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HYBRID SIMULATION-BASED ALGORITHM TUNING FOR PRODUCTION SPEED MANAGEMENT SYSTEM AS A STAND-ALONE ONLINE DIGITAL TWIN

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ABSTRACT

One of the primary in-built components of smart, continuous manufacturing lines is the production speed management system (PSMS). In addition to being overly cautious, the decisions made in these systems may center on making local adjustments to the manufacturing process, indicating a major drawback of such systems that prevents them from acting as proper digital twins. This study delves into hybridizing the continuous and discrete event simulation, DOE, and V-graph methods to redefine PSMS's internal decision algorithms and procedures, giving it an aerial perspective of the line and turning it into a stand-alone online digital twin with decisions at a system level. The proposed approach is applied to a practical case from the food and beverage industry to validate its effectiveness. Numerical results demonstrated an intelligent, dynamic balancing of the production line, a substantial increment in productivity, and up to 37.7% better resiliency against new failure and repair patterns.

1 INTRODUCTION

The rapid development of Industry 4.0 has introduced technological innovations that improve efficiency, flexibility, and resilience in production systems in all industries. Meanwhile, the concept of digital twins has developed as a crucial instrument for connecting the physical and virtual environments (Grieves 2014; Attar et al. 2024a). A digital twin is a real-time virtual depiction of a physical system, enhanced with seamless integration of sensors' data, Internet of Things (IoT) devices, and sophisticated analytics (Tao et al. 2018). In continuous production lines, where uninterrupted flow, high throughput, and little downtime are essential, digital twins can provide exceptional prospects for optimization, predictive maintenance, failure mitigation, flow routing, and process management (Uhlemann et al. 2017; Veuger 2024). Simulation methods have evolved to address the dynamic and interconnected nature of smart factories, where technologies like digital twins rely on it to replicate and predict system behavior (Rosen et al. 2015). Discrete event simulation (DES), system dynamics (SD), and agent-based simulation modeling (ABS) are among the techniques employed, with hybrid approaches gaining traction to handle the complexity of smart manufacturing environments (Negri et al. 2017).

Özgün and Barlas (2009) investigated the differences between discrete event and continuous simulation modeling by using a queuing system. They pointed out that continuous simulation is fitted for systems where continuous processes and feedback significantly affect the behavior of the systems, while DES excels at systems involving leaner processes and discrete changes. As an example of DES twins for production lines, Shao et al. (2019) employed this method to optimize the production flow, evaluate throughput, and test reconfiguration scenarios in a smart manufacturing context. They used Siemens Tecnomatix Plant Simulation (TPS) to model and analyze a real-world assembly line, integrating it as a digital twin. Applied to an automotive assembly line, the study demonstrated how the digital twin could mirror real-time operations and support decision-making. Notable results included a 15% increase in throughput and reduced bottlenecks, highlighting the practical value of simulation-driven digital twins in enhancing smart line efficiency.

Pekarcikova et al. (2021) studied a manufacturing firm using Tecnomatix simulation software to optimize production lines using lean manufacturing. The goal was to improve production line material flow and identify bottlenecks to increase capacity and efficiency. Jung et al. (2022) implemented the real-time power monitoring data from garment workers' sewing machines into a DES — with bottleneck identification and measuring productivity as their modeling objectives. Their notable results include an 18.8% increase in accuracy compared to conventional methods, demonstrating the potential of smart factory technologies in improving garment production efficiency. Even though external simulation-based digital twins were proven to be applicable in various other complex systems (Attar et al. 2024b), for smart manufacturing lines, studies have overlooked the potential capacity of internal production speed management systems (PSMS).

The PSMS is a primary integral component of production systems that typically analyzes a limited range of input data and can make changes in the production line. However, decisions made in these systems are often overly conservative, primarily concentrating on localized alterations to the manufacturing line. These factors create a fundamental disadvantage and limitation for management systems, resulting in a performance significantly inferior to the standards one would anticipate from a digital twin. These PSMSs have the ability to execute immediate commands in the production line and have real-time access to sensor data. Thus, a properly customized and tuned decision algorithm can assist in converting them into a stand-alone online digital twin, a concept that has been neglected in the literature. In algorithm development and tuning, the design of experiments (DOE) class of methods has become a prominent approach for identifying optimal parameter choices, especially when computational resources are constrained. Traditional trial-and-error methods or grid searches often become computationally infeasible as the number of parameters increases, whereas DOE leverages fractional designs to reduce experimental runs (Box et al. 2005). As an example from the simulation research area, Attar et al. (2016) utilized DOE to systematically tune simulation parameters in a novel inventory policy under stochastic conditions. This method successfully reduced lost sales and inventory expenses by identifying the ideal configurations, demonstrating the efficacy of DOE in parameter optimization for simulation-based studies.

The literature suggests that DOE still remains underutilized in the smart manufacturing domain, presenting an opportunity to extend its application to improve operational efficiency and system resilience in digital twin models for continuous production lines. Still, selecting an appropriate experimental design—such as full factorial, fractional factorial, or Taguchi methods—requires domain expertise to balance accuracy and computational cost (Montgomery 2017). On the other hand, identifying different segments of the system with high potential for developing a bottleneck in complex production lines is crucial for designing action plans for such processes. One of the available tools for this task is the V-graph, which uses graphical illustration for identifying these potential segments. Arena et al. (2019) presented a successful application of this method for improving productivity in the brewing and beverage production industry. In another attempt for the same industry, recently Veuger (2024) deployed the V-graph approach for continuous production lines, developing several control charts that could be updated manually to optimize the production flow.

Therefore, this paper aims to utilize a combination of simulation, V-graph, DOE, and optimization methods to propose a structured framework for redesigning and tuning the internal PSMS algorithms, which can provide these systems with the necessary features of digital twins in mitigating blockage as well as handling unexpected failures and prolonged repairs. We also offer a real case study from the food and beverage industry to better demonstrate the functionality of the proposed approach. With the fluid flow and processing steps of the beverage industry in mind, our simulation model employs a hybrid of continuous and discrete event modeling techniques. The rest of the paper is organized as follows: the proposed methodology is described in the next section. It also includes the implementation of the framework on a practical case study. Experiment results and numerical resiliency analysis are presented in Section 3. Finally, some concluding remarks and future research directions are provided in Section 4.

2 METHODOLOGY

This section presents the proposed framework to mitigate blockage and improve productivity in Industry 4.0 continuous production lines dynamically and efficiently. This approach aims to achieve this improvement and resiliency by redefining the built-in setup capabilities of the management system, without necessitating further investments in new machines or production methods. The proposed approach is also committed to maintaining the existing production sequence in the manufacturing lines. This method comprises five primary steps that can be summarized as follows: (i) conceptual modeling, (ii) simulation modeling, (iii) PSMS algorithm definition, (iv) DOE and tuning, and (v) real-system implementation.

The first step of this framework involves recognizing the real system's process, identifying the primary events and distributions, and capturing all relevant technical constraints. Just like any other simulation-based approach, this is the most important step of the framework that forms the foundations of the methodology, directly affecting the accuracy and applicability of the refinements. Then, the system should be modeled using a suitable simulation technique (e.g., continuous, discrete event, hybrid) to emulate the process adequately. In this step, any rules in the system's existing PSMS setup should be taken into account to ensure the system passes the validation tests and ultimately guarantee the credibility of the predicted improvements. In the next step, the built-in algorithms are redefined to achieve a system-level decision perspective with the overall profitability in mind. Here, we also need to list any amendable parameters for tuning purposes.

The fourth step of the framework employs DOE and optimization methods to finetune the proposed algorithm. It is essential to select the appropriate method for designing the experiments to achieve the defined goal in an acceptable time. This step also includes verifying the estimated optimal performance from the DOE method by using the simulation model. Eventually, the new algorithm with the tuned parameters is imported into the real system. In this stage, the tuned PSMS will automatically trigger the required actions to mitigate blockage and disruption, acting as an internal online digital twin in real time. Thus, after this step, the simulation model will no longer be needed. In order to demonstrate the applicability of this framework in the industry, in the following subsections, we apply this approach to a real case study from the food and beverage industry.

2.1 Conceptual Modeling

The considered case in this paper is a continuous production line for beverage packing in Western Europe that currently produces drinking water in 500 ml polyethylene terephthalate (PET) plastic bottles. This line produces the bottles onsite and stores the final products (in pallets) in its warehouses. The line comprises nine main components that include three sources of material (namely, Beverage supply, Plastic PET preform supply, and Pallet supply), and six machines (namely, Combi machine, Labeler, Cluster packer, Over packer, Palletizer, and Stretch wrapper). The production process of this line is graphically illustrated in the flow chart of Figure 1.

In this process, the first step is to feed the PET preforms and the beverage itself to the Combi machine. This machine is responsible for two sub-operations: (i) Forming the PET bottles from the reform through a blow molding technique and preparing them for the filling process, and (ii) Filling the bottles with the supplied beverage and capping them. The beverage supply subsystem, on the other hand, processes the beverage, stores a specific amount in temporary tanks, and eventually provides it to the Combi machine in the required amount. Unlike other parts of this production line, the beverage supply subsystem is, in nature, a continuous process with all elements connected through pipes, and entities in this portion of the system experience continuous, gradual events that are mainly constrained by the supported volumetric flow rate of the pumps, pipes, valves, and other types of equipment. After the Combi machine, the unit of measurement for the main entity that moves in the system always remains discrete.

The filled bottles are then transferred to the labeling station — from which stage, all transfers in the line will be done by conveyors. These conveyors are where the system keeps the temporary inventory

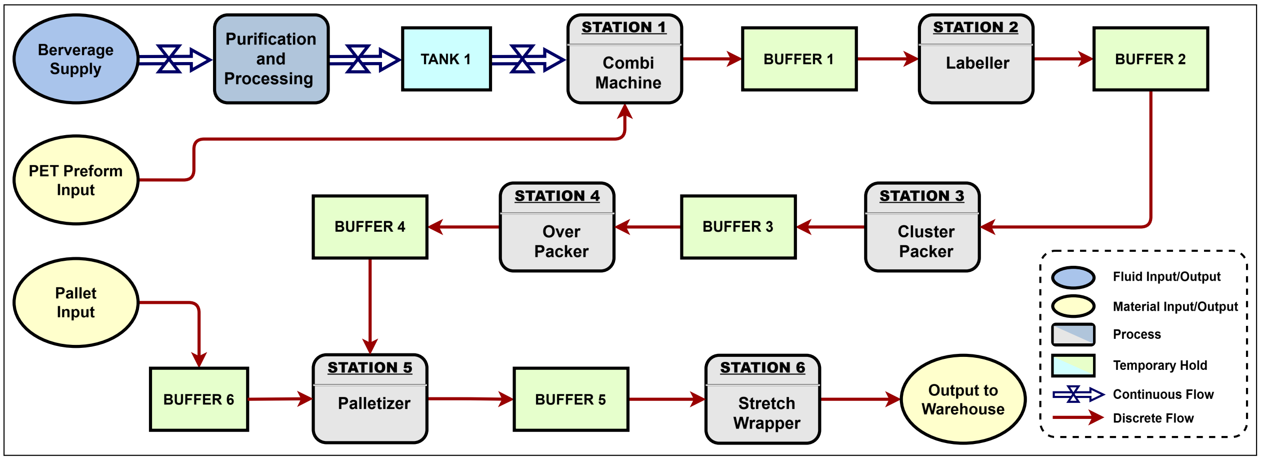


Figure 1: The manufacturing process flow of the production line in the case study.

between the stations, i.e., work in process (WIP). Thus, in this study, the conveyors are seen as intermediary buffers, each of which has a distinct capacity; i.e., 1250, 750, 750, 500, and 580 product units for buffers 1-5, respectively. The cluster packer machine packs 6 bottles into 1 cluster followed by the over packer machine, which packs 4 clusters of bottled water into 1 pack. Subsequently, the palletizing station loads the clusters on a pallet. Based on the data gathered from this production line, there are 13 packs per layer and 7 layers per pallet; thus, each pallet contains 2184 units of products (i.e., bottled water). Eventually, as the last stage of production, the stretch wrapper wraps the pallets with stretch film, delivering the finished goods to the shipping/warehousing stage. The nominal capacity of all machines of this production line is given in Table 1. To maintain the consistency of the data provided in this table, all speed values (even for the palletizer, cluster packer, and over packers) are converted to bottle units per hour (UPH).

Table 1: Production rate and maintenance parameters for the main machines of the line.

Machinery	**Production Rate (UPH)**			**Maintenance**	
	Low Speed	Normal Speed	High Speed	Uptime (%)	MTTR* (sec.)
Combi	30000	30000	30000	97.80%	112
Labeler	7200	30000	36000	96.00%	90
Cluster packer	25000	30000	37500	98.00%	74
Over packer	20000	30000	39000	97.40%	80
Palletizer	30000	30000	40500	97.50%	75
Stretch wrapper	30576	30576	43680	98.30%	80

* MTTR: Mean Time to Repair

Table 1 also includes the failure and repair data extracted from the maintenance records of this manufacturing line. The line can also be supplied with as many pallets as required, and there is no limit on the hourly supply of preformed PET material input for the system. The beverage supply part of the system has an output flow between (approx.) 25 to 30 m^3/h. Given the current product specification, this beverage flow could support the production of between 50k and 60k bottles per hour.

2.2 Simulation Modeling

Based on the conceptual model provided in the last subsection, we use a simulation platform to build our hybrid model. For this study, we chose Siemens TPS, which has long been used for modeling sophisticated industrial systems (see, for instance, Pekarcikova et al. 2021; Alfas et al. 2025; Shao et al. 2019). One of the advantages of this simulation platform for such a study is its ability to handle fluid continuous flow and discrete events of material seamlessly. The 2D view of the proposed simulation model in TPS is shown in Figure 2. In this model, two sources and one Fluid source object are used to input the material/fluid into the system. The inter-arrival time in the two sources (for the preforms and pallets) is set to 0 seconds to make sure these materials are available as much as required for the production with no restriction. In the continuous part of the simulation model, we used a tank object to represent the real tank in the system and a Portioner object that allows for merging the continuous flow with the flow in the discrete part of the model. Since the volumetric flow rates of these pieces of equipment were almost the same in the real system, we set the capacity of all of them to 25 m^3/h.

The Combi machine is modeled by an assembly station that merges one portion of the liquid with the PET plastic bottles, outputting a new part object that represents the filled bottle. Similar to the flow chart in Figure 1, the conveyors are modeled using buffer objects. For each buffer (i.e., conveyor), we have set the capacity to the values reported in the last section. Furthermore, each buffer has a dedicated method (e.g., *M_Conv1* for Conveyor 1) that is executed at the entrance of every element to the conveyor. These methods, in fact, contain the logic of the PSMS's decisions on machine speeds. The existing algorithms in these parts of the PSMS are given in Figure 3 for a sample conveyor (i).

In order to validate the proposed simulation model, we collect 30 samples of the model (with the existing PSMS setup), and compare its throughput with the real system. Based on the information provided by the company, this line is currently producing 200k bottles per shift (8 hours). Our model, on the other hand, gave us a very close average throughput of $199,239.3$ in these samples with a standard deviation of 2945.8. To test the validity of the model statistically, we use the t-test hypothesis test for which the t-statistic could be easily computed as -1.41. Consequently, with a p-value of 0.17, which is greater than the typical significance level ($\alpha = 0.05$), the test fails to reject the null hypothesis. This means, there is insufficient evidence to conclude that the population mean differs from $200,000$. Therefore, the model is valid and can be utilized reliably for further investigation and improvements.

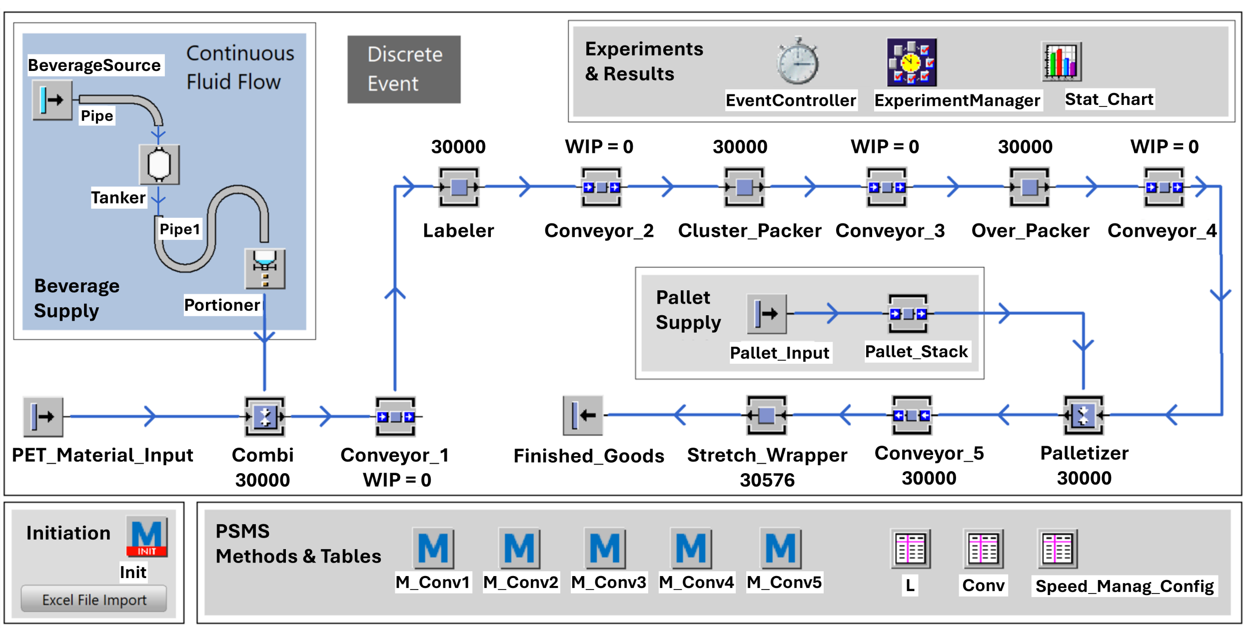
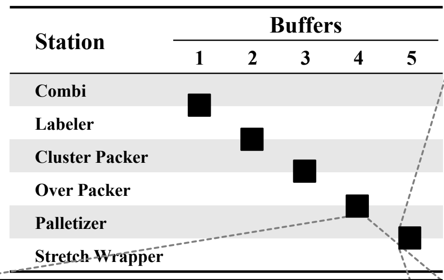


Figure 2: A glance at the hybrid simulation model developed for the system under study.



Existing Setup of PSMS

Condition		Predecessor Set to
If	$WIP_i > 0.7\ C_i^B$:	*Low Speed*
Else If	$WIP_i < 0.45\ C_i^B$:	*Normal Speed*

Proposed PSMS Algorithm

Rule	Condition		Stations	Set to
1	***If***	$WIP_i < (L_{i1})\ C_i^B$:	Predecessor	*High Speed*
2	***Else If***	$WIP_i < (L_{i2})\ C_i^B$:	Predecessor	*High Speed*
			Successor	*Low Speed*
3	***Else If***	$WIP_i < (L_{i3})\ C_i^B$:	Predecessor	*High Speed*
			Successor	*Normal Speed*
4	***Else If***	$WIP_i < (L_{i4})\ C_i^B$:	Predecessor	*Low Speed*
			Successor	*High Speed*
5	***Else If***	$WIP_i > (L_{i5})\ C_i^B$:	Successor	*High Speed*

Figure 3: The proposed algorithm for the PSMS and the existing speed management decision setup; For conveyor i, WIP_i, C_i^B, and L_{ij} are respectively the real-time inventory, capacity, and threshold level j.

2.3 Redefining the PSMS Algorithm

Before defining the new algorithm for the PSMS, we would need to observe the available speed limits for each segment of the line. As explained in Section 1, drawing a V-graph is one of the best graphical approaches for identifying the bottlenecks in such continuous lines. Based on the collected data, this system's V-graph is given in Figure 4. This graph shows that the most influential station in this system is the Combi machine. That is, this machine defines the cap of achievable improvements in this line. It is also observed that the beverage supply in this line will always exceed the required capacity, regardless of the chosen speed for any other machine. It is also observed that keeping the labeler, cluster packer, or over packer machines constantly on low speed will risk the system turning these stations into a bottleneck.

Based on these observations, we define a new algorithm for the PSMS that overwrites the existing setup in the system. This algorithm is graphically presented in Figure 3. As seen in this figure, unlike the existing setup, the decisions are now affecting both the predecessor and successor stations. Furthermore, multiple rules and levels are defined to take the most out of all the options we have for the machine speeds. Here, the algorithm benefits from separate threshold level sets for each conveyor (i.e., L_{ij} for threshold level j of conveyor i), allowing for independent calibration and tuning of the decision rules in each conveyor. This feature provides us with better tuning and optimization compared to the static coefficients considered in the existing setup. Given that the system has 5 conveyors, the threshold level matrix L is a 5×5 matrix. It can be observed that in this algorithm, these thresholds are checked sequentially, and thus when assigning values to these thresholds, the following relationship should logically hold for them:

$$L_{i1} < L_{i2} < L_{i3} < L_{i4} < L_{i5}, \quad \forall i \tag{1}$$

2.4 Tuning by Design of Experiments (DOE)

In this study, the Taguchi method is employed to optimize and tune the proposed PSMS algorithm by systematically evaluating the influence of the above 25 factors, each considered at 3 distinct levels. In order to make sure that in all experiments the statement in Eq. (1) holds for each $i \in \{1,2,...,5\}$, we define a set of mutually independent auxiliary factors L'_{ij}, and use them instead of the original L factors for the DOE purposes:

$$L'_{i1} = L_{i1}, \quad \forall i \tag{2}$$

$$L'_{ij} = L_{ij} - L_{i(j-1)}, \quad \forall j > 1, i \tag{3}$$

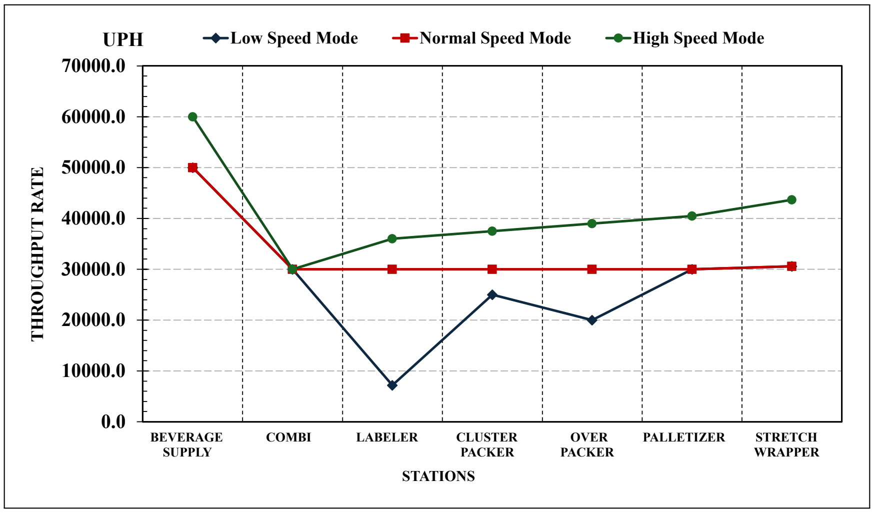


Figure 4: The V-graph for important stations of the case study.

The L81 orthogonal array is chosen to effectively organize the experimental design, facilitating a comprehensive analysis of the factors' effects and interactions while reducing the number of necessary experiments. This methodology, tied to Taguchi's philosophy of design, seeks to improve algorithm performance by determining optimal configurations that maximize efficiency and minimize resistance to noise (Taguchi 1986). The employed L81 array, as a fractional factorial design, efficiently manages our extensive parameter space, consistent with established methodologies for multi-factor optimization (Roy 2001). The data from the performed experiments is then used to develop a linear model and find the optimum factor values.

One of the main advantages of this method over its counterparts from the DOE class is that it requires significantly fewer runs than a full factorial design, which would require $3^{25} = 8.47 \times 10^{11}$ experiments (Antony 2014; Attar et al. 2016, 2025) . This makes the deployed method less complicated compared to the response surface-based ones by Attar et al. (2016, 2025), ideal for tuning production management algorithms, like PSMS, with numerous stations and factors, and ultimately offering a reproducible framework for future research in algorithmic optimization within analogous computer-operated production systems.

3 RESULTS AND DISCUSSIONS

In this section, we apply the proposed tuning approach to the refined PSMS and compare the achieved results with the existing setup of the system from multiple perspectives. To have an in-depth understanding of the performance of the system and its reliability in real practice, first, we deploy the proposed approach to the existing failure and repair patterns explained in the previous section. Subsequently, we conduct sensitivity analyses to test the resiliency of the proposed PSMS under a set of unforeseen disruptions in different parts of the production line.

3.1 Performance in Normal Conditions

Based on our preliminary experiments, the acceptable values for L'_{ij} factors would fall in the following ranges: $[0, 0.10]$ for $j = 1$ and $[0.05, 0.30]$ for all other j values. For each of the 81 experiments designed using the Taguchi method, we collected 30 samples from the simulation model. This sample size was shown to be statistically effective in the literature based on the central limit theorem (Attar et al. 2016). The data obtained from the experiments (i.e., design and responses) is then analyzed by fitting a linear model to the data and solving it to optimality using MATLAB. This resulted in an R-squared value greater than 0.9; the fitting results demonstrate a statistically rigorous assessment of the factors' impacts on the PSMS

Table 2: The optimum values of the auxiliary DOE factors and corresponding algorithm parameters.

		L'_{ij}					L_{ij}				
Rule (j)		1	2	3	4	5	1	2	3	4	5
Conveyor (i)	1	0.00	0.05	0.05	0.30	0.05	0.00	0.05	0.10	0.40	0.45
	2	0.10	0.05	0.05	0.05	0.30	0.10	0.15	0.20	0.25	0.55
	3	0.10	0.30	0.05	0.05	0.05	0.10	0.40	0.45	0.50	0.55
	4	0.00	0.05	0.30	0.05	0.05	0.00	0.05	0.35	0.40	0.45
	5	0.00	0.05	0.05	0.30	0.05	0.00	0.05	0.10	0.40	0.45

algorithm's performance. Table 2 reports the optimum factor settings for the proposed PSMS algorithm, both for the auxiliary factors and their translation to the original L factors.

By achieving the optimal values for the L factors, we can now test the expected performance of the proposed tuned PSMS against its simple ancestor, i.e., the existing setup, from Figure 3. To have a statistically valid comparison between the approaches, we collect 30 samples of each method and report their statistics for the main key performance indicators (KPIs). These results are presented in Table 3, along with the value and percentage of change achieved by our method. As seen in Table 3, the tuned PSMS has achieved a significant increment in the expected throughput (per shift) of this production line. Apart from the high increment of approx. 18% in the throughput mean, we also observe that the variations of the results were slightly decreased in this method. Even though a 3.4% reduction in the standard deviation might not seem very significant, it can signal that the proposed tuned PSMS was more successful in mitigating machine failures while maintaining acceptable WIP levels and avoiding blockage. This all should be considered together with the fact that the new PSMS algorithm offered a drastic reduction in the average WIP of the system in the buffers — lowering it from over 964 units to the negligible amount of 41 and scoring 95.7% of reduction. Furthermore, Figure 5 illustrates the performance of the new PSMS in eliminating the blockage in the Combi machine as well as reducing the block state in other critical segments of the line.

Table 3: KPI Comparison between the existing setup and the proposed tuned PSMS.

KPI		**Model**		**Change**	
		Baseline	Tuned PSMS	Amount	Percentage
Throughput	*Mean*	199239.3	234218.6	+34979.3	+17.6%
	Std Dev	2945.8	2846.2	−99.6	−3.4%
Average WIP		964.3	41.7	−922.6	−95.7%

3.2 Resiliency Analysis

The drastic reduction in the WIP levels reported in Table 3 may raise some concerns regarding the ability of the new PSMS algorithm to withstand changes in the failure patterns of the production line assets. It is also important for the new algorithm to handle new patterns and longer durations of repairs. In order to investigate the proposed approach from such resiliency aspects, we defined 8 scenarios in which different parts of the system would encounter new failure and repair distributions. As defined in Table 4, the first half of these scenarios maintains the existing assumption of perfect conveyors and considers no failures for them. For the second group (i.e., Scenarios 5-8), we added failure-prone conveyors with 95% uptime and

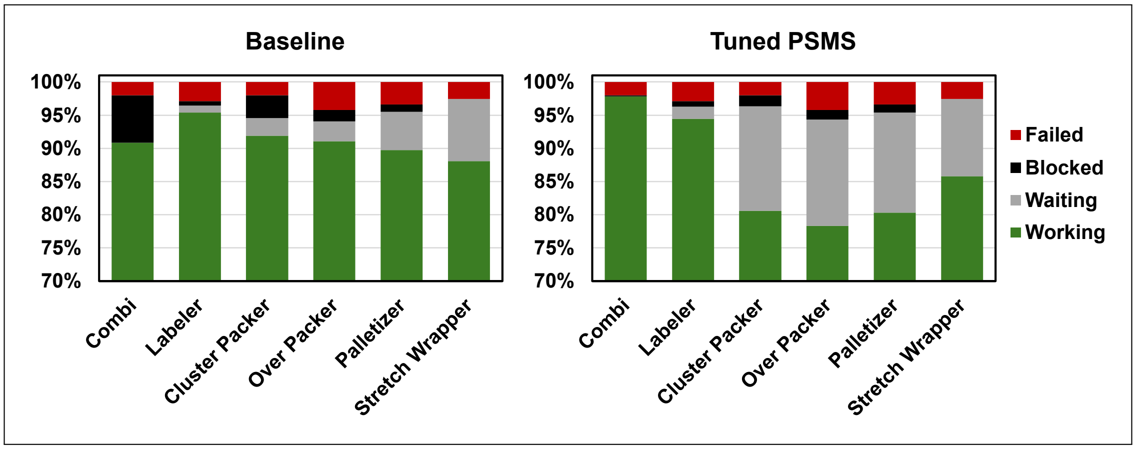


Figure 5: Performance of the proposed approach vs the baseline in mitigating the blockage in the bottleneck.

an average repair time of 1 minute. For each of these two scenario groups, we considered a combination of the availability drop of the six main stations and significant increments in their repair time.

The availability drop considered for these experiments is set to the realistic amount of 10%. For repair time increment, on the other hand, it was assumed that the system would face machine repairs that could take twice as long. Both models were run under all these scenarios to collect 30 samples, and the results are summarized and compared statistically in Table 4. Here, for each scenario, we report a relative improvement (*RI*) percentage achieved by the proposed method compared to the baseline model. Considering Scenario 1 as a reference point for normal conditions, we calculated the deviation percentage (i.e., *Dev*) from the corresponding normal throughput (Scenario 1) as well. The common definitions of the *RI* and *Dev* relative performance indices were adopted from Attar et al. (2024a) and used for calculating the values reported in this table. The results reported in Table 4 disclose that the proposed PSMS algorithm is significantly more resilient than the existing setup of the system. The superiority of the proposed approach ranges from 17.56% up to the very high level of 37.65% in different scenarios. To demonstrate the significance of this gap more clearly, we plotted the collected samples in Figure 6 for both models under all scenarios.

Table 4: Throughput resiliency analysis and comparison; Existing setup vs The proposed tuned PSMS.

Scenarios	**1 (N ∣ N ∣ N)***		**2 (N ∣ N ∣ Y)**		**3 (N ∣ Y ∣ N)**		**4 (N ∣ Y ∣ Y)**	
	Baseline	*Tuned PSMS*	*Baseline*	*Tuned PSMS*	*Baseline*	*Tuned PSMS*	*Baseline*	*Tuned PSMS*
Mean	199239.3	234218.6	182330.2	231059.3	150330.2	197621.5	132010.1	177962.0
Std Dev	2945.8	2846.2	6220.9	4434.3	4171.1	4830.6	8507.3	9633.4
RI (%)		*17.56*		*26.73*		*31.46*		*34.81*
Dev (%)	-	-	*8.5*	*1.3*	*24.5*	*15.6*	*33.7*	*24.0*
Scenarios	**5 (Y ∣ N ∣ N)**		**6 (Y ∣ N ∣ Y)**		**7 (Y ∣ Y ∣ N)**		**8 (Y ∣ Y ∣ Y)**	
	Baseline	*Tuned PSMS*	*Baseline*	*Tuned PSMS*	*Baseline*	*Tuned PSMS*	*Baseline*	*Tuned PSMS*
Mean	168207.6	216854.7	157910	212847.3	129912.4	174234.6	114684.2	157858.1
Std Dev	3462.8	4582.4	4779.8	5062.5	3953.0	5127.7	7718.7	9888.8
RI (%)		*28.92*		*34.79*		*34.12*		*37.65*
Dev (%)	*15.6*	*7.4*	*20.7*	*9.1*	*34.8*	*25.6*	*42.4*	*32.6*

* Scenario specifications: (Conveyor Failure ∣ Availability Drop ∣ MTTR Increment); Y: Yes; N: No

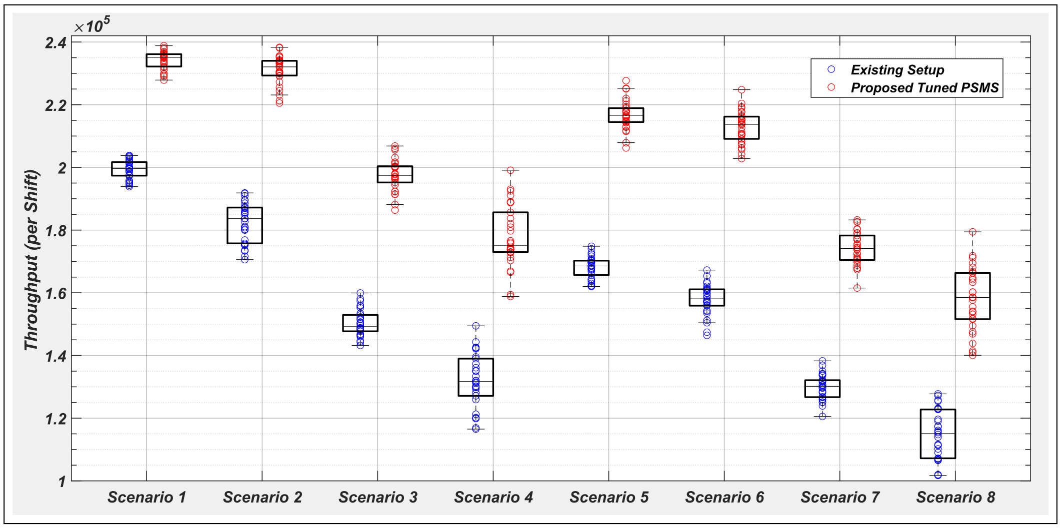


Figure 6: Resiliency of the proposed approach and the existing setup of the system under several unforeseen scenarios for failure and repair fluctuation.

As illustrated in Figure 6, there is a significant gap between the data points of the proposed PSMS and those of the baseline model in all scenarios, and the box plots of these methods did not overlap at any point. These plots also show that in both models, the availability drop considered in the scenario definitions can have a more significant effect on the throughput of the system than the increment in the MTTR. Furthermore, comparing the results of these models for Scenarios 1 and 2 shows that the new algorithm is less sensitive to the MTTR changes and it encounters only a negligible 1.3% reduction in its productivity. This observation is also repeated in the transition from scenario 5 to 6, where the tuned PSMS only sees a 1.7% further throughput reduction. Meanwhile, the system seems to be noticeably more sensitive to fluctuations in the availability ratio of the machines (i.e., the failure rates), with the *Dev* values rising to 35% and 25% for the Baseline and tuned PSMS models, respectively.

As expected, the combination of the availability drop and MTTR increment assumptions simultaneously in Scenarios 4 and 8 causes more disruption in the production line under both model setups. Additionally, adding the failure-prone conveyor assumption causes between 8.7% and 15.6% reduction in the throughput of the base model and lowers the productivity in our tuned system by 7.4 to 10 percent. That is, the tuned algorithm was more successful in maintaining the added failure pattern in these transportation types of equipment. In general, comparing the *RI* values in Table 4 with that of normal conditions (i.e., Table 3) reveals that the new failure and patterns did not weaken the superiority of the proposed PSMS algorithm over the current baseline. In fact, these disruptions even noticeably increased the performance gap between the two setups. Therefore, these findings, together with the ones reported in Table 3 and Figures 5-6, strongly support the implementation of the new approach in the real system.

4 CONCLUSIONS

Digital twins play a pivotal role in managing continuous production lines by enabling real-time monitoring, simulation, and optimization of complex manufacturing processes. With a particular emphasis on continuous smart manufacturing lines, this study analyzes the proposition of transforming the PSMS into an online digital twin that is capable of optimizing the system in normal conditions and properly mitigating unforeseen fluctuations, faults, and congestion that may be experienced in these lines. Default PSMS settings that might come from the equipment manufacturers can be excessively conservative, generic, simple, or imbalanced, and thus their decisions may rely on local remedial adjustments to the manufacturing process, overlooking the overall productivity of the system. In addition, these systems are usually running continuously alongside the real system and have real-time access to all sensors' data. As the name implies, the PSMS also has the highest required privileges to set and adjust the speed of all parts of the line at any point in time.

That is, the PSMS inherently has the real-time monitoring feature required for being a digital twin, and it also has the power to execute the necessary commands. This all signals an interesting opportunity for decision algorithm refinements and tuning for these systems. This study proposes a five-step framework to accomplish this task: (i) conceptual modeling, (ii) simulation modeling, (iii) PSMS algorithm refinement, (iv) DOE and tuning, and (v) real-system implementation. To illustrate the application of this framework in a practical context effectively, we examined a case study from the food and beverage sector. After defining the initial conceptual model of the system, we utilized Siemens TPS to build the simulation model. Here, we used the available features of this simulation platform to model and merge the continuous and discrete event segments of the system effectively. The model included all the existing setups and rules of the system for the PSMS, and it was validated against the collected real data using a statistical hypothesis test.

In the next step, we attempted to redefine the internal logic of PSMS by using the collected data, system description, and the validated simulation model. To identify potential bottleneck stations and the cases they can be problematic, we deployed the V-graph method. Unlike the simple existing decision procedure, the proposed step-wise algorithm for the PSMS benefits from five distinct rules that are evaluated sequentially to find the best speed for both upstream and downstream stations. This algorithm also makes use of the whole available speed range for each machine if necessary. Another advantage of the proposed algorithm is that the decision thresholds of the rules are adjustable independently for each part of the production line. This feature provides a very high level of customization and adaptability. Due to the numerous decision thresholds in this algorithm, we employed the Taguchi DOE and utilized an L81 orthogonal array to systematically structure the experimental design. This approach enabled a thorough examination of the factors' effects and interactions while minimizing the required experiments, enhancing both the efficiency and robustness of the study.

The results of the tuned PSMS were numerically contrasted with the existing setup, which showed around an 18% improvement in the overall throughput along with a drastic WIP reduction. However, the noticeable drop in WIP could cause concerns for management about the performance of this method in the event of new, significant disruptions in the system. This concern was also investigated using a variety of numerical scenarios for possible changes in the repair and failure patterns of the system components. This resiliency analysis revealed that the significance of the performance gap gets even greater under such disruptions (i.e., approx. 38%), making the benefit of switching to the new tuned PSMS for production management more remarkable. For future research, one may consider applying this framework to manufacturing lines in other industries such as textiles or steel manufacturing. Examining how algorithms perform amid the uncertainties introduced by human resources, or by exploring their impact within production systems across different industries, could broaden its practical relevance.

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