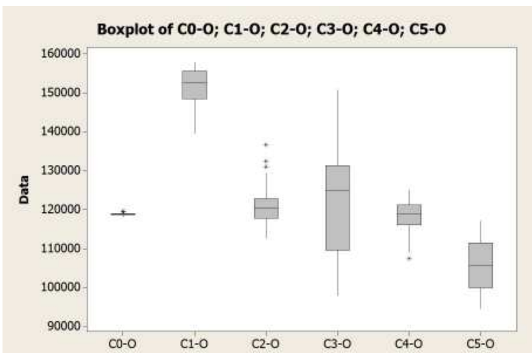


Figure 4: Decision by occupancy level.

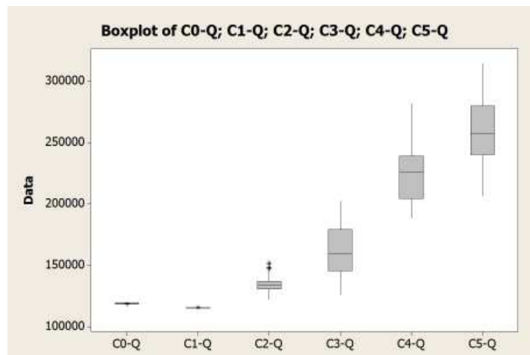


Figure 5: Decision by inventory size.

Here, two distinct situations are observed (figures 4 and 5). The first graphic, where the decision criterion is based on the workstation occupancy level, shows that there is no visual and statistical evidences of an improvement on the financial index with the addition of auxiliary operators. The second graphic has the two-sample-t test showing that the addition of one, two or three operators increases the value of the financial index. The test also displayed that the inclusion of only one operator is better than the other two options. The financial index increased from \$ 118,846 to \$ 151,745 on average. A practical explanation for these results is that the more operators available, the lower the occupancy level of a workstation. There were cases in spite of the low occupancy level of the workstation, the additional operator remained idle for a period of one hour. Moreover, the use of decision-making process through inventory size is physically more feasible than the occupancy rate.

Different from figure 4, on figure 5 one can see that, by changing the manager’s decision model when there is an increase of additional operators, the financial index tends to follow this increase. Statistically, the two-sample-t showed that only in the situation where there was an addition of only one operator, there was no improvement in the financial index. And, among the remaining situations, the inclusion of 5 additional operators was the best fit. On average, the financial index increased from \$ 118,846 to \$ 258,394.

5.2 Comparisons Between the Number of Additional Operators

In this section, the analysis and the comparisons of the simulation results were performed by considering an incremental inclusion of the additional operators. Consequently, the five scenarios, which are shown below, represent the inclusion of 1 to 5 additional operators, according to the logic of the decision adopted. A further analysis of the cases, without including additional operator, was not made, as they were shown statistically equal.

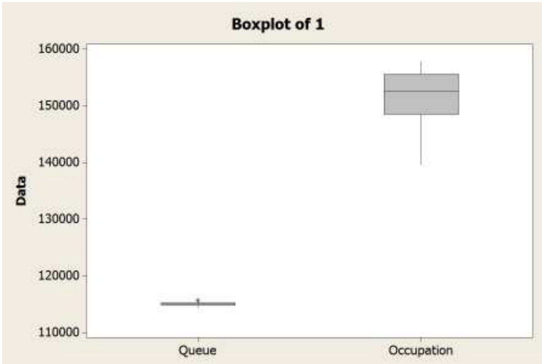


Figure 6: One additional operator.

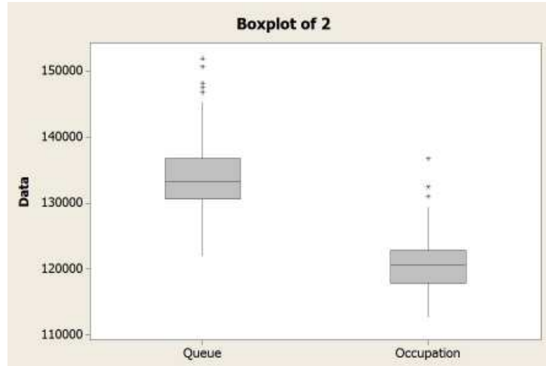


Figure 7: Two additional operators.

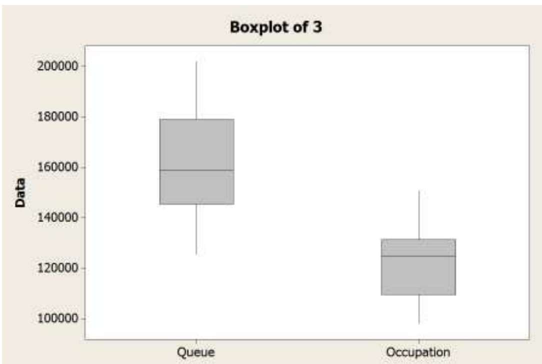


Figure 8: Three additional operators.

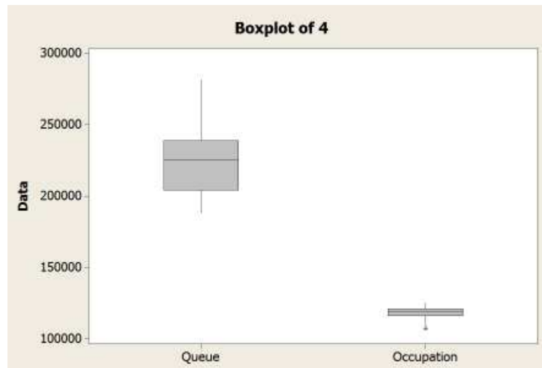


Figure 9: Four additional operators.

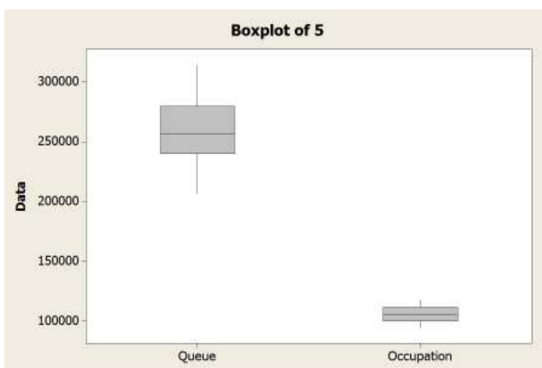


Figure 10: Five additional operators.

All P-values resulting from this analysis were zero, which means that, statistically, each interval of comparison showed different values according to the logic of the decision taken. Therefore, if the company manager chooses to use the decision criteria of the workstation occupancy level, it is recommended the inclusion of only one additional operator. This was the best option since, when adopted the criterion of the intermediate inventory size, the model did not result in any advantage without an additional operator.

If there is the possibility of hiring some extra operators, it is recommended that the rule of the decision is the insertion of the additional worker when the station has an inventory size bigger than 500 units.

6 CONCLUSIONS

As experienced in this work, it is a proven fact that when the agent-based simulation is used, both in the pure or in the hybrid form with other simulations (discrete event and/or dynamic), it provides an increase of computational ability to mimic some natural behaviors such as human work. But, because it is a relatively new tool, ABS requires further investigation. Furthermore, a formalization is also necessary due to the scarce number of academic papers that address this human aspect.

When working at the food industry, it is necessary an efficient process of production because of the necessary quality in this kind of product. This company has an intensive manual labor with a few mechanization steps. With these characteristics of the process, two scenarios were created where the number of operators was increased gradually since that was a need for more operators due to the exceeded occupancy rate or the total inventory between the workstations.

The conducted hybrid simulation (discrete events and agent-based) examined two proposals for increasing the average daily production by changing the number of additional resources. The conclusion reached was the consideration of only one additional operator based on the rule of the occupancy level. And the second option was to adopt the size rule of the intermediate inventory.

This second option is, on average, the best rule to be considered, because it provides the biggest increase in the financial index, which is 117.41%. On the other hand, this option would require a great investment by the company, once it would be necessary the hiring of five additional operators. Another fact that should be taken into account is that, in this work, the focus was considering that all products would be sold.

As a final point, it is worth highlighting that working with the human aspects involves more knowledge than just logical, analytical, and computational conditions. It is also noticeable that the aspects that were left out, such as psychological, cultural, among others, directly affect the productivity of the company's employees.

It is suggested that, for future work, the use of optimization to find out the set of optimal values for the following parameters: the number of additional operators, the maximum occupancy level, and the maximum amount of intermediate inventory. Moreover, one human should simulate other manager's decision-making alternatives, including a hybrid one between the both considered in this work. Also, is expected the use of more formal decision-making tools such as the reinforcement learning, the game theory, the multi-criteria and others. Lastly, it is important to represent the operators as intelligent agents capable of making independent decisions during the course of the process.

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