MODELING AND SIMULATION OF A CUTTING LINE IN A REFRIGERATOR FOR LINE CONTROL USING FLEXSIM

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ABSTRACT

The meatpacking industry faces challenges in modernizing its processes due to the complexity and prevalence of manual methods. Discrete event simulation, particularly with FlexSim, emerges as a solution for modeling and analyzing such processes. The developed study utilized FlexSim to create a comprehensive model, incorporating variables such as process time, sanitary restrictions, and operator fatigue. The model demonstrated high accuracy, with an average error of only 9% compared to actual production, making it a powerful tool for process analysis and improvement. The simulation identified idle operators and proposed a strategic reallocation, resulting in a significant increase of 26.45% in the production rate of 5kg packages, without the need for additional resources. These results demonstrate the potential of modeling and simulation to optimize production management in meatpacking plants, promoting resource optimization, data-driven decisions, and driving efficiency and competitiveness in the sector.

keywords: Discrete event simulation, Flexsim, Poultry processing, Production Management, Perishable goods.
Paper topics: PO in industry, Simulation, computational intelligence

RESUMO

A indústria frigorífica enfrenta desafios na modernização de seus processos devido à complexidade e predominância de métodos manuais. A simulação de eventos discretos, particularmente com o FlexSim, emerge como solução para modelar e analisar tais processos. O estudo desenvolvido utilizou o FlexSim para criar um modelo abrangente, incorporando variáveis como tempo de processo, restrições sanitárias e fadiga dos operadores. O modelo demonstrou alta precisão, com erro médio de apenas 9% em relação à produção real, tornando-se uma ferramenta poderosa para análise e aprimoramento de processos. A simulação identificou operadores ociosos e propôs uma realocação estratégica, resultando em um aumento significativo de 26,45% na taxa de produção de pacotes de 5kg, sem a necessidade de novos recursos. Esses resultados demonstram

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o potencial da modelagem e simulação para otimizar a gestão da produção em frigoríficos, promovendo a otimização de recursos, decisões baseadas em dados e impulsionando a eficiência e competitividade do setor.

Palavras chaves: Simulação de eventos discretos, Flexsim, Processamento de aves, Gerenciamento de Produção, Bens perecíveis.

Tópicos: Simulação: PO na indústria, Simulação, inteligência computacional

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1. Introduction

The meatpacking industry faces significant challenges in terms of line control and production scheduling due to the perishable nature of products, predominantly manual processes, and the complexity of procedures involved. This study aims to address this industry through a discrete event simulation (DES) model, which will allow the organization to test scenario changes and optimize its production processes without the need for implementation on the actual production line [Ross, 2013].

As mentioned, one of the main problems in the food industry is the perishability of products. In addition to predetermined production, allocation, and logistics rules, it is essential to consider specific restrictions such as expiration date, deterioration, temperature, and proximity to contaminated products [Ketzenberg et al., 2018; Liu et al., 2018]. Each type of product has unique characteristics, making it unfeasible to apply a global production rule that covers all operations, requiring operator intervention in specific cases or adapted rules to meet production demand.

It is a challenge for the organization to reconcile the rapid market movement with the perishability of products. In the case study, a poultry slaughterhouse, a chilled product cannot spend more than two days from slaughter to shipment to the end customer, however, this end customer has very variable demands that are passed on daily to the slaughterhouse, which needs to adapt to rapid variations in customer demand.

According to [Ferreira et al., 2018], when dealing with perishable products, the deterioration factor becomes an aggravating factor for production planning and control (PPC) due to the shelf life of products. Each industrial plant deals with a specific variety of products, each with its own sanitary and perishability requirements, which results in unique operating characteristics for each system. Due to these particularities, standard production rules are unable to cover all the necessary restrictions. Therefore, it is essential to develop specific decision rules that meet the individual restrictions of products, ensuring efficient and safe operation.

Production planning and control (PPC) is a vital function in any organization that involves the coordination and optimization of production processes to ensure efficiency and effectiveness of production. PPC aims to ensure that products are produced according to demand, within the established deadline, with the required quality and using available resources in an optimized manner [Slack et al., 2010; Stadtler et al., 2015]. In the case study, this is the organization's biggest challenge: how to plan the production of a product whose demand changes daily and varies at the same time that the product is manufactured?

To answer this question, this research aims to apply a simulation model for production planning and control in a slaughterhouse, motivated by financial and efficiency losses due to inadequate scheduling and unnecessary movements in empirical tests based on supervisor experience. Using modeling and simulation, the study seeks to describe the production system, identify problems, and assist in decision-making.

2. Problem Description

As mentioned above, the problem in question is to plan and control the operation in a poultry slaughterhouse. The operation of a poultry slaughterhouse involves several rigorously controlled steps to ensure the quality and safety of products. The process begins with the reception of live poultry, followed by the slaughter and cleaning of the poultry. Next, the poultry goes to the cutting room, where the poultry is classified to be sold whole or in parts depending on the weight of the poultry and the production demand for each type of product.

Cuts are also made according to market specifications, including filleting and boning. The pieces are then rapidly chilled to maintain perishability, packaged and stored in cold rooms until distribution. The entire process is carried out in accordance with several sanitary regulations to prevent contamination and ensure product quality. Figure 1 shows a simplified flowchart of this process

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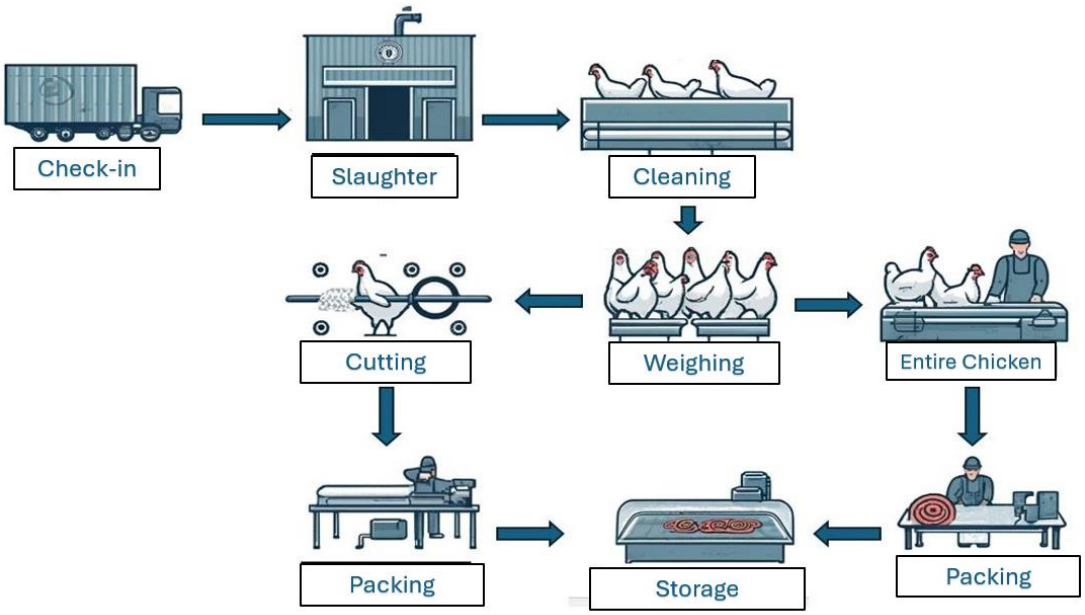


FIGURE 1: Flowchart of the production process of a slaughterhouse (Source: this research)

In the specific case of the slaughterhouse in question, the cuts are subdivided into 4 assembly lines: wing cuts, leg cuts, breast cuts and breast fillet cuts. The scope of this work included the simulation of all cutting lines and whole chicken assembly lines. However, for the purposes of this article, we will detail the simulation of the process with the greatest variability: the chicken wing line. This is because a wing can be sold whole, as half a wing (drumstick) and wing tip, and the cutting line needs to be adjusted for each type of product to be packaged. In addition, the process also involves 3 package sizes, which can be sold in trays, 5kg packages and bulk as raw material for restaurants and the factory itself in other sectors, such as the sale of seasoned products.

The wing line has 4 production configurations: whole wing producing trays and 5kg packages, half wing and tip producing trays in both, half wing and tip producing trays and 5kg packages (and vice versa). This line has 12 operators, who are reallocated from their functions depending on which production configuration the line is running. To simplify the analysis in this article, we will consider the case where the production line is manufacturing the half wing and the tip, where 6 operators are responsible for assembling the half wing tray, 2 operators are responsible for assembling 5kg packages, one operator responsible for weighing 5kg packages, one operator for stapling 5kg packages, one operator responsible for the packer and a line supervisor.

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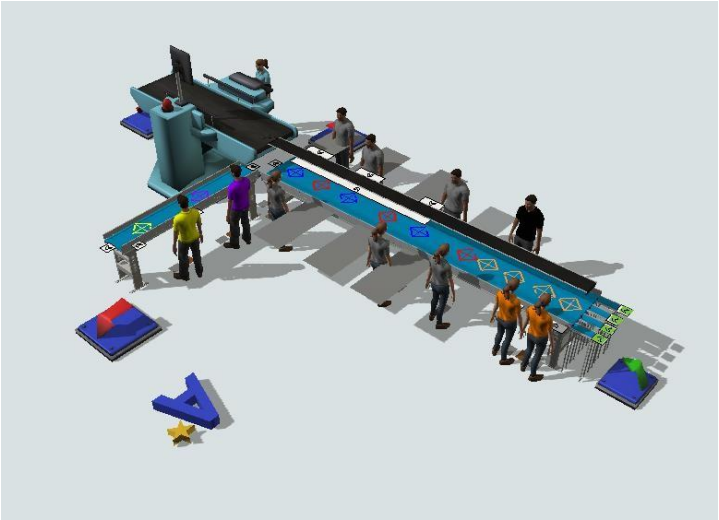


FIGURE 2: Layout of the cutting line (Source: this research)

3. Theoretical Foundation and Literature Review

3.1 Discrete Event Simulation

Simulation is the experimentation of a real system through models. Simulation is a powerful tool in terms of developing more efficient systems [Birta & Arbez, 2013; Ross, 2013]. Because they are very complex, some systems cannot be interrupted, or even there are no analytical methods capable of modeling them.

The simulation of a probabilistic model requires the generation of the stochastic mechanisms of the model to then observe its resulting flow over time [Ross, 2013]. However, according to [Albrecht, 2010], it is not always easy to determine a logical structure that represents the interactions of physical entities. In this context, discrete event simulation (DES) is a methodology that uses mathematical models that basically analyze the behavior of the model at each instant in time that a change in its current state occurs [Albrecht, 2010; Huseby & Natvig, 2013].

The applications of a simulation model, according to [Dos Santos et al., 2015], are quite diverse, ranging from manufacturing, logistics and service models to simulations of complex processes such as fluid transport in a refinery. The process of developing a simulation model can improve the solution to the problem in a collaborative manner, among the various parts of an organization [Ross, 2013]. Simulation can promote communication between these parties, allowing those involved to better visualize the results of their ideas and the impact that decisions have on the organization's objectives and the work of others involved [Avdekins & Savrasovs, 2019; Burinskienė et al., 2018; van Geest et al., 2022].

The use of simulation software such as FlexSim, AnyLogic, Plant Simulation, etc. is becoming increasingly common in solving problems that are impossible to solve analytically, as can be seen in the works of [Dong & Wang, 2017; Pawlewski & Hoffa, 2015; Qian & Sun, 2013; Wang & Chen, 2016; Zhang & Tian, 2017; Zhu et al., 2014]. As in the cited works, this article uses discrete simulation to solve production problems.

3.2 Production Planning and Control in Perishable Systems

Production planning and control (PPC) is a critical area for the operational efficiency of any industry, but it takes on an even more vital role in perishable product industries. In these environments, the nature of the products imposes additional restrictions, such as the need for rigorous time control and storage conditions, to avoid significant losses and ensure the final quality of the product. [Martelli & Dandaro, 2015; Tortorelli et al., 2022]

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According to [Slack et al., 2010], the central objective of PPC is to ensure that production takes place efficiently, with optimal use of available resources, to meet customer needs in a timely manner. In the context of the target industry of this work, the perishable product industry, production management presents unique challenges. The rapid deterioration of products requires rigorous control of production and storage conditions, such as temperature and humidity.

According to [Ketzenberg, Gaukler and Salin 2018], demand for perishable products can be highly variable due to seasonal factors and consumer preferences, requiring flexible scheduling and a control system capable of quickly adjusting production operations. Furthermore, food safety is a paramount concern, requiring rigorous control processes and frequent audits to prevent contamination that could lead to costly recalls and reputational damage [Satiti & Rusdiansyah, 2018].

[Mirabelli & Solina, 2022] provide a major literature review on optimization strategies in perishable product supply chains. [Gioia et al., 2023] explore the management of perishable product stocks, such as fresh foods, using linear discrete choice models. The study uses simulation to optimize order rules and maximize long-term profit, taking into account variability in supply, demand and product quality, as well as seasonal factors and consumer behavior, which is very similar to the objective of this project. [de Keizer et al., 2017; Ketzenberg et al., 2018; Satiti & Rusdiansyah, 2018, 2018] also contributed significantly to the literature on optimization models for supply chains using simulation.

As with several of the aforementioned works, this article uses discrete event simulation through models developed in FlexSim software to optimize the processes of a perishable product production line. In this work, the main focus is to balance production lines in order to optimize the time spent on the chicken wing assembly line in a slaughterhouse.

4. Methodology

This applied research, of an explanatory nature and with data of a predominantly quantitative nature, has as its main focus the application of a simulation model in a perishable product production system. This research aims to create a simulation model that is capable of generating improvement scenarios that can balance and optimize the separation and packaging process of a slaughterhouse cutting line.

To this end, this work uses the experimentation methodology for discrete simulation presented in [Slack et al., 2010]. First, what is called the Conceptual Model was created, in which the entire process is described and simulated based on observations of the logic and restrictions of the production process. Subsequently, a time study was conducted on the activities to ensure that, statistically, the collected data is faithful to the actual operation.

According to [Montgomery & Runger, 2014], the number of measurements to be collected depends directly on the variability of the measurements, the desired precision (ε) and the level of confidence (α). The method used for the quantity of measured cycles needed was verified according to the following formula defined by [Barnes, 2009], in order to guarantee 95% certainty (α) that the real time is ε% more or less than the average value obtained in the time measurements [Montgomery & Runger, 2014].

$$N = \left(\frac{TS}{\mathcal{E}\bar{x}}\right)^2$$

Where:

$N =$ Minimum number of cycles to be timed;

$S =$ Sample standard deviation of the collected timings;

$\mathcal{E} =$ Precision, i.e., the permissible variation of the actual average time in relation to the average obtained in the sample, with the desired confidence.

$T =$ Number obtained from the t-Student distribution table with N-1 degrees of freedom in the 0.025 column (single tail, equivalent to 0.05 with double tail; since the confidence of 95% was chosen).

$\bar{x} =$ Sample Average

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In this work, all the data from the wing line activities was collected, which underwent a goodness-of-fit test in FlexSim's ExpertFit to identify which probability distribution best fit the data. It is important to emphasize that all probability distributions were approved in three goodness-of-fit tests: Anderson-Darling, Kolmogorov-Smirnov and Chi-Square [Montgomery & Runger, 2014] and the distribution that best fit the collected data was chosen. Due to data confidentiality and because it is very sensitive to production information, it was decided not to describe which distributions and which parameters were found in the goodness-of-fit tests.

5. Simulation Model

This work chose FlexSim as the tool for discrete modeling and simulation. The main reason for this choice was the fact that the simulator has a powerful tool for modeling complex process flows: process flow. As already mentioned, the problem in question deals with several manual activities, subject to various rules and sanitary restrictions, as well as thermal pauses, change of function depending on the scenario, etc.

In this context, discrete event simulation (DES) is a methodology that uses mathematical models that basically analyze the behavior of the model at each instant in time that a change in its current state occurs [Albrecht, 2010; Huseby & Natvig, 2013]. The use of simulation software such as FlexSim is highly recommended in solving problems that are impossible to solve analytically, such as the case study.

As shown previously in figure 2, the model was made for the entire cutting room, but with a focus on the chicken wing separation and assembly line of the target industry in this work. For modeling, in addition to the 3D model in FlexSim, it was also necessary for each operator to have their process flow simulated exactly like their activities on the line that vary according to the configuration of the line. To simulate this process flow, 12 specific process flows were created, linked to the 3D model, which will define the operator's action according to the scenario being run, as can be seen in figure 3.

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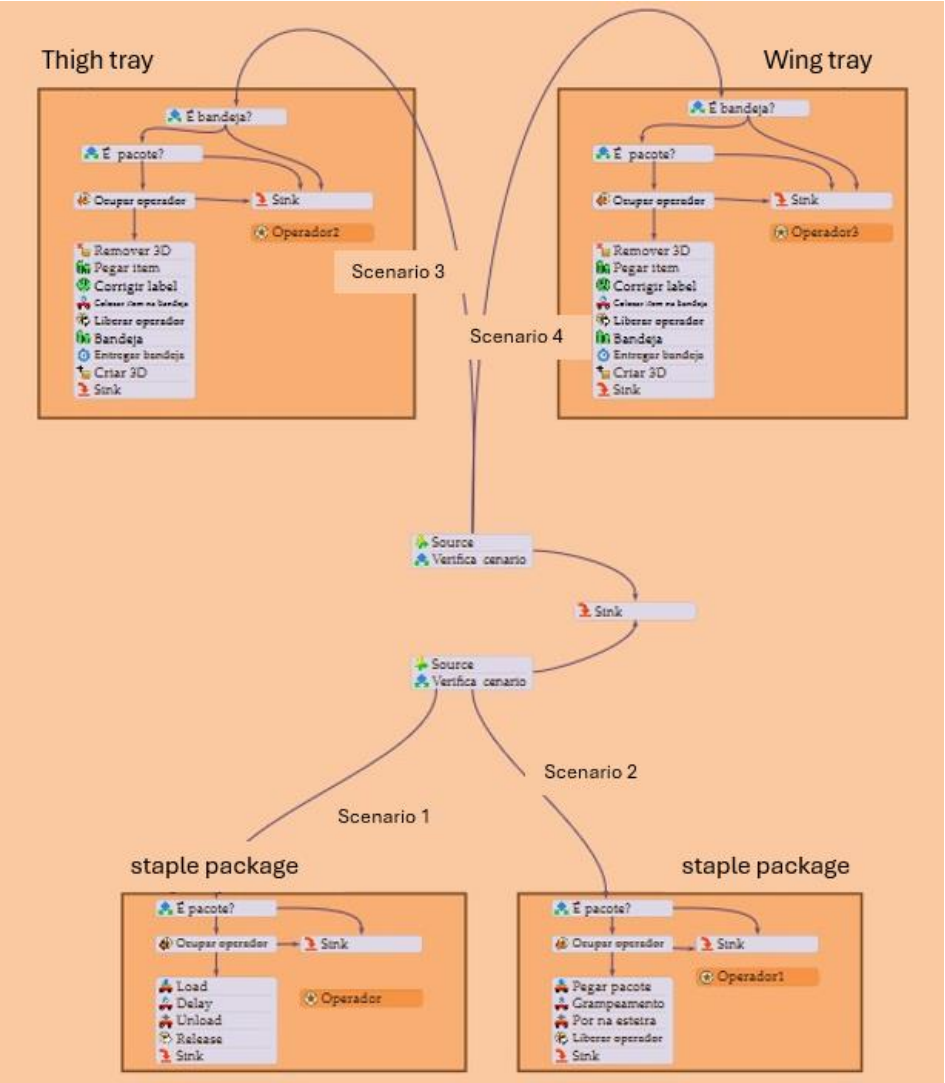


FIGURE 3: Modeling in Process Flow for the flow of activities of an operator

With the 3D model made, and the models in Process Flow linked for each operator, the model can finally go to the validation stage. This is the main stage of a simulation modeling, if not validated, the model is useless to the organization. To perform validation, data was collected on different days, in which a comparative analysis was made between the model results and the processor results.

In the validation stage, it was found that it would be necessary to use correction factors to simulate operator fatigue during the day. Since this is a manual process, it is to be expected that operators will be more tired at the end of the shift than at the beginning. To simulate this fatigue, this work created correction variables that act as weights for the process times, i.e., the simulation can use ergonomics studies and the factory's own productivity as input to correct the variations in operator fatigue.

Upon performing validation, it was found that for the scenario shown in this study, the model has an average error of 9% compared to real production. Given that this is a purely manual job, this error is at a very acceptable level for the operation, so it can be validated as an analysis tool for changes in the process. Since the model corresponds to the actual operation, it is now possible to perform tests in the simulation that provide relevant analysis regarding changes in the actual operation.

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5.1 Analysis of Simulation Model Results

For the wing line process, it is rare for a configuration to run for more than an hour without needing the line to perform a setup for a configuration change. For example, an operator may be performing an activity of assembling a whole chicken wing tray and, when the line changes, he may change his activity to assemble a 5kg package of the half wing, for example.

In order to try to understand how the process can be revised so that the execution of a scenario is carried out with greater utilization of its operators, it was sought to evaluate the status of the executors to understand which ones are idle and which ones are free, and then reallocate their activities in a way that increases the production of products using the same amount of resources.

We observed 1 hour of simulation of scenario 1, we saw that operators 1 and 2 are always busy, operators 3, 4, 5, 9, 10, 11 are also always busy, but they show a value of idleness due to the consideration of 3 minutes for changing a half wing box.

However, operators 6, responsible for the package weighing activity in scenario 1, and operator 7, responsible for package stapling in the scenario, show idleness, explained by the waiting time to assemble a 5kg package, so this same scenario was tested using only 1 operator to weigh and staple the packages instead of two operators with separate activities. Figure 4 shows the initial status of the operators before the modification of their respective activities.

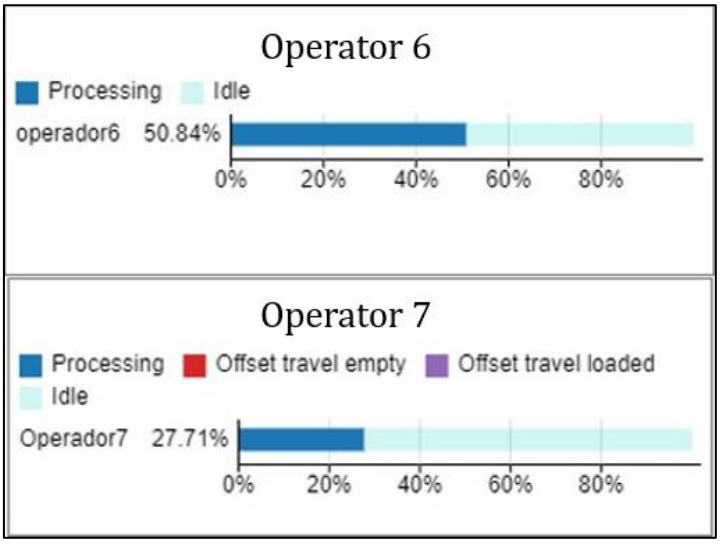


FIGURE 4: Status of idle operators 6 and 7

After making an adaptation in the process flow that is executed by operator 6, we made the operator perform the two activities in sequence, weigh and staple the 5kg package. We performed some simulations to verify if the absence of operator 7 could impact the production line in any way. The simulations indicated that the production of packages was not impacted, in addition to operator 6, even now with 2 activities, was still idle, indicated in figure 5, after an increase of 52.3% in his activity time.

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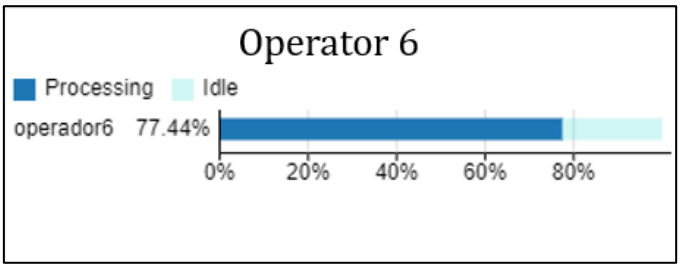


FIGURE 5: Status of operator 6 with 2 activities and 2 assemblers

After the success of the first tests, we now seek to reinsert operator 7, this time with a new function, we decided to allocate him to the activity of assembling 5kg packages, going from 2 assemblers to 3 assemblers and check if a single person weighing and stapling would be able to support this configuration. Some necessary adaptations were made to the process flow of operator 7, it was also considered for these tests that the arrival rate of products is sufficient to meet the work pace of 3 assemblers simultaneously.

Thus, we performed new simulation tests, and surprisingly it was observed that operator 6 is able to absorb the arrival of packages with 3 assemblers, a scenario shown in figure 6. In addition, due to the presence of a new packer on the simulation line, an increase of 26.45% in the package production rate was also observed in the tested time interval, shown in the figure.

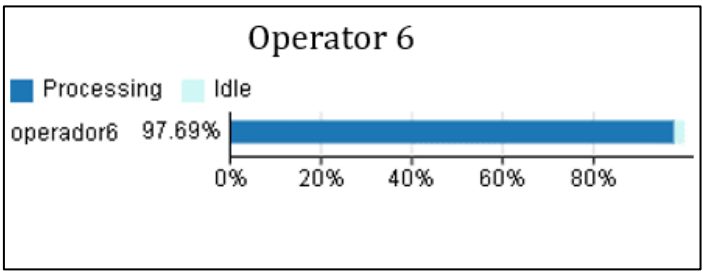


FIGURE 6: Status of operator 6 with 2 activities and 3 assemblers

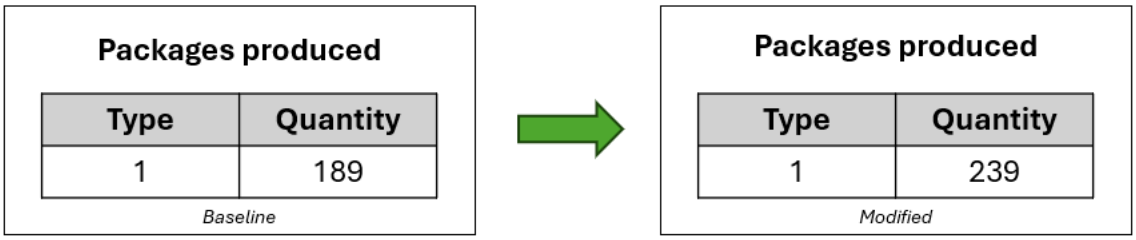


FIGURE 7: Status of operator 6 with 2 activities

The results of the tests carried out by reallocating the operators' activities on the production line demonstrated a significant gain in terms of efficiency and utilization of available human resources. By identifying idle operators and strategically redistributing their tasks, it was possible to increase product production without the need to acquire new resources or increase installed capacity. This approach of optimizing existing manpower proved to be an effective solution to maximize the productivity of the slaughterhouse's cutting line, highlighting the potential of modeling and simulation to promote operational improvements without major additional investments.

Conclusions

Upon concluding this study of modeling and simulation of a cutting line in a slaughterhouse, it is possible to highlight several significant contributions. First, the application of

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simulation allowed a detailed and dynamic analysis of the separation and packaging process of perishable products, providing insights into the actual operation and identifying potential areas for improvement. The ability to simulate different scenarios and configurations of the production line allowed for a comprehensive evaluation of the system's performance, assisting in strategic decision-making and optimization of available resources.

Furthermore, the validation of the simulation model, which presented an average error of 9% compared to real production, demonstrated the effectiveness and accuracy of the approach adopted. This level of accuracy is considered acceptable for manual operations, highlighting the usefulness of simulation as an analysis and planning tool. The incorporation of correction factors to simulate operator fatigue throughout the day also highlighted the importance of detailed and realistic modeling to capture operational and behavioral nuances that impact process efficiency.

Finally, the results obtained in this study reinforce the importance of modeling and simulation as powerful tools to improve production management in complex environments, such as slaughterhouses. The ability to forecast scenarios, test hypotheses, and evaluate operational performance virtually before practical implementation is essential to promote innovation, efficiency and competitiveness in the sector. Therefore, the integration of simulation modeling in production planning and control can generate significant benefits in terms of efficiency, quality and data-driven decision-making.

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