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Enhancing efficiency in the food industry: a simulation model for optimizing production processes

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Abstract

The food industry, characterized by its inherent dynamism and complexity, constantly facing numerous challenges. Simulation emerges as an indispensable tool for enhancing production processes, optimizing resource allocation, and facilitating informed decision-making. Simulation models play a pivotal role in pinpointing bottlenecks, augmenting productivity, cost reduction, and waste minimization. Particularly within the food industry, simulation is instrumental in achieving enhanced production efficiency and mitigating resource wastage. Although simulation models are strong in several industrial sectors, a lack of simulation models on food production systems has been identified. This paper presents a focused case study of an automated potato production system, providing a comprehensive overview of the system and its production processes. A simulation-based approach utilizing Tecnomatix Plant Simulation is employed to define an optimized configuration. An experimental project is undertaken to assess the plant's performance, and through the utilization of Analysis of Variance, the authors discovered the optimal configuration for the industrial system. The results underscore the tangible benefits derived from a specific and improved production system configuration, resulting in an overall enhancement of industrial performance.

Keywords: Modeling and Simulation, Food Industry, Tecnomatix Plant Simulation, Bottleneck Analysis, What if Analysis

1. Introduction

The food industry is a complex and dynamic sector that involves various processes, systems, and stakeholders. For this reason, simulation models play a vital role. In recent years simulation has been considered as a key decision-making tool in various streams of sciences. More realistic virtual models of manufactured products are essential to bridge the gap between design and manufacturing and to mirror the real and virtual worlds. Today, modeling and simulation are standard processes in system development, e.g. to support design tasks or to validate system properties. In this sense, simulation merges the physical and virtual worlds in all life cycle phases. Siderska (2016) in her study simulates discrete events and creates digital models of logistic systems, optimizing the operation of production plants, production lines, as well as individual logistics processes.
Feng e Gao (2019) proposed two logistics solutions for an automatic plant factory using Tecnomatix Plant Simulation to compare all the possible improvements before asses the system into operations. Furthermore, Hovanec et al. (2015), due to the increasing pressure on the efficiency of logistics and transport operations, provide a practical application of the Plant Simulation software. The problem of bottlenecks is a key issue in

optimizing and increasing the efficiency of manufacturing processes. In this sense, a lot of authors analyze the issue. Kikolski (2016) shows the possibility of using a computer simulation as a method for analyzing problems connected with limiting the production capacity. Simulation models capture the interdependencies and interactions between different components and enable analysts and decision-makers to explore different what-if scenarios, evaluate strategies, and assess the potential impact of changes, allowing stakeholders to analyze and understand the behavior of the food industry without the necessity for costly physical experimentation.

The simulation also helps to diagnose and predict potential problems in supply chains that will improve food quality and reduce food loss. In this sense, Cai et al. (2022) present a smart cold chain logistics simulation model with IoT technology to enhance the product refrigeration supply chain. Moreover, Kliment et al. (2020) present a study focused on evaluating production efficiency and enriching product quality using simulation techniques. By using simulation models, the food industry can address numerous challenges and opportunities. Koulouris et al. (2021) discuss the potential benefits of implementing a digital modeling approach to a food process. Parthanadee et al., (2010) demonstrate the effectiveness of the simulation and analysis approach to support the decision-making process in the production scheduling of fruit products. G.A.J. van der Vorst et al. (2009) use simulation software to conduct their experimentation in the case of a food supply chain to embed food quality models and sustainability indicators in discrete event simulation models. Companies can optimize production processes by simulating and analyzing factors such as equipment utilization, material flow, and labor efficiency. Simulation models also aid in managing the food supply chain effectively, identifying and mitigating bottlenecks, optimizing inventory levels, and improving transportation logistics. They enable stakeholders to gain valuable insights, optimize operations, reduce costs, enhance product quality, and make informed decisions. Moreover, simulation models contribute to sustainability efforts by reducing waste, improving resource allocation, and optimizing energy consumption. Industry 4.0 has recognized Digital Twin (DT) as the game changer for manufacturing industries in their digital transformation journey according to Jones D. et al. (2020). Nowadays DT models are becoming popular in various industries as simulation environments or as digital representations within the virtual environment. Because of that Liu et al. (2021) analyze in-depth DT literature from the perspective of concepts, technologies, and industrial applications. Singh et al. (2021) intend to consolidate the different types of DT and different definitions of DT throughout the literature for easy identification. Modeling DT is a complex task because it requires using information from real-world phenomena that are incorporated into digital representations. The work of Martinez et al. (2021) represents a step toward the creation of a Digital Twin of a manufacturing process. In the food industry, DT can revolutionize various aspects of the supply chain and production processes. Zhou et al. (2015) present a simulation model designed to improve the efficiency of machinery operations in a potato production system to optimize operations, enhance productivity, and minimize resource waste. The food processing sector is expected to embrace Industry 4.0 progressively. Hence Hasnan et al. (2018) make a review about all the enabling technologies applied to the food processing field. The management of perishable food inventory demands special attention and for this reason, Melesse et al. (2022) create a digital twin to anticipate future events. Simulation transforms the food industry through virtual experimentation, optimization, and streamlined operations. Despite the strong presence of simulation models in different industrial sectors, the authors have identified a lack of simulation applications and studies in the food sector. In particular, a gap in the study of food manufacturing systems' behavior and the related statistical approach has been identified. To fill this gap, the authors present a practical case study solution involving an automated potato production line. The objective of this research involves creating a simulation model able to investigate potential production enhancements achieved through what-if analysis. Moreover, the simulation model has been developed to provide the company with a decision-making support tool to explore strategies and scenarios, all while avoiding the costs and risks associated with real-world experimentation. Furthermore, the researchers developed the model to identify and reduce waste in manufacturing processes. Simulating production lines, enables the identification of bottlenecks, inefficiencies, and material waste areas, leading to potential process improvements and resource-saving strategies. To support this study, a Discrete Event Simulation environment, Tecnomatix Plant Simulation, has been utilized. The remainder of the paper is structured as follows. Section 2 presents the description of the production line; Section 3 discusses the simulation model; Section 4 the experimentation. After that, Section 5 regards Results and Discussion and finally, Section 6 the conclusions.

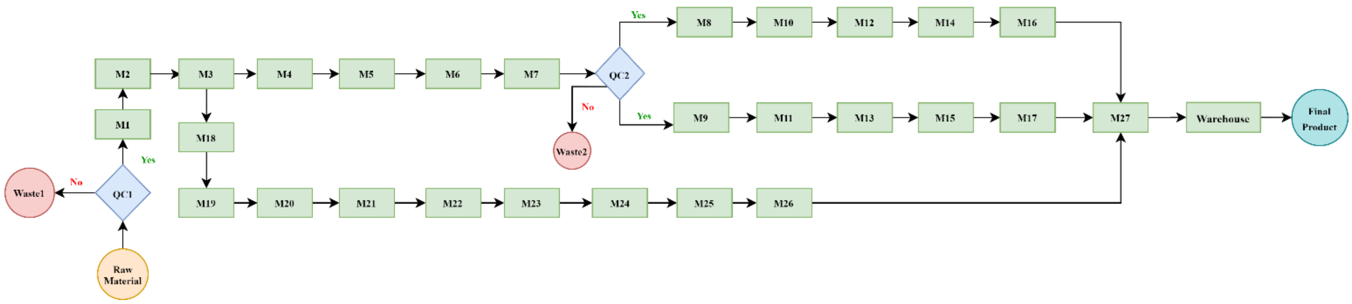

Figure 1. Flow chart – Conceptual model

Table 1. Flow chart legenda

Machine	Name
M1	Washing1
M2	Peeling
M3	Slicing
M4	Washing2
M5	Drying
M6	Frying
M7	Deoiling
M8	Flavouring Tomato
M9	Flavouring Classic
M10	Portioner Tomato
M11	Portioner Classic
M12	Portioner Tomato
M13	Portioner Classic
M14	Metal Detection
M15	Metal Detection
M16	Tomato Pack
M17	Classic Pack
M18	Blanching
M19	Drying FF
M20	Frying FF
M21	Pre Cooling
M22	Freezing
M23	Portioner FF
M24	Packaging FF
M25	Metal Detection
M26	French Pack
M27	Labeling

2. Case study

This paper presents a practical application of a potato production system. This work focuses on the production of two different products: frozen french fries and potato chips in bags. Modeling and simulating a potato production line can help to analyze and optimize various aspects of the production process, such as throughput, efficiency, resource utilization, energy consumption and employment level. The production process of potato chips involves several steps from selecting the right potatoes to packaging the final product. The flow chart used to explain the conceptual model is shown in *Figure 1* and *Table 1*. The first step concerns quality control in which there's a 3% rejection rate according to the potato size.

The potatoes are thoroughly washed, peeled and then sliced. From this point, the manufacturing process continues with two separate lines. The production process of frozen french fries involves several steps, from potato selection to freezing the final product in the proper warehouse. Then the partially french fries are cooled to room temperature to stop the cooking process and remove excess oil, and after that, a deep-freezing process proceeds in a few minutes. Once frozen, the french fries are packaged in bags of 1kg. The line of classic and tomato chips, on the other hand, continues with a second washing stage to reduce the amount of starch and ensure a crispier finished product. After blanching, the potato slices are dried to remove excess moisture. This step is crucial as it prevents the chips from becoming soggy during frying. Once the chips are fried, they undergo visual inspection to remove any defective or broken chips and subsequently, they may be seasoned with various flavors, in this example salt and tomato. To facilitate the transportation and storage of potato chips, it is usually necessary to use a portioner. So, the final product is sorted in 125 g small packs. This includes monitoring and testing the raw potatoes, conducting quality checks during processing, and inspecting the final product with quality control through a metal detector to check the presence of any foreign part inside the single package.

The objective of the case study is to arrive, through a simulation model, at an optimized configuration of the production process. The authors aim to streamline and enhance the production process by minimizing both processing time and energy consumption in the manufacturing system's machinery.

3. Simulation Model

The manufacturing process (*Figure 2*) is modeled with the simulation software Tecnomatix Plant Simulation software developed by Siemens (further information on Plant Simulation can be found at www.sw.siemens.com). Parallel station objects have been used to reproduce automated machining processes, ensuring greater speed. Assembly station or dismantle station objects to define manual processes with operator use, or processes that require assembly or subdivision of the Mobile Units (MUs) of the production line. In addition, there are conveyor-type objects to have a fast and efficient movement of the parts and have a continuous process.

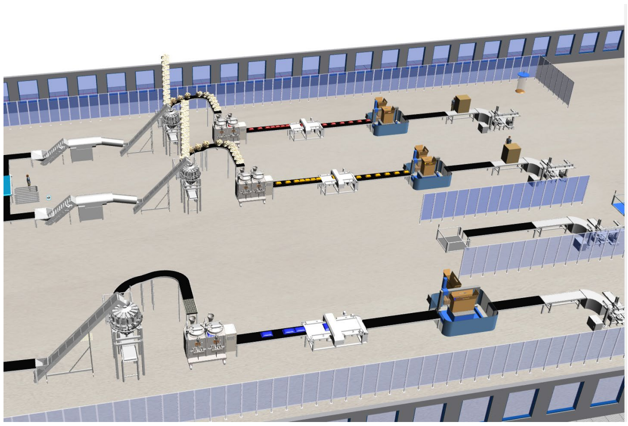

Figure 2. 3D packaging line of the system

After each quality control machine (QC1, QC2), there are drain-type objects in which the processing waste that does not pass the quality control ends. In the production line, operators are employed on the machines where quality control is carried out and in the packaging phase. The number of operators present in the packaging phase varies between 1 and 3 depending on how many packaging machines are active. Finally, there is a warehouse where the final products are stored, destined for sale. In the model, the processing time and the energy consumption of each station are taken from different Excel files as input data. The imported capacity machine data are listed in the following *Table 2*. The set-up time of each station is equal to zero.

Table 2. Capacity of machines

Machine	Capacity[kg/h]
QC1	400
Washing1	1000
Peeling	800
Slicing	250
Washing2	1000
Drying	800
Frying	700
Deoiling	1000
QC2	700
Flavoring	700
Portioner	350
Packaging	350
Metal Detection	350
Blanching	700
Drying FF	1000
Pre-Cooling	700
Freezing	700
Portioner FF	400
Packaging FF	400
Metal Detection	200

Also, raw materials demand planning data comes from an Excel file and is daily generated via the generator object. Also, thanks to the implementation of the generator, the delivery table inserted in the source helps to daily recall each method.

The annual production is equal to 104950 bags per chip and 50000 packs of French fries. The production mix is made as follows: 40,38 % classic chips, 40,38 % tomato chips and 19,24 % french fries. The analysis has been conducted during two work shifts (6:00–14:00; and 14:00-22:00). The calculation of flow time starts when the MU leaves the first buffer and it ends when the MU enters the store. As a result of the first modeling (with higher processing time than the other configuration) statistics of resources (Figure 3) and energy consumption (Figure 4) come out.

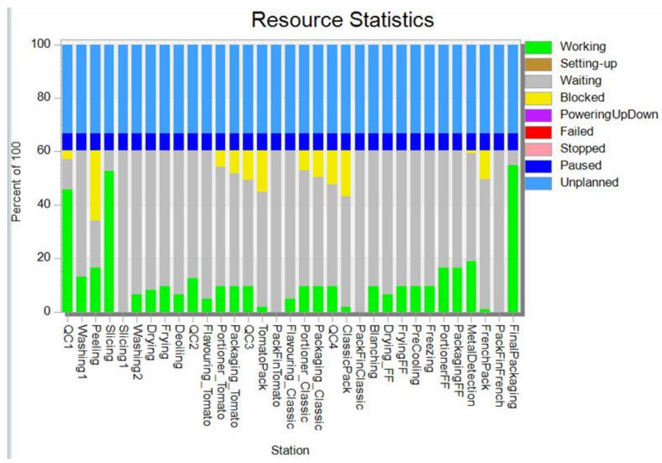

Figure 3. Statistics of resources

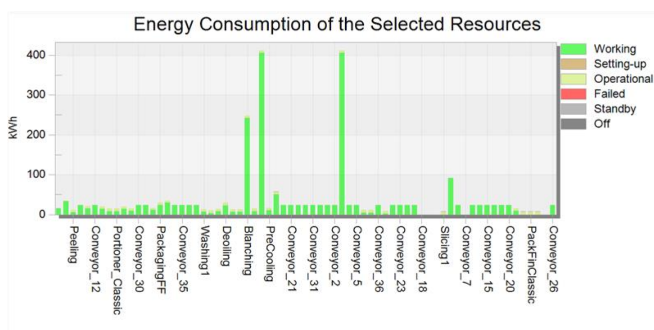

Figure 4. Energy Consumption

Resource statistics is a crucial tool for understanding the workload and bottlenecks at each station in manufacturing or industrial processes. It helps to identify which stations are operating at or near capacity and which might be causing delays or inefficiencies in the process. Identifying bottlenecks is essential for optimizing the process flow. In this work, the slicing operation is the principal bottleneck, which means it's the station with the highest demand relative to its capacity. The other graph indicates the energy consumption of the selected resources highlighting that the frying stations have the highest energy consumption. The Energy Consumption Graph tracks the energy usage of the selected resources, measured in terms of kilowatt-hours (kWh). It can help to assess the environmental impact and costs associated with the production process. This information is important for sustainability efforts, cost control, and making informed decisions about resource allocation.

4. Experimental Design

Once the authors have clarified the logic of the running of the plant and completed the construction of the simulation model, the so-called Design of Experiment (DOE) is made up. This experimentation regards the evaluation of the performances on the variation of some factors. In this work, the performance measures measured are the average flow time of the three products, the average energy consumption of the system, the utilization level of the plant and the employment level (an exhaustive description will be detailed in section 4.1).
The factors considered are processing time, Final pack, Conveyor speed and Slicing. Each factor is characterized by 2 levels (*Table 3*) and are described below:

- Processing time: it corresponds to the duration required to carry out a process. Currently, a traditional approach is applied (Configuration1). This factor is used to evaluate a new optimized approach (Configuration2). In particular, the optimization of a part of the production process is evaluated which reduces downtime.
- Final pack: it is the machine designated for the package closing and labeling. The current configuration (Old) considers just one packaging machine. This factor is used in the experimentation to evaluate the adoption of a packaging machine for each type of product (New).
- Conveyor speed: it represents the speed of the conveyor moving raw materials and semi-finished products from one station to another or from buffer to station or vice versa. The current conveyor speed (speed1) is equal to 1 m/s. A faster configuration (speed2) equal to 8 m/s is evaluated.
- Slicing: it is the machine designated to the cutting phase. The current configuration (Old) considers just one slicing machine. This factor is used to evaluate the purchasing of a new machine to use two machines in parallel (New).

Table 3. Factors

Factor	Min level	Max level
ProcessingTime	Configuration1	Configuration2
Final Pack	Old	New
SpeedConveyor	Speed1	Speed2
Slicing	Old	New

The authors have carried out a Full Factorial Design performing 80 experiments. Moreover, 5 replications have been designed to mitigate all possible experimental errors. Downstream the experiments, the results have been exported to the statistical software Minitab (further information on Minitab can be found at www.minitab.com) to perform Analysis Of Variance (ANOVA).

4.1. Performance Measures Analysis

The effects of factors on the performance measures are observed through ANOVA. Firstly, the authors have been verified the linearity of the model. For this purpose, a residual analysis has been performed to determine if the errors are distributed according to a normal distribution. An example of residual analysis is shown in Figure 5 by checking the linearity of the average flow time of tomato chips (AVGFTTomato). Similar graphs have been also obtained for the other performance measures. These graphs and p-values confirm the linearity of the model.

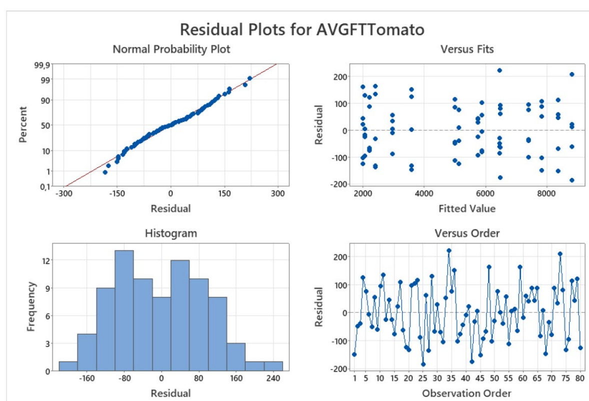

Figure 5. Residual plots of AVGFTTomato

Downstream the linearity check, the effects of the factors on each performance measure have been evaluated. It helps to validate the results of the simulation and to understand the effect of these factors on the system behavior.

Average Flow Time

It is the average time (defined in minutes) taken by each type of product to complete its journey within the production system. The same effects shown in Figure 6 are obtained for each product (tomato chips classic chips and french fries). In detail from Configuration1 to Configuration2, the flow time is reduced because the downtime is reduced, the machines take less time and consequently the process is faster. The final pack configuration from Old to New reduces the flow time as there is a packaging line for each product and therefore there are fewer bottlenecks during the process. Conveyor speed reduces flow time because the lower speed causes less congestion on the production line. The different number of slicing machines produces a reduction in the flow time as less queue is created at the entrance to the single slicing machine.

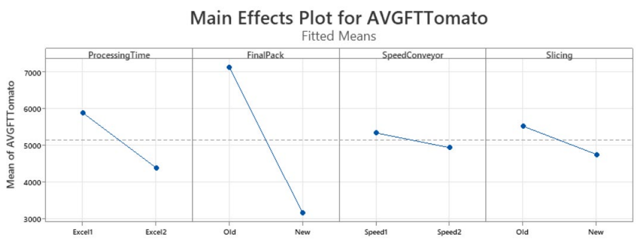

Figure 6. AVGFTTomato Main Effects

Employment level

It represents the worker's average employment in the system. From Configuration1 to Configuration2 the employment level is reduced because the new approach reduces the processing time and consequently the operators work with a lower percentage. Passing from the old configuration to the new one, considering the FinalPack factor, the employment level is smaller because, in the old configuration, there is just one operator on the packaging line, while in the new configuration, there are three different lines, each one with an operator. So, in that scenario, the workload that was previously assigned to a single worker is now distributed over three resources. The speed conveyor effect remains constant because there are no operators employed on any of them (p-value > 0.05 because it has no impact on the measurement). Even the slicing effect remains constant since it is an automated machine and it doesn't require the presence of the operator (p-value > 0.05 as for the speed conveyor).

Energy Consumption

It is referred to the overall energy usage of machines. With the new approach, the processing time is faster from Configuration1 to Configuration2, the energy consumption is lowered. The energy consumption, considering the variation of factor FinalPack from Old to New, is reduced because the machines work less and so the flow time is also lower. The conveyor speed from speed1 to speed2 has no impact on the energy consumption. The duplication of the slicing machines affects energy consumption. It decreases because the workload that was previously assigned to a single machine is now distributed between the two slicings.

Utilization Level Plant

Utilization Level Plant (ULPlant) represents the average utilization rate of machines. Switching from Configuration1 to Configuration2 the ULPlant is reduced because the new configuration increases the efficiency of the process and therefore the working portion of each one is smaller. The ULPlant remains constant when the conveyor speed varies from Speed1 to Speed2 because the calculation refers just to the working portion of the machine. As for slicing, moving from the old configuration to the new, the average ULPlant is reduced because the workload is better-balanced thanks to the presence of an additional machine (which is in parallel to the other one already working along the production line). The same thing happens when FinalPack switches from Old to New.

5. Results & Discussion

The primary purpose of this project is to illustrate some of the issues associated with a real manufacturing system through a discrete event food processing simulation model. The model acts as an efficient tool to test different scenarios, as well as understand the production process and the possible improvements. In this study, the authors simulate the behavior of the frozen french fries and chips manufacturing system to improve it. For this reason, a full factorial experimental design with 5 replication is carried out.

The outcome highlights that by applying a different configuration to the machines, there is an overall improvement in all performance measures (employment level, ULPlant, energy consumption and flow time of the three products). In addition, by setting a lower speed for the conveyors, fewer blocks are recorded along the line and the flow time is reduced accordingly. The analysis of the results points out that having a packaging line for each product makes the production process more streamlined and consequently less flow time and employment level along the line. It emerges the same by using two slicing in parallel there's an overall upgrade in the flowtime and also in terms of energy consumption and the utilization level of the machines.

As a result, the best configuration of the production system is obtained by adopting a new configuration of the production system, three packaging lines, two slicings and lower conveyor speed. The overall considerations demonstrate that the best configuration (*Table 4*), among all the experiments, allows a significant improvement of all the performance measures, in which there is a global reduction (Var. [%]) of performance measures as shown in *Table 5*.

Table 4. Level of factors in the worst and best configuration

Factor	Worst configuration	Best configuration
ProcessingTime	Configuration1	Configuration2
Speed Conveyor	8 m/s (Speed1)	1 m/s (Speed2)
FinalPack	Old	New
Slicing	Old	New

Table 5. Percentage variation of performance measures

Performance measure	Worst configuration	Best configuration	Var. [%]
AVGFTTomato [min]	128	33	74,22 %
AVGFTClassic[min]	128	33	74,22 %
AVGFTFrench [min]	110	30	72,73 %
Energy [kW]	12345,40	8626,87	30,12 %
ULevelPlant	0,1185	0,0751	36,61 %
Employment Level	0,641	0,206	62,87 %

Simulation models are powerful tools that help the food industry to navigate its complex landscape. By creating virtual environments, stakeholders can analyze, optimize, and make informed decisions about various aspects of the system, considering different factors and performance measures. With the ability to simulate different scenarios, the food industry can innovate, improve efficiency and ensure the delivery of safe and high-quality food products to consumers. The model shows that it is possible to overcome the gap by proposing a simulation model in the food industry. It allows better production planning with an efficient use of raw materials and resources (for example energy, workforce), ensuring a leaner and faster production process. Also, for future changes in the system and the process, the model will act as an effective tool for testing the feasibility of actual implementation and for improving problems in the food industry, such as the perishability of food and raw materials.

6. Conclusion

In conclusion, this paper introduces an industrial simulation model developed using Tecnomatix Plant Simulation to analyze performance measures and define more optimal configurations maximizing production line utilization and minimizing losses. While the model successfully identifies improved configurations, it does exhibit certain limitations. Specifically, it lacks real-time data integration with the actual production system and currently lacks a user-friendly interface for scenario simulation and adaptation. Addressing these challenges opens up avenues for future research. First, establishing a real-time data connection between the digital model and the physical system is important because it would enhance the model's accuracy and responsiveness to real-world changes. Moreover, to enhance usability and accessibility, incorporating a user interface is important. Such an interface would empower users to interact with the model, input parameters, visualize results, simulate various scenarios effortlessly. In summary, pursuing these research directions promises to yield a more robust and effective simulation model, offering real-time insights, optimizing resources, and facilitating scenario planning for enhanced production system performance.

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