SIMULATION-BASED ANALYSES AND IMPROVEMENTS OF THE SMART LINE MANAGEMENT SYSTEM IN CANNED BEVERAGE INDUSTRY: A CASE STUDY IN EUROPE

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ABSTRACT

Canned water is one of the thriving markets in the food and beverage industry. Given the tight competition in this market, realistic analysis in such production lines has become even more attractive for all participating parties. In this paper, we apply a KPI-driven simulation-based approach to a smart production plant of a key player in the European beverage market. The project covers realistic discrete-event modeling and analysis of the system together with the suggested scenario-based optimization for performance improvement. Here, the smart line management system is modeled and re-coded while considering machine characteristics, failures, and their overall influence on the production process. Our proposed optimized scenario demonstrates noticeably better results in all performance indicators when compared to the existing state of the system. The total increment of the production speed reaches up to 45 percent, resource utilization is evenly optimal, and the overall work-in-progress inventory is reduced significantly.

1 INTRODUCTION

The manufacturing industry is adopting various digital technologies related to smart factories to increase efficiency in the product design stage, optimize production lines, and enhance the core competencies of companies (Cortés, Ramírez, Villagomez, Batres, Velilla, Gonzalez, Puente, Esparza, Cruz, and Molina 2021). In this context, Industry 4.0 offers advanced solutions for improving the competitiveness of production companies (Ratnasingam, Ab Latib, Yi, Liat, and Khoo 2019). The smart factory is a certain deployment of Industry 4.0, which includes advanced equipment like sensors, robotic actuators, embedded programmable logic controllers (PLCs), or other network-connected objects in order to collect and analyze all the information required for putting forward better decisions (IBM 2022). Furthermore, given the significant impact of digitization on production speed, it has become one of the main drivers of change in modern production systems. This includes the digitization of services and products, as well as the digitization and optimization of all production processes (Bambura, Sujová, and Čierna 2020). The beverage industry is one of the industries that have adopted the latest smart factory models. Simulation tools are providing us with the excellent opportunity to analyze systems with their realistic specifications and minimal simplifications. Such methods are the main building blocks of a digital twin that may make realistic and highly applicable optimization scenarios attainable by business owners.

With its features, simulation allows for rapid testing of multiple parameter settings, analysis, and prediction of outcomes while considering various uncertainties in operating time and efficiency. Additionally, simulation models are safe analytical tools to test and explore these 'what-if' scenarios without purchasing, installing, changing, or reinvesting in any physical equipment. Virtual experiments using simulation models are less time-consuming and less costly than real experiments (Robinson, Nance, Paul, Pidd, and Taylor 2004). Unlike spreadsheets or solver-based analysis, simulation models are able to help optimize production lines by observing and studying system behavior in detail over time (Uriarte, Ng, and Moris 2018). Digital models of the manufacturing plant can be used not only to describe production processes or to see the bottlenecks but also can act as a decision-support to deal effectively with unexpected situations and failures (Mosalam, Alibrandi, Lee, and Armengou 2018; Attar, Raissi, and Khalili-Damghani 2017). Furthermore, trials have found that production managers implementing simulation techniques earlier in the design cycle are able to investigate larger design spaces faster through digital exploration, all before decisions are made and costs are determined (Cortés, Ramírez, Villagomez, Batres, Velilla, Gonzalez, Puente, Esparza, Cruz, and Molina 2021). Clearly, this idea of saving manufacturers time and money through the use of simulation models is attractive, and the growing development of simulation technology seems to make it likely to be more sought after.

This paper focuses on the simulation and scenario-based optimization of the production process for one of the key players in the canned-beverage industry in Europe. Our objectives are to diagnose resource wastes, identify bottlenecks, reduce wasted investments in inventory, and improve overall throughput. We create and analyze the production line using the well-known discrete-event simulation (DES) technique using Tecnomatix Plant Simulation (TPS) software. In order to achieve the project goals, some key performance indicators (KPIs) are collected and analyzed from the model. These indicators cover multiple dimensions of the system such as machine efficiency, throughput, accumulation quantity, and operation speed of the stations. Given that smart lines in the food industry may have similar processes to the line under study, we believe that the method proposed in this research can be of interest to decision-makers in this industry.

The rest of the paper is organized as follows: Section 2 presents a brief review of the related literature; system modeling methodology is explained in Section 3; numerical results, improved scenarios, and managerial recommendations are discussed in Section 4; finally, in the last section, the conclusion and future research directions are provided.

2 LITERATURE REVIEW

Simulation is receiving a great deal of attention from manufacturers as it helps the modern industry to meet unprecedented challenges from market behavior. This technology is able to simulate the performance and behavior of real-life or production processes, systems, or facilities (Allen, Spencer, Gibson, Matthews, Allwood, Prosser, and Pitt 2015). It typically models queuing systems, using limited resources, and describes the movement of modeled entities (e.g. people, products, materials, etc.) through a network of queues and activities (Wainer 2017). As computers continue to increase in speed and memory, the technique is increasingly being applied to production line problems of large scale and complexity (Allen, Spencer, Gibson, Matthews, Allwood, Prosser, and Pitt 2015).

There are many examples of the application of simulation to complex manufacturing systems. Depending on the needs and experimental objectives, experts and academics have used a variety of methods and simulation software to study different assembly lines. In this section, first, we provide a brief review of the available DES software and then confirm the practical feasibility of simulation for line optimization using previous real-life case studies.

2.1 Simulation Software for DES

In recent years, DES method has been used frequently in various engineering and manufacturing fields. A large number of successful simulation models of production lines have been carried out by companies using

DES technology, which has led to a multitude of highly specialized research methods and simulation tools for different application fields. Simulation is versatile; it allows scenarios to be created to foresee the impact of any change on realistic conditions (Uriarte, Ng, and Moris 2018). The software allows manufacturers to simulate a complete factory even before commissioning the production line. The simulation model can animate the production process in 2D or 3D, which will make it easier to validate, understand and discuss the concept and idea. ARENA, AnyLogic, Enterprise Dynamics (ED), MATLAB (Simulink), SIEMENS Tecnomatix Plant Simulation (TPS), and SIMUL8 are among the 3D-enabled packages that are commonly used for modeling production and inventory processes (Cortés, Ramírez, Villagomez, Batres, Velilla, Gonzalez, Puente, Esparza, Cruz, and Molina 2021; Zupan and Herakovic 2015; Attar, Raissi, and Khalili-Damghani 2016; Kuncova and Zajoncova 2018).

2.2 Production Line Simulation

Simulating production lines in real practice is very interesting and challenging. A number of studies have demonstrated the capabilities of simulation-based methods for manufacturing line improvements. Table 1 summarizes the details of some existing real applications of simulation in production lines.

Table 1: A brief summery of the related literature with real case studies

Ref.	Method	Software	Case study
(1)	Nabla Model simulation cycle	TPS	Bocar Group in Lerma, Mexico
(2)	Accurate real-time productivity assessment	AnyLogic	Garment production line
(3)	Production line balancing	TPS	Manufacturing process with two production lines and an assembly hall
(4)	Production line balancing	SIMUL8	Cisco routers production line (Foxconn, CZ)
(5)	Kanban System	TPS	Logistics flow of a manufacturing company
(6)	Redesign of buffer allocation	ARENA	Cement production line
Current Study	Re-coding flow management settings, KPI analysis	TPS	Canned beverage production line

[1] Cortés, Ramírez, Villagomez, Batres, Velilla, Gonzalez, Puente, Esparza, Cruz, and Molina (2021) ; [2] Jung, Kim, Park, Lee, and Suh (2022) ; [3] Zupan and Herakovic (2015) ; [4] Kuncova and Zajoncova (2018); [5] Pekarcikova, Trebuna, Kliment, and Dic (2021); [6] Heshmat, El-Sharief, and El-Sebaie (2013)

As seen in Table 1, the chosen simulation software in this paper, i.e., TPS, is among the simulation platforms that are practically utilized for real-life simulation in recent years. Unlike the existing studies in the literature, we investigate the speed management system of a smart and automatic line for which some KPIs will be used as guides to the optimized solution.

3 SYSTEM MODELING METHODOLOGY

In this section, we discuss the DES-based methodology proposed in this study. The existing beverage packaging plant of this company is divided into three main product streams: PET bottles, Glass bottles, and Aluminum cans. However, for this study, only aluminum canned beverage is considered. In this production
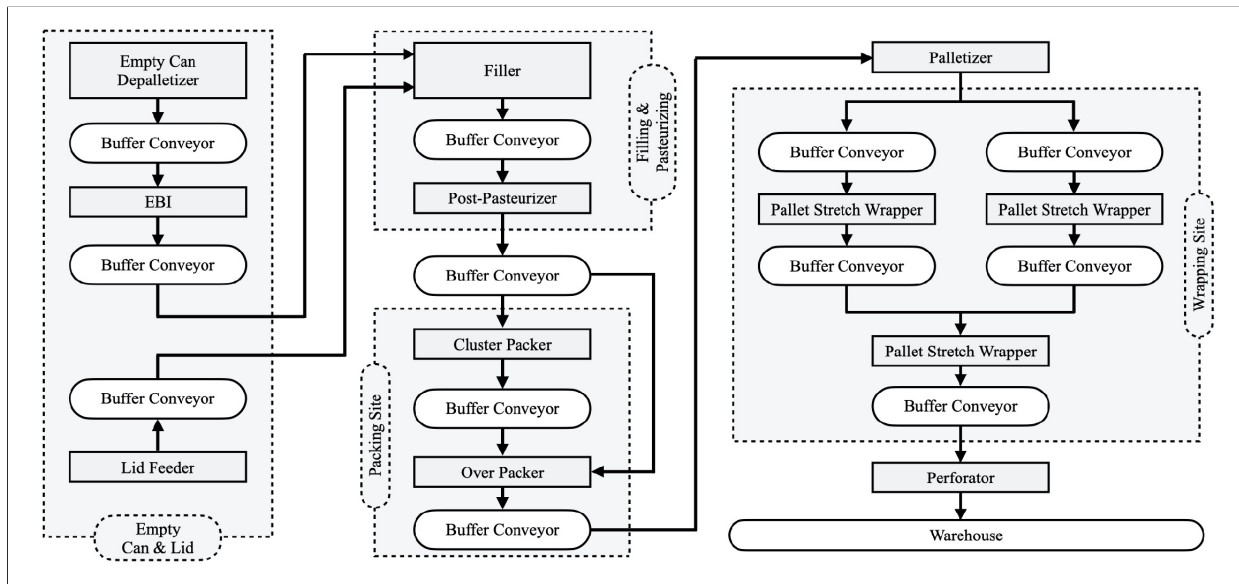
Figure 1: The flowchart of canned beverage production process

line, we have identified two types of entities, namely, Lid and Can. The production process in this line is schematically illustrated in the flowchart in Figure 1.

According to Figure 1, the key production steps include: (i) Depalletizing, (ii) Lid feeding, (iii) Filling, (iv) Pasteurizing, (v) Packaging, and (vi) Stretch wrapping. Transportation between different stations is done by conveyors, and the production line is equipped with CNC Technology that allows convenient regulation and control of the entire production line. For instance, the empty can depalletizer is an automatic, PLC-controlled aluminum can unloader which is loaded from the bottom via a conveyor belt while the unloading process takes place from the top. The empty cans are transported from the buffer conveyor to the empty bottle/can inspection (EBI) station in which poor-quality empty cans are eliminated. Cans with acceptable quality are subjected to a sequential filling operation at the filling station and afterward, they are fitted with a lid. The filled cans are then transported to a pasteurization station where they are sequentially sterilized before entering the buffer conveyors of the packing steps.

In the packing site, disinfected aluminum cans are split evenly into two streams. The first portion will be cluster-packed and then over-packed, while the other will skip the cluster-packer station and be transported directly to the over-packer station. Later on, two intelligent robots in the palletizer station stack the packed products in an orderly manner. This is followed by two steps of fully automatic stretch balling: (i) the initial stretch wrapping for which two buffer conveyors will transfer the stacked cans to two small pallet stretch wrapper stations; subsequently (ii) a secondary stretch wrapper for all processed products from both streams. The last step in this production line is the quality inspection and spot check after which the products are sent to the warehouse.

Based on the described production process, we build a simulation model in TPS software (Figure 2) and use it for analyzing the production process for one shift (i.e., 8 hours). The model consists of two sources, i.e., Input 1 & 2 (for the lid and can, respectively), and 12 station objects that represent the various processes in Figure 1. On the other hand, instead of conveyor belts, we used a buffer object to better visualize the accumulated work in progress (WIP) in the line. Just like the real conveyor belts, the used buffer objects have limited capacities. Each buffer is tagged with the Accumulation Quantity (AQ) showing the real-time amount of WIP products in that part of the line. One major objective of this project is to increase the total throughput by optimizing the speed of the canned beverage line. Thus, for each station, we display and record the speed (as product/hour) and throughput data that we will use for performance analysis.
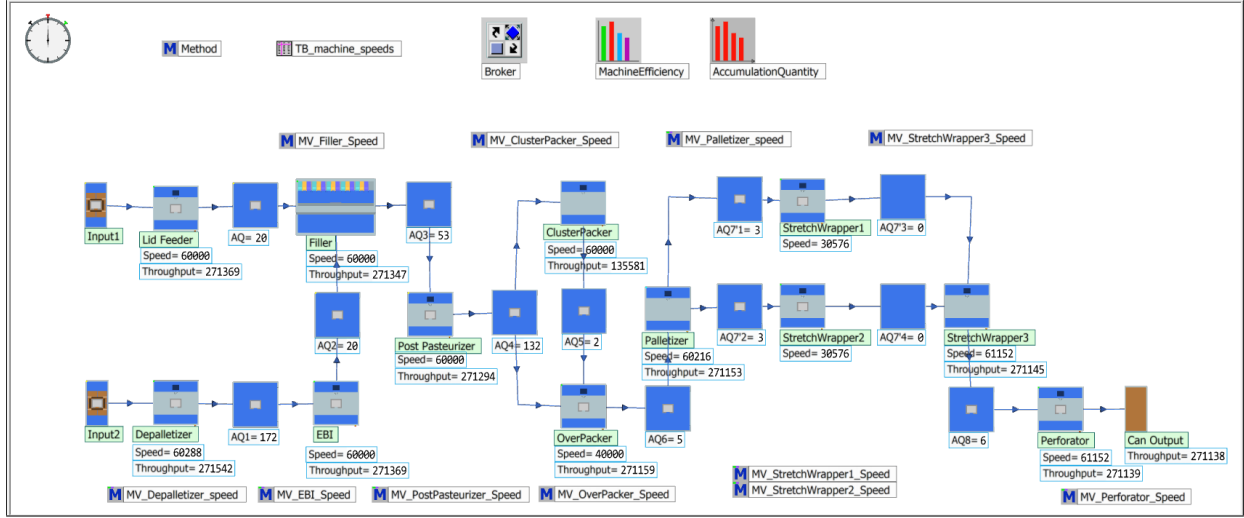
Figure 2: A snapshot of the simulation model built using TPS software for the system in the current state

Table 2: Production speed (can per hour) data for each station in the production line

Equipment Type	Low Speed (cph)	Nominal Speed (cph)	High Speed (cph)	MTTR (m:s)
Lid feeder	60000	60000	62500	1:30
Empty can depalletizer	60288	60288	64998	1:00
EBI	60000	60000	62500	0:30
Filler/capper	60000	60000	62500	1:52
Post pasteurizer	60000	60000	60000	0:30
Cluster-packer	40000	60000	66000	1:14
Over-packer	40000	60000	72000	1;20
Palletizer	60216	60216	75504	1:15
Pallet Stretch wrapper(s)	61152	61152	82992	1:20
Perforator	61152	61152	82992	1:15

Table 2 contains the production speed ranges of different stations based on the current values in the operation speed management (OSM) of the manufacturing plant. A similar table, namely *TB_machine_speeds*, is created to replicate these speed ranges in the model. The mathematical correlation between the speed data (Table 2) and the processing time of each machine (in seconds) is given by (1).

$$Process\ Time\ (s) = \frac{3600}{Machine\ Speed\ (cph)} \tag{1}$$

The OSM system determines the speed of each station based on the amount of congestion in the predecessor and successor conveyors (here, buffer objects) and may stop feeding the subsequent conveyor if necessary. Figure 3 illustrates the logical flow control code in an example station. Note that, the programming language used in this piece of code (or method object as called in TPS software) is SimTalk™ which is introduced by SIEMENS™ specifically for this software. For further information about this language, one may refer to Bangsow (2010).

In this code, AQ represents the real-time load quantity of the buffer, while x_1,x_2, and x_3 are the operation speeds of the station according to the requirements extracted from the speed management table, i.e., low, nominal, or high speeds, respectively. As seen in Figure 2, each station has its method object with a code

```
    // y: Line of data related to this Station

if AQ' > S1  then

        Station.procTime := 3600/TB_machine_speeds[x1,y]

    elseif AQ' > S2  then

        Station.procTime := 3600/TB_machine_speeds[x2,y]

    else

        Station.procTime := 3600/TB_machine_speeds[x3,y]

end
```

```
if AQ'' > S3 then

        Station.ExitLocked := True
        waituntil AQ'' < S4
        Station.ExitLocked := False
end

if AQ''' < S5 then

        Station.EntranceLocked := True
        waituntil AQ''' >= S6
        Station.EntranceLocked := False
end
```

Figure 3: Settings code (i.e., Method in TPS) for speed control in the simulation mode

similar to that in Figure 3. In the event of an idle or overloaded buffer belt, the previous station and subsequent workstations can adjust the production status, i.e. close the output or input ports. For example, when the buffer is carrying more than 95% of its maximum capacity in real-time, the previous station will close the output port (using *exitlock* command) to relieve the blockage; when the buffer is below 5% of capacity, however, the subsequent station will close the input port (i.e., *entrancelock* command), which helps save on running costs and reduce energy waste. Nevertheless, when the accumulated quantity gets back into the normal range (i.e., $[S_4, S_3]$ or $[S_5, S_6]$), the applied entrance or exit closures are automatically lifted by using the *waituntil* command. Table 3 reports S_1-S_6 thresholds and the relevant buffer conveyor in the current speed management system for each station.

Table 3: Decision threshold data S_1-S_6 for each station in the production line

Station Name	S_1, S_2	AQ'	S_3, S_4	AQ''	S_5, S_6	AQ'''
Filler	-		90%, 80%	AQ3	10%, 20%	AQ2
Depalletizer	90%, 50%	AQ1	95%, 95%	AQ1	-	
EBI	90%, 50%	AQ2	95%, 95%	AQ2	10%, 20%	AQ1
Post-Pastorizer	-		90%, 80%	AQ4	-	
Cluster-Packer	25%, 30%	AQ4	90%, 80%	AQ5	10%, 10%	AQ4
Over-Packer	25%, 30%	AQ5	90%, 80%	AQ6	10%, 10%	AQ5
Palletizer	15%, 30%	AQ6	90%, 80%	AQ7'1&'2	10%, 10%	AQ6
Stretch-Wrapper1	10%, 0%	AQ7'1	-		5%, 5%	AQ7'1
Stretch-Wrapper2	10%, 0%	AQ7'2	-		5%, 5%	AQ7'2
Stretch-Wrapper3	10%, 0%	AQ7'3&'4	90%, 80%	AQ8	-	
Perforator	10%, 0%	AQ8	-		-	

The availability of machines in the system under study is fairly good with their uptime being 98.5% on average. In this plant, a dedicated team is responsible for the maintenance of the machines which brings about the mentioned high availability and keeps the repair time in an acceptable range. Table 4 contains the estimated mean time to repair (MTTR) for each of the machines in this system which also includes minor faults and any human interference in the operation. Given that the current availability and MTTR values of the system are already very competitive, this study only focuses on the smart production management system and will keep the maintenance specifications of the machines untouched.

4   RESULTS AND DISCUSSION

After building the simulation model in Section 3, in this section, we use the proposed model to analyze the current state of the production line, propose the optimized scenario for achieving the project goals, and eventually, measure the effectiveness of the new settings quantitatively using multiple KPIs.
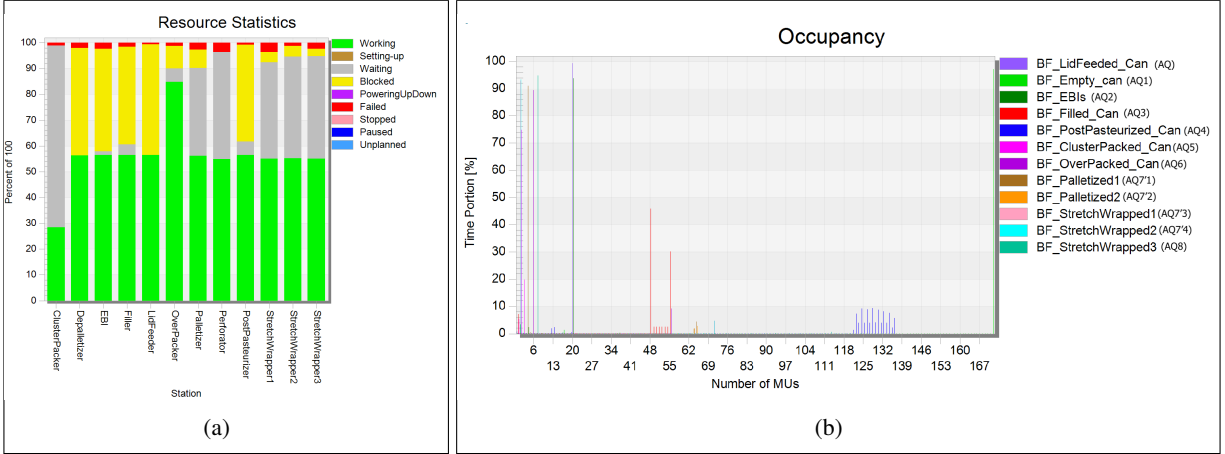
Figure 4: Performance charts of the current state: (a) Station performance, (b) Buffer conveyor occupancy

4.1 Current Status of The Canned Beverage Line

In order to understand the weaknesses of the current settings of the production line, we run the simulation model for one shift. As seen in Figure 2, in its current state, the system has a throughput of around 271k (per shift). The work in progress in this state is 404 units which can be calculated by (2).

$$WIP = Total\ Input\ (Depalletizer) - Total\ Output\ (Can\ Output) \qquad (2)$$

Figure 4 illustrates the performance of the stations and the load on the buffers (conveyors) under the existing settings. In Figures 2 and 4-b, we observe that the buffers before the cluster-packer and over-packer stations (i.e., AQ1, AQ3, and AQ4) accumulate a large amount, while the ones after these two stations carry too little loads. The value of AQ4 remains between 48 and 55 products, while the value of AQ5 remains between 118 and 139, representing. This indicates that the filling and pasteurization stations have the greatest potential for speed optimization. Furthermore, the machine efficiency of the original model is not high (see Figure 4-a). Except for the Over-Packer, efficiency rates (working/total time) of all machines are around 60%. This also indicates that considerable improvements may be achieved by applying proper amendments to the system.

4.2 Scenario Definition and Optimization

In general, from both charts, we can conclude that the flow management system has a good potential to be re-configured to achieve better performance. For this purpose, we propose a multi-step approach as follows:

Step1: New Speed Control for Filler Machine

As the first choice of improvement, we amend the speed management mechanisms in the filler machine. It is the first important machine in the production process and feeds the entire line. Thus, balancing the speed here will potentially help improve the total throughput and may affect AQ, AQ2, and AQ3 buffers. The current scheme for managing the production speed is based on the temporary inventory in AQ2 and AQ3. However, according to Tables 3 and 4, it only manages the operational status of the entrance and exit of the Filler, and the machine will work at its nominal speed all the time with no speed variations. To refine the speed control of the filler, we set more conditions on its downstream (succeeding) buffer. In addition, the machine efficiency chart (Figure 4-a) shows that there is some waiting time (gray color) at the filler site. So, an attempt is made to remove the minimum threshold related to the upstream (preceding) buffer, i.e., AQ2. Therefore, by reference to the precursor site production rates, the speed

Table 4:   Speed management settings comparison between the original and improved models for the Filler machine

Object	Original		Proposed	
	Occupancy	Action	Occupancy	Action
AQ2	$< 10\%$	Filler stop		
	$> 20\%$	Filler restart		
AQ3	$> 90\%$	Filler stop	$> 99\%$	Filler stop
	$< 80\%$	Filler restart	$< 90\%$	Filler nominal speed
			$< 50\%$	Filler high speed

of the filler is adjusted as summarized in Table 4 to align its speed range with the rates of its upstream objects.

Step2: New Speed Control for Depalletizer and Pasteurizer Machines

The pasteurization machine serves as a dividing station in the line, and we observe that the succeeding stations are kept waiting/idle for a long time. This means that more product output is required from the upstream stations which feed the Post-pasteurizer. In view of this observation, in this step, we increase the maximum threshold by which the upstream buffer feeds this machine. Theoretically, this should increase the efficiency of some key stations and alleviate blockages. As shown in Table 5, the highest thresholds for Depalletizer and Post-pasteurizer stations were all raised to 99%. Note that, in the previous step, this threshold was already set to 99% in the filler station, so we are sure that the maximum possible flow is provided to the stations downstream of the pasteurization site.

Table 5:   Speed management settings comparison between the original and improved models for the Depalletizer and Pasteurizer

Object	Original		Proposed	
	Occupancy	Action	Occupancy	Action
AQ1	$> 95\%$	Depalletaizer stop	$> 99\%$	Depalletaizer stop
AQ4	$> 90\%$	Post-pasteurizer stop	$> 99\%$	Post-pasteurizer stop
	$< 80\%$	Post-pasteurizer restart	$\leq 99\%$	Post-pasteurizer restart

Step3: New Speed Control for The Packers

According to the assembly line sequence, the cluster-packer and the over-packer are both downstream of the pasteurization station. Nevertheless, it is observed that the pasteurized semi-finished products are unevenly distributed, which leads to significant blockages upstream of the packers and high waiting times at their downstream objects. In this step, we deal with the speed control of this portion of the line.

(a) Over-Packer Machine Speed Adjustment

The buffer (conveyor) subsequent to the pasteurization site (i.e., AQ4) consistently exhibited high levels of WIP in the original model (Figure 4-b). It can be perceived that this observation may be related to the coding/settings at the downstream sites. In reference to the current speed control system in Table 3, it appears that the Over-packer is not regulated by the AQ4 buffer, rather only adjusts its speed and running state after approaching some limits in AQ5 and AQ6. Table 6 demonstrates our proposed amendments to the speed control mechanisms of the Over-packer to address this issue and connect its speed to the status of its upstream conveyor. We also amended the threshold for applying the nominal speed and it is now

Table 6: Speed management settings comparison between the original and improved models for the Over and Cluster Packer Machines (Step 3.a and 3.b)

	Object	Original		Proposed	
		Occup.	Action	Occup.	Action
(3.a)	AQ4			> 25%	Over-packer nominal speed
				> 30%	Over-packer high speed
	AQ5	< 10%	Over-packer stop	< 10%	Over-packer stop
		< 15%	Over-packer low speed	> 15%	Over-packer nominal speed
		> 25%	Over-packer nominal speed	> 30%	Over-packer high speed
		> 30%	Over-packer high speed		
	AQ6	> 90%	Over-packer stop	> 90%	Over-packer stop
		> 80%	Over-packer restart	> 80%	Over-packer restart
(3.b)	AQ4	< 10%	Cluster-packer stop	> 15%	Cluster-packer nominal speed
		< 15%	Cluster-packer low speed	> 30%	Cluster-packer high speed
		> 25%	Cluster-packer nominal speed		
		> 30%	Cluster-packer high speed		
	AQ5	> 90%	Cluster-packer stop	> 90%	Cluster-packer stop
		> 80%	Cluster-packer restart	> 80%	Cluster-packer restart

done after the machine restarts. This attempt should help reduce the total accumulated WIP in AQ4 even further.

(b) Cluster-Packer Machine Speed Adjustment

As the last step in addressing the bottleneck of the packer sites and eliminating the idle time of this section of the line, we adjust the speed management mechanism of the cluster-packer as given in Table 6. The applied approach for this packer is similar to the one used for the Over-packer with minor differences. This packer is already regulating its flow based on AQ4 inventory, hence we do not need to define a new category of rules. The stopping threshold (concerning AQ4) is also removed to smoother the production process. Just like the other packer, the machine is set to start with its nominal speed to avoid congestion in its upstream stations. This step finalizes our proposed improvement scheme for the system under study, and thus the new model can be used for performance analysis and comparisons.

4.3 Results of The Optimized Model and Managerial Insights

In subsection 4.2, we defined the proposed changes in the speed management system of the production line to improve the overall performance of the process. We put the proposed scenario into test in this subsection and compare the achieved results with the ones presented in subsection 4.1 for the original state of the system. Comparing Figure 5-a with the original chart in Figure 4 reveals that the performance of all stations is improved significantly under the proposed optimization scenario. All stations (except for the cluster-packer) are now in a working state for more than 80% of the time whereas, in the original model, this KPI was around 55%. Table 7 compares the existing status of the system with the proposed optimized state using different KPIs. Here, for station status KPIs, we reported the worst case (i.e., Min./Max. whichever applies) in addition to the average value. With reference to the achieved results, the proposed version offers noticeable improvements in all aspects. The maximum blocked state among all stations was over 40%, but in the new model, this was decreased to around 16%. Furthermore, the box plot in Figure 6 shows that the model is now performing in a more balanced way and the differences between the 1st and 3rd quartiles of idle and blocked states were decreased significantly.
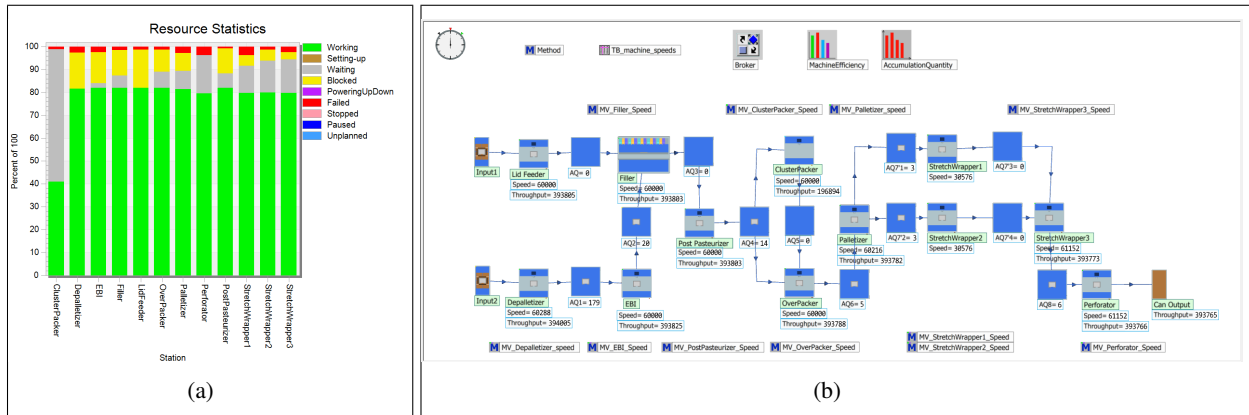
Figure 5: The proposed optimized speed management: (a) station performance chart, (b) model snapshot

Table 7: Key Performance Indicators of the improved version compared with the original state

KPI	Original	Proposed	Improvement
Total Accumulated WIP	404	240	40.59%
Total Throughput	271138	393765	45.23%
Working State (Avg. ǀ Min.)	55.99% ǀ 28.37%	77.80% ǀ 41.02%	38.95% ǀ 44.59%
Waiting State (Avg. ǀ Max.)	23.21% ǀ 70.59%	12.04% ǀ 57.94%	48.13% ǀ 17.92%
Blocked State (Avg. ǀ Max.)	18.89% ǀ 42.83%	8.16% ǀ 16.76%	56.80% ǀ 60.87%

As defined in Section 1, one of our goals was to improve the total throughput of the system. Table 7 reveals that we expect the suggested amendments in the speed control system to bring about a 45% increase for this KPI. The total investment required for the WIP inventory of this line was also lowered by 40% which fulfills another goal of this project. One of the major sources of this considerable reduction is that we were successful in eliminating the unnecessary inventory in AQ4 from 132 to the negligible value of 14 (see Figure 2 and 5-b). With all the achievements of this new optimized model from the WIP perspective, we still observe that the AQ1 conveyor is carrying almost the same amount of inventory as it had in the original model. In the meantime, the other source of the Filler station has nothing left in its buffer (i.e., AQ=0). According to this observation, we may conclude that the existing Lid Feeder is slow for this line since we have used up all products in its succeeding buffer conveyor while the buffer downstream EBI was still holding some WIP inventory. Given that the Lid Feeder is operating at its maximum allowed speed, the managers may consider a redundant machine or faster alternatives for this station.
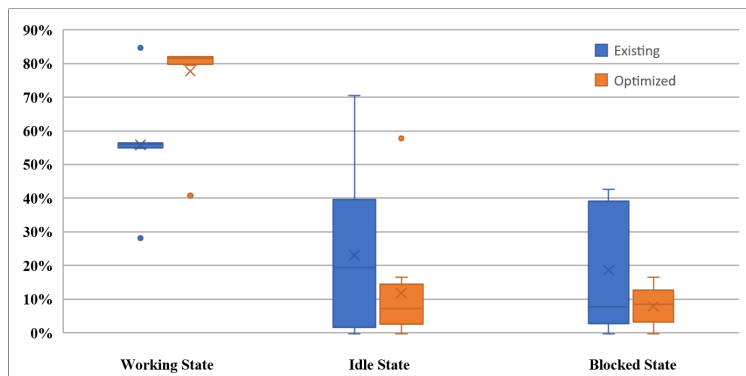

Figure 6: Three main KPIs for the stations before and after applying the proposed optimization

Moreover, Cluster-Packer is still encountering a considerable waiting time (Figure 5-a). With the status of the buffers in mind, we can conclude that this issue may be resolved by two means: (1) adding a new Over-Packer as a redundant to the existing one, (2) changing the product distribution method between the over-packer and cluster-packer in AQ4 (i.e., setting it to some values other than the current 50%-50% scheme). However, both of these changes (and the ones mentioned about the Lid Feeder) require decisions to be made by the management/stakeholders which is out of our current scope.

5 CONCLUSION

This paper studies a production line in the food and beverage industry and proposes a new speed control scheme based on some Key performance indicators (KPIs). The production line under study is smart and automated and is equipped with advanced computer monitoring, robotic arms, PLC-controlled machines, and fully computer-controlled conveyors. In this study, we aim to increase the throughput of the system and reduce the overall inventory within the production line. So as to archive these goals, a multi-stage method is applied that comprises: (i) conceptual modeling of the processes, (ii) replicating the conceptual model in the simulation software, (iii) using the simulation model to calculate the current values of the KPIs as well as to identify the existing bottlenecks and potential improvement opportunities, (iv) proposing the optimized settings based on the identified weaknesses, and finally (v) applying the proposed settings in the model and demonstrating the improved KPI values.

The KPIs are usually defined in line with the scope and goals of each project. The main KPIs used in this study include the total throughput, the accumulated work-in-progress (WIP) in conveyors, the time portion during which the stations are blocked, the waiting time, and the working states of stations. Furthermore, in order to balance the line more effectively, we consider both the average and the worst case for the last three KPIs. Our results showed reassuring conditions for the proposed optimized model in all aspects and some of the KPIs were improved by over 50%. Due to the smoothly balanced working state of all stations, the new throughput is predicted to increase by 45% and the total WIP in the system is decreased by about 40% in each shift. Given these results, the applied method in this research has successfully fulfilled the defined goals and may be adopted for other similar production lines in the industry.

In this research, we focused on optimizing the speed management system of the production line. As a future work, one may consider improving the system while considering possible investments in new facilities and stations. On the other hand, the maintenance and failures considered in this research were assumed to be fixed. Possible improvement in the maintenance plans is another future direction for extending this work either in the food industry or in a completely new area.

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