Proceedings of the 2025 Winter Simulation Conference
E. Azar, A. Djanatliev, A. Harper, C. Kogler, V. Ramamohan, A. Anagnostou, and S. J. E. Taylor, eds.

DIGITAL TWINS FOR OPTIMIZING THE TRANSITION FROM JOB-SHOP TO MASS PRODUCTION: INSIGHTS FROM MARINE PUMP MANUFACTURING IN SCANDINAVIA

Sebastian Pihl[1,2], Ahmad Attar[1], Martino Luis[1], and Øystein Haugen[2]

[1]ExDES laboratory, Department of Engineering, University of Exeter, Streatham Campus, Exeter, UK
[2]Department of Production Engineering, FRAMO, Bergen, Norway

ABSTRACT

Marine pumping systems are among the most essential equipment for maritime operations. Typically, this type of equipment is manufactured to order in small quantities, thereby increasing the cost and time to market. The rising demand for this equipment has made the transition to mass production even more attractive for key players, which can potentially lead to significantly higher competitiveness for these companies. However, to maintain the competitive advantages of such a transition, it is crucial to make optimal decisions, taking into account all influential aspects. This study, assisted by experts from pioneering companies in this industry, proposes an integrated approach that applies redundancy analysis, inventory policy calibration, and GA-based optimization to address these challenges—all built upon a DES-based digital twin. Applying our framework to the studied case drastically reduced the cycle time from more than a week to about one day, raising the annual capacity over the projected demand.

1 INTRODUCTION

Manufacturing companies transitioning from job-shop to mass production face significant operational challenges, driven primarily by increased market demand and competition. Job-shop systems, characterized by their flexibility and suitability for customized, small-volume production, often become inefficient and inadequate when tasked with scaling up production volumes (Mohan et al. 2021). Such transitions demand comprehensive restructuring across processes, facilities, and organizational management practices, introducing risks related to cost, resource allocation, and operational disruption. Within the marine pump manufacturing sector, particularly in high-labor-cost regions such as Scandinavia, companies frequently grapple with rising demand and heightened expectations for shorter lead times and improved resource efficiency (Edh Mirzaei et al. 2021).

Traditional production setups in the marine pump industry struggle severely under such conditions, resulting in persistent bottlenecks, extensive lead times, and suboptimal utilization of available resources. This highlights an urgent necessity to conduct analyses and reconfigurations of production environments in order to align with the observed evolving market demands. Here, the complex and expensive equipment involved in the marine pump production, the complex network of procured and manufactured parts, and the stochastic sequence-dependent changeover (setup) time for the manufacturing and assembly steps in this system all increase the intricacy of optimization efforts in this context. This perception of such a manufacturing system renders it intractable for traditional mathematical modeling techniques, turning the attention of industrial managers and stakeholders to advanced simulation-based modeling and digital twins that can offer a realistic representation of these restrictions and complexities.

Among the available simulation techniques, discrete event simulation (DES) has been used successfully in various industries, some of which are summarized in Table 1. The selected DES platforms are widely recognized and effective, offering advanced modeling capabilities that align with industry standards. Additionally, company managers prefer such commercial packages due to their visualization and robust technical support. Thus, while non-commercial alternatives exist, our focus in this table is on the practical

Table 1: Summary of the related discrete event simulation literature with industry case studies.

Reference	Simulation Platform						Product / Industry	Improvement Method
	AnyLogic	Arena	ED	FlexSim	SIMUL8	TPS		
Heshmat et al. (2013)		☑					Cement	Buffer re-allocation
Zupan and Herakovic (2015)						☑	Metal	Cycle time analysis
Attar et al. (2016)			☑				Diesel Generator	RSM-based Metamodeling
Kuncova and Zajoncova (2018)					☑		Electronics	General line balancing
de Groot and Hübl (2021)	☑						Smart Phone	Utilization-based calibration
Gola et al. (2021)						☑	Powertrain	Line Balancing
Grznár et al. (2021)						☑	Shipping	Demand optimisation by GA
Pekarcikova et al. (2021)						☑	Solar Panels	Kanban
Jung et al. (2022)	☑						Garment	Productivity assessment
Attar et al. (2023)						☑	Beverage	Re-coding flow management
Boj'ic et al. (2023)						☑	Textiles	Multi-Objective GA
Ugheoke et al. (2024)				☑			Kaolin	Systematic Layout Planning
This Study						☑	**Marine Pumps**	**Redundancy allocation & Inventory policy calibration by GA**

utilization of such established platforms. From the cement, metal, and automotive industries to garment, beverage, and smartphone manufacturing lines, DES-based models and digital twins were utilized for monitoring systems and optimizing their key performance indicators (KPIs). For instance, Heshmat et al. (2013) focused on the simulation modeling of a cement production line to address various allocation problems, such as the workload allocation, server allocation, and buffer allocation. Using ARENA simulation software, they developed a DES model to analyze and resolve bottlenecks causing severe congestion in different areas of the production line. By collecting workstation failure data over a year, they identified optimal buffer sizes and increased the production rate by more than 15%, while economizing 34% of buffer capacities.

Using Anylogic platform, de Groot and Hübl (2021) explored a Dutch phone and subscription retailer case during COVID-19 and addressed its long waiting times. Their calibrated model simulated the queueing system and evaluated employee scheduling improvements. The results suggested that the improved scheduling scheme can significantly reduce multiple KPIs, i.e., mean waiting times by 20-33%, maximum waiting times by 12-20%, while increasing service levels by 3-11%, and eventually resulting in an enhanced customer satisfaction without increasing working hours. Similar but relatively simpler attempts were also reported by Zupan and Herakovic (2015), Gola et al. (2021), and Kuncova and Zajoncova (2018) in the other industries that applied cycle time analysis and general line balancing practices for achieving the desired improvement. Other innovative improvement methods include a smart dynamic buffer recalibration algorithm deployed by Attar et al. (2023) in the beverage and the systematic layout planning proposed by Ugheoke et al. (2024). From the simulation platform perspective, the literature reviewed by Kovbasiuk et al. (2021) and Kliment et al. (2025) supports our observation from Table 1 in favor of the advanced features of Tecnomatix Plant Simulation (TPS) for manufacturing line simulation purposes.

As seen in Table 1, the marine and offshore equipment manufacturers have been neglected in the literature. In its current state of transformation from a customized low-volume production pace to the new era of mass production, this industry has unique specifications and requirements that are in focus in this study. The existing literature highlights the significant improvements of inventory policy calibrations for reducing finished goods and work-in-progress (WIP) inventory costs and streamlining manufacturing processes (Attar et al. 2016; Pekarcikova et al. 2021; Xu et al. 2019). On the other hand, the use of redundancy allocation for meeting desired serviceability levels was reported successful in other segments of supply chains (Cheng et al. 2012; Attar et al. 2017, 2024). Therefore, hybridizing this method with simulation-based line optimization can potentially form an interesting improvement approach. With the natural challenges of transformation to mass production in mind, batch-size optimization studied in other industries (e.g., Mehra et al. 2006; Hung and Liker 2007) may also be effective for reducing the dependence of new strategies on excessive redundancy in the system.

Therefore, the contributions of this paper are threefold: (i) proposing a practical digital twin for the marine pump manufacturing industry using the DES method in the TPS environment, (ii) considering redundancy allocation and batch sizing to meet the required capacity for the expected demand, and (iii) deploying metaheuristic optimization techniques to calibrate the parameters of the pull inventory policies of the buffers for a streamlined production process. The rest of the paper is organized as follows: the proposed methodology framework, simulation model, and optimization method are explained in the following section. Section 3 reports the numerical results, observations, and discussions. Finally, some concluding remarks and future research directions are presented in Section 4.

2 METHODOLOGY

In this study, we apply a framework with five main steps to achieve the mass production capacity intended for the system. This framework is schematically illustrated in Figure 1. As the first step, we study and model the existing system using simulation tools. This step involves conceptual modeling, deployment in the selected simulation software, and validation. In the second step of the framework, we analyze the existing system using the validated model to identify the segments with high potential for developing a bottleneck. Based on these analyses, we define the required reconfigurations in the stations and the new levels of redundancy for various parts of the system. Step 4 in this framework attempts to optimize the system by calibrating the pull inventory system applied to manage the work-in-progress (WIP) stocks in the critical buffers of the system. Eventually, the last step is meant to provide a numerical comparison of the projected performance of the system after applying different combinations of the proposed methods, helping production managers choose the most desirable scenario based on their goals and preferences.

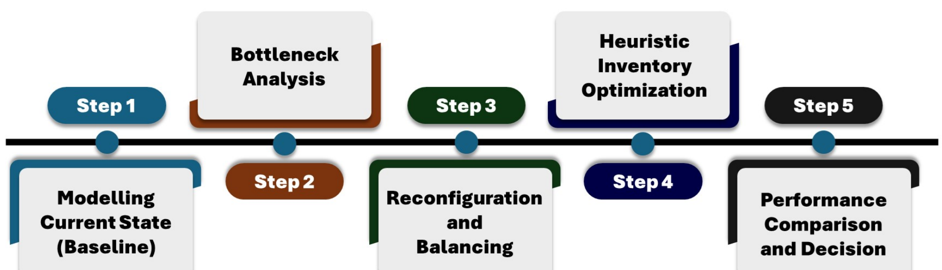

Figure 1: Overview of the applied framework.

2.1 Conceptual Modeling

The initial stage of the simulation methodology involved developing a detailed conceptual model to represent the structure and logic of the marine pump manufacturing process. The conceptual model includes the key production steps, resource interactions, and inventory flow pathways. Process mapping techniques were applied in collaboration with the company's manufacturing engineers to identify critical operations, machine dependencies, and workflow constraints. The system under study comprises 26 main stations that can be classified into four main classes: 6 assembly stations (Assy1-6), 10 automated machining (Mach1-10), 8 labor-based stations (Stat1-8), 2 finishing treatment stations (Treat1-2). Based on the manufacturing system's bill of materials (BOM), 12 different parts are defined in this line, each of which uses a set of the available stations based on the sequence mentioned in Table 2. Minor parts, procured ones, or those that do not need processing before assembly have been discarded in this table.

Table 2: Process sequence and the prerequisites for producing each part in this line.

Part ID	Prerequisite ID	Sequence
1		Mach4→ Mach9→ Mach2→ Treat1
2		Mach4→ Treat1
3		Mach4→ Mach9→ Mach2→ Treat1
4		Mach6→ Stat3→ Mach7→ Stat7→ Stat1→ Treat2→ Mach3→ Mach8→ Treat1
5		Mach6→ Stat3→ Mach7→ Stat7→ Stat1→ Treat2→ Mach3→ Mach8→ Treat1
6		Assy7→ Treat2→ Mach9→ Stat4
7		Assy7→ Treat2→ Mach3→ Stat4
8		Assy2→ Mach1
9		Assy3
10	1, 2, 4, 7	Assy5→ Mach5→ Stat5→ Mach3→ Mach2
11	3, 5, 6, 8	Assy6→ Stat2→ Stat8→ Mach5→ Mach3→ Stat5→ Assy1→ Mach10
12	9, 10, 11	Assy4

This manufacturing facility makes use of various types of advanced metal processing technologies such as TIG and MIG/MAG welding, CNC laser welding, and plasma cutting. The patented process sequence of this manufacturing system is anonymized in this paper by using station codes (Mach, Assy, Stat, and Treat) instead of process names. For instance, regarding the production of Part ID 10, we need to assemble the prerequisite parts, send them through machining, and perform a manual handling step before performing the last two machining processes. The final product in this system is Part ID 12, which concludes the assembly of all parts in Table 2. Furthermore, our field study identified the following assumptions and constraints in the system:

- One production year comprises 230 working days, each consisting of a single 8-hour shift with a 30-minute break, totalling 1,725 operational hours.
- Process times represent the complete duration of the work at each station, and a noticeable setup time is required for some operations.
- Consecutive parts of the same type require 15-30% shorter setup time.
- The frequency of machine breakdowns, defective parts, and rework in this system is negligible.
- Transportation times between stations and worker behavior are disregarded at this planning stage.
- The WIP in all buffers is controlled using a periodic-review base-stock inventory policy, i.e., the (R, T) policy; in which R and T stand for the reorder point and review period, respectively.

Based on our observations, the setup time reduction mentioned in the assumptions is approximately 15% for Mach5 and 30% for all other stations with non-zero setup time. The review period T is a constant 30 minutes for all buffers in the existing state of the system, and the corresponding reorder point values will be reported later in this paper in Table 4. These specifications, assumptions, and constraints ensure that the simulation model authentically mirrors the practical operational conditions within the manufacturing facility while maintaining necessary simplifications for efficient and accurate simulation analysis.

2.2 Simulation Modelling and Validation

The initial phase for developing this simulation model is extensive data collection at the factory site. Historical production data, including cycle times, machine processing times, and setup times, were gathered from the company's existing production records through their Enterprise Resource Planning (ERP) software. Interviews and consultations with process engineers and operational managers further enriched the dataset, ensuring a high degree of model fidelity and validity, and reflecting the real system. The collected data for each manufacturing step was statistically analyzed and best fitted to Weibull distributions. This distribution is known to provide suitability for accurately modeling the variability and reliability characteristics commonly

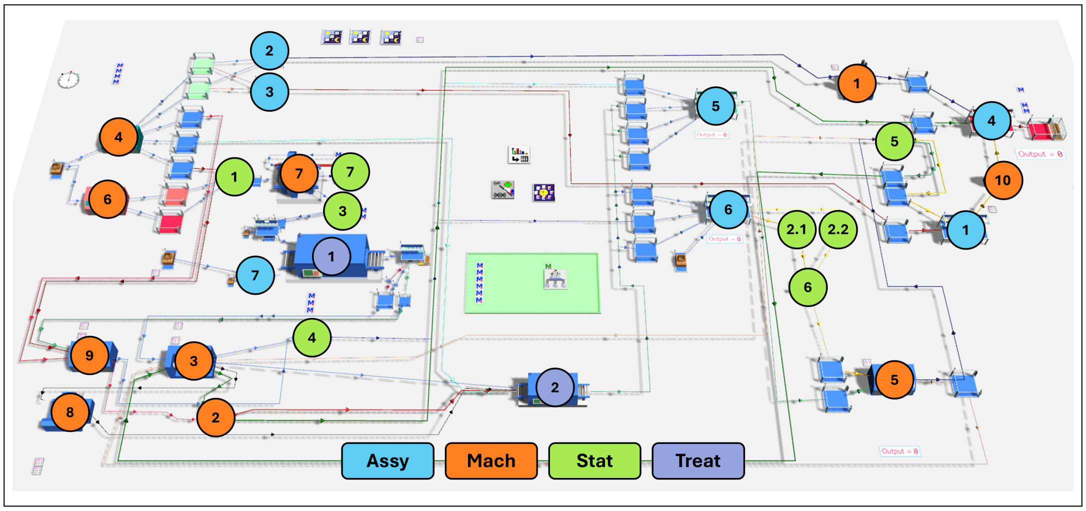

Figure 2: Simulation model of the studied system in TPS for the baseline state.

observed in manufacturing processes, enabling precise representation of operational uncertainties within the simulation (Attar et al. 2017). For CNC machining steps (i.e., Mach), the process duration was split into separate cycle and setup times. Based on our observations, CNC machines only experienced stochasticity in their manual setup, followed by a fairly constant cycle time.

In this study, we develop the simulation model in Siemens Tecnomatix Plant Simulation (TPS) software, which has been used practically in various companies in Europe (see, for instance, Alfas et al. 2025; Attar et al. 2023; Boj'ic et al. 2023). The statistically refined data, the concept, and the logic of this system were integrated into a comprehensive DES model that accurately represented the existing job-shop manufacturing layout and processes. Each workstation, buffer, and production resource was explicitly modeled, enabling detailed analysis of workflow dynamics and bottleneck identification. Buffer objects were used to manage intermediate storage, ensuring parts were readily available for downstream processing. Standard and parallel station objects, assembly, and dismantle stations are among the main built-in objects used to model various segments of this manufacturing system.

An aerial 3D view of the proposed simulation model is shown in Figure 2. As presented in this Figure 2, the model has one instance of all stations mentioned in Section 2.1 except for Stat2 which has a redundancy level of 2 (marked by 2.1 and 2.2 in the layout). While the standard blocks provided the foundational structure, complex control logic — such as dynamic routing, prioritization, and trigger-based responses — was also implemented using the Method object class written in SimTalk programming language. This enabled responsive and condition-driven behaviors aligned with real operational dynamics and the predefined Bill-of-Materials (BOM). To model the pull WIP inventory policy in the buffers, we defined a customized set of controller method objects that would trigger the replenishment orders based on the preset reorder point and review period values of each buffer. For more details on modeling such base-stock policies, one may refer to the comprehensive DES-based studies by Attar et al. (2016) and Xu et al. (2019).

In the next step, the proposed baseline simulation model was validated and verified from multiple aspects to ensure that it accurately represented the structure and behavior of the real production system. For each product type, part flows and processing durations at individual stations were analyzed and cross-checked against ERP-reported cycle times by setting tags and attributes to the entities of the simulation model. Furthermore, the total number of parts required for a complete unit was confirmed to enter the system using the pull inventory logic, and the accumulated processing time per station matched the expected values. In addition to the above quantitative checks, the model was reviewed and validated in collaboration with FRAMO's Production Engineering department. Moreover, in order to assess the long-term behavior of the digital twin, the baseline scenario was executed for an extended batch of 1,000 units (five times the annual target). This test ensured operational sustainability over time and verified that resource utilization, buffer behavior, and part sequencing remained stable under extended production runs.

2.3 Optimization

To support the transition toward a balanced and scalable production system, the optimization phase focused on aligning individual process capabilities with the system's overall production target. The defined goal was to produce 200 units of Product A within a single-shift operational calendar of 230 working days, resulting in an effective Takt time of 8.625 hours per unit:

$$\text{Takt Time} = \frac{\text{Available Production Time}}{\text{Customer Demand}} = \frac{230 \times 7.5\,\text{hours}}{200\,\text{units}} = 8.625\,\text{hours/unit.}$$

A detailed analysis of the processing times across all stations in the baseline simulation model was conducted to evaluate system capacity relative to this Takt time. Stations operating above this threshold were identified as bottlenecks, indicating areas requiring intervention. Several line-balancing strategies were explored, including the addition of process redundancies, deployment of extra workers where applicable, and minimization of part switching to reduce setup durations. For example, multi-part stations, reduction factors were applied to setup times when consecutive parts were of the same type, reflecting realistic operational behavior stated in the model assumptions

To further mitigate idle time and prevent upstream blocking, buffer reallocation was implemented. Buffer capacities and locations were systematically adjusted to ensure that each station maintained a consistent flow of parts and that upstream workstations could continue operating without interruption. These modifications enhanced material flow continuity and stabilized workstation utilization. As an additional attempt, the production system is equipped with rule-based flow control mechanisms. These controllers functioned as entry gates to stations, prioritizing parts based on downstream demand and proximity to final assembly. By dynamically sequencing part entry according to strategic production demand, flow controllers reduced congestion and improved synchronization across the line. Collectively, these modifications contributed to improved throughput, better resource utilization, and alignment with production targets.

2.3.1 Redundancy Allocation

In this part of the study, we attempt to reallocate the number of redundant stations in the system based on the observed results from the baseline model. The optimal reallocation of redundancies has long been considered an effective approach for improving the overall service-level and enhancing throughput in manufacturing and supply chain design (Cheng et al. 2012; Attar et al. 2015, 2017, 2024). The projected annual demand to be satisfied in this system is 200 units. Here, to measure the proper performance of each segment of the system in meeting this target, we use the process serviceability KPI, defined as the percentage of the target demand fulfilled by the station in the given time frame. Calculating this KPI for all stations revealed that six stations are not capable of handling the intended demand load in full. Table 3 reports these critical stations, the corresponding number of workers allocated to each group, the average time per unit (E), and the calculated values of the local serviceability percentage.

As shown in Table 3, these station groups currently have an available capacity for fulfilling between 18 and 79.7 percent of the projected annual demand. We explored the following three potential improvement pathways to address these issues: (a) increasing the number of redundants in these station groups, (b) adding redundants to the workers dedicated to these station groups, and (c) allocating specific parts to some of these redundants to eliminate the repeated station preparation and setup time. Upon initial examination of these pathways and consulting the production experts, the second pathway was eliminated. The automated machines were naturally functioning with very minimal supervision from the human workers, and several automated machines can be supervised by each existing operator. On the other hand, further workforce additions to the Assy4 and Stat2 station groups were not feasible due to space constraints at each station. The new layout of the system after applying the proposed redundancy is graphically demonstrated in Figure 3.

Table 3: Station groups with insufficient capacity before and after the redundancy allocation pathways.

Process	Baseline				Proposed			
	Redundancy	Worker	E (hh:mm)	Serviceability	Redundancy	Worker	E (hh:mm)	Serviceability
Assy4	1	2	15:00	58.0%	**2**	2	07:30	115.0%
Mach1	1	1	16:24	53.0%	**2**	1	08:12	105.0%
Mach3	1	1	25:04	34.4%	**3**	1	**07:59**	108.0%
Mach5	1	1	48:00	18.0%	**5**	1	**08:34**	100.7%
Mach9	1	1	15:15	56.6%	**2**	1	07:37	113.3%
Stat2	2	3	10:50	79.7%	**3**	3	07:13	119.5%

For Mach3 and Mach5, a hybrid strategy was pursued involving both redundancy increases (i.e., pathway a) and dedicated part-type routing (i.e., pathway c). In particular, pathway c for these two station groups takes advantage of the existing setup time reduction rules described in Section 2.1 (30% for Mach3 and 15% for Mach5 when processing the same part sequentially). More details on the analysis and proposed actions related to these two critical station groups are provided below:

- **Mach3 Optimization:** Analysis of Mach3's cumulative process time revealed that meeting the takt target would require tripling its capacity. Among the five distinct part types processed by Mach3, Part IDs 4 and 5 demonstrate the potential to meet the takt time when processed in batches, attributable to a notable decrease in setup time. These parts were assigned to dedicated stations (i.e., Mach3.1 and 3.2, respectively) to reduce setup frequency and improve flow stability. To further balance the system, a third station, Mach3.3, was introduced to intermittently process Part ID 4 and the remaining lower-volume parts. A parameterized SimTalk control method is implemented to redirect Part ID 4 to Mach3.3 whenever Mach3.1 falls behind Mach3.2 by a specified output threshold θ. At this stage of the optimization, this threshold was experimentally set to 4. The proposed configuration improved the output's regularity and decreased the overall setup-to-working state ratio. Most importantly, as seen in Table 3, this workaround increased usable capacity by reducing the average time per unit of this station group from 8:22 (after redundancy) to 7:59.
- **Mach5 Optimization:** Initial examination of this station group indicated that six stations of this type would be required to meet takt time using redundancy alone. However, in Table 2 only two distinct part types cycle through Mach5, making it a suitable candidate for sequence-based optimization. Thus, we proposed 5 redundant Mach5 stations accompanied by a part-type-based routing controller to eliminate excessive setup frequency. Four of the redundants were configured to process a single part type exclusively (i.e., Part ID 10 or 11), leveraging the 15% setup time reduction achievable through series production. The fifth station, Mach5.5, was shared between both part types and programmed with a batch-based switching

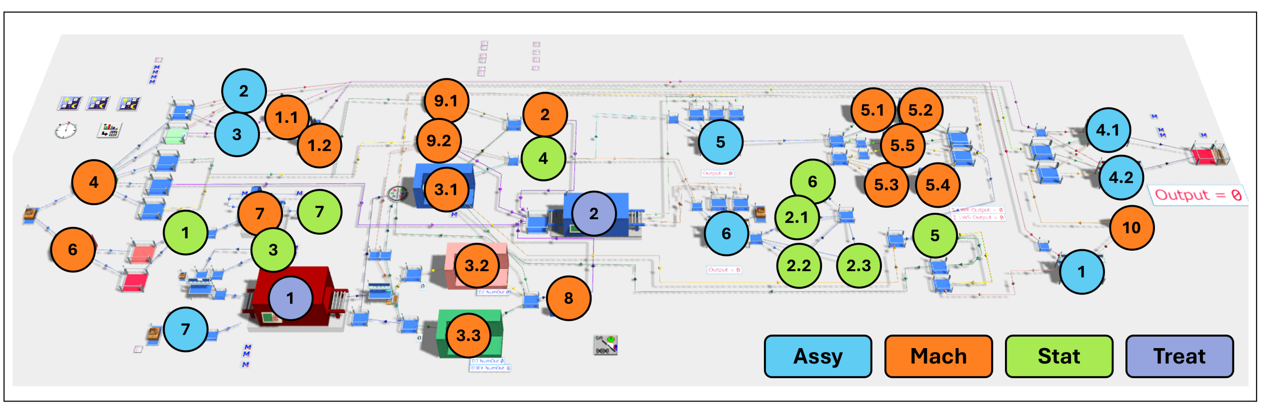

Figure 3: A glance at the proposed system layout in TPS after redundancy allocation.

logic to minimize setup overhead. Here, a controller balances the output by alternating part types based on preset batch sizes of γ_1 and γ_2 for part IDs 10 and 11, respectively. At this stage of optimization, the batch size values for Mach5.5 were arbitrarily set to 3. These all reduced the E value of this group of stations from 9:36 (for 5 redundants) to the acceptable value of 8 hours and 34 minutes (see Table 3).

2.3.2 Ordering and Flow Optimization using Genetic Algorithm

In this section, we use a metaheuristic algorithm for optimizing another aspect of the system. Buffer management and ordering policy play a pivotal role in ensuring smooth material flow and minimizing the resource idle time across the manufacturing system. As a foundational step for this type of optimization, buffers are restricted to store only a single part type, enabling targeted flow control and more accurate WIP tracking. This design supported the implementation of selective routing strategies, where part-specific controllers governed the release of parts from buffers to downstream stations. This was particularly effective in high-variability areas such as the aforementioned Mach3 and Mach5, where controlling setup frequency and balancing throughput were critical. To regulate the WIP levels and prevent overproduction, each buffer was linked to a stock controller that periodically monitors buffer levels and temporarily halts upstream production when a predefined threshold is met. This (R, T) policy stabilizes part availability throughout the system and ensures stations are operated without excessive inventory buildup or shortages.

In this model, we define 13 variables, representing the reorder points of the important buffers. These buffers are upstream of the Assy2, Mach3, Mach5, Stat3, and Treat1 station groups. We also add an extra variable for determining the inventory review period length for these buffers (see Table 4). Additional routing logics are also introduced using some *Flow Control* objects in the bottleneck stations (such as the laser welding CNCs in Mach5 group), which manage the part entry into processing stations based on real-time buffer conditions. Flow priority was assigned to part types from buffers with the lowest output count or lowest relative fill level, effectively prioritizing components needed by downstream processes. Each flow controller covers multiple dedicated input buffers simultaneously, enhancing the responsiveness and synchronization of part supply throughout the line. Collectively, these flow control strategies can potentially contribute to a more balanced and predictable production environment, reducing variability and improving the overall alignment of part availability with takt-driven throughput demands.

In order to refine these variables, we utilize the built-in *GAWizard* in TPS. The genetic algorithm (GA) in the backend of this optimization tool — inspired by natural selection principles — offers an effective method for navigating complex search spaces to identify near-optimal solutions. In this case, the above-mentioned global variables are set as decision variables for this metaheuristic method. Furthermore, the acceptable range for each of these variables is determined based on the existing physical limits of the buffers and by consulting experienced manufacturing system managers in this industry. Additionally, to approach the ideal goals of mass production in this industry, we introduce replenishment batch sizes for the critical machines, especially the Mach5 CNC group. Applying these additional variables (already declared as γ_1 and γ_2 in Section 2.3.1) helps the optimization algorithm explore alternative possible options for reducing the setup time of these stations by sending consecutive identical parts to the same machine. As an extra optimization freedom for the optimization algorithm of this calibration process, we also include the threshold value used in Mach3 optimization (i.e., θ) as a decision variable.

Aligned with the company's goals for this project, the optimization algorithm is set to minimize the total production time required to reach an annual target output of 200 units. During each iteration, simulation runs evaluate candidate solutions based on this fitness criterion. The algorithm iteratively evolves the variable set through selection, crossover, and mutation until convergence. The population size, number of generations, crossover rate, and mutation probability of this algorithm were experimentally set to 100, 20, 0.8, and 0.1, respectively. This approach ensures systematic tuning of buffer attributes and reorder policies, resulting in an improved balance and minimized lead time across the system. Figure 4 demonstrates the algorithm's convergence across iterations for a reprsentative case based on Scenario III.

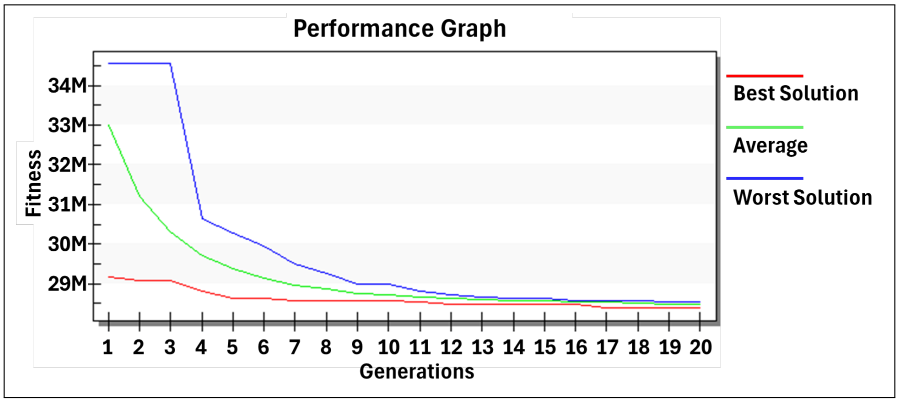

Figure 4: The convergence diagrams of the genetic algorithm for a sample scenario (Scen. III).

3 RESULTS AND DISCUSSIONS

In this section, we define three improvement scenarios based on different combinations of the proposed improvement methods and compare them with the performance of the system in its baseline state. In the first scenario, we use the baseline scenario and deploy the proposed GA-based ordering and flow optimization (GA-OFO) approach. The second scenario, however, benefits from the redundancy and batch sizing features introduced in Section 2.3.1. Eventually, the last scenario encompasses a hybrid of both proposed improvement methods. The system is run for a maximum duration of 10 years with a termination criterion of meeting the projected 200-unit demand. Other specifications of the system (probability distribution of process times, production sequence, part types, etc.) remained unchanged for all scenarios. The simulated performance results, values of decision variables, and the corresponding relative improvement percentage against the baseline are reported in Table 4 for all scenarios.

As seen in Table 4, the fulfillment of the expected demand takes about 1235 days in the current state of the system. That is, by assuming the unfulfilled portion of the demand as lost sales (or backlog in the most optimistic way), the company would only satisfy 18.6% of the annual demand on time if no capacity expansion is applied to this line. It is also observed that deploying the GA-OFO with no redundancy (i.e., Scen. I) would have a negligible effect on the lost sales ratio, highlighting the necessity of investments in the new redundant stations. Even though both Scenario II and III have achieved significant improvement compared to the baseline, applying the redundancy approach with no buffer inventory optimization still causes a significant loss of sales of up to 66 units (based on the new cycle time of 1.71 days). That is

Table 4: Variable settings and system performance under various scenarios.

Variables		**Baseline**	**Optimization Approach***		
			I	**II**	**III**
WIP Review Period (in min)		30	41	30	60
Buffer Attribute	ROP_{1-4}	10, 10, 10, 10	3, 3, 19, 17	10, 10, 10, 10	29, 27, 5, 1
	ROP_{5-8}	24, 5, 45, 10	20, 2, 2, 43	6, 4, 4, 4	12, 1, 4, 27
	ROP_{9-13}	10, 4, 2, -, -	43, 12, 5, -, -	4, 10, 10, 4, 4	23, 6, 22, 8, 5
	γ_1 , γ_2 , θ	-, -, -	-, -, -	3, 3, 2	2, 2, 1
Demand Fulfillment Time **		*1235:09:13*	*1226:14:24*	*342:10:45*	*214:13:49*
Cycle Time (days/unit)		6.18	6.13	1.71	1.07
Improvement (%)		**-**	**0.7%**	**72.3%**	**82.7%**

* I : GA-OFO, II : Redundancy Allocation, III : Redundancy Allocation & GA-OFO; ** Format: *days: hours: minutes*

Table 5: Mean utilization statistics by category for the baseline and the best scenario.

Station Type	Baseline				Scenario III			
	Working	Set-up	Waiting	Blocked	Working	Set-up	Waiting	Blocked
Assy	11.17%	0.00%	65.09%	23.75%	56.17%	0.00%	43.82%	0.01%
Mach	12.26%	10.73%	67.92%	9.08%	36.00%	30.82%	27.92%	5.25%
Stat	10.10%	0.00%	89.82%	0.07%	42.43%	0.00%	57.30%	0.26%
Treat	4.17%	0.00%	95.83%	0.00%	22.78%	0.00%	77.22%	0.00%
All	**10.51%**	**3.83%**	**76.46%**	**9.20%**	**41.88%**	**14.45%**	**41.16%**	**2.52%**

while the last hybrid scenario fulfills the demand in less than one year and promises no lost sales. The new expected cycle time for each pump has reached the record low of only one day, which would substantially increase the competitiveness of this company in the market.

Comparing the performance of various types of stations in the baseline and the best scenario in Table 5, shows that the overall waiting time of the stations has been lowered significantly from 76.46% to 41.16%. This value for our automated CNC machines has dropped from around 68% to less than 28% which indicates considerable savings in the available time of these expensive assets of the company. It is worth noting that for the CNC machines (i.e., the Mach type), the changeover (setup) time is a vital part of the process. For this reason, we believe that the amount of reduction in the average waiting time can be the best performance measure for this category of stations. Moreover, based on the results of Table 5, the assembly stations of this manufacturing system experienced the highest amount of improvement in their utilization, with their working state estimation reaching over 56%. Further exploring the status results of different station groups (Figure 5) indicates that the blockage in all stations was effectively mitigated and the working state has been improved noticeably. More specifically, Stat2, Mach3, and other station groups that were diagnosed with insufficient capacity were all effectively strengthened in the proposed scenario.

It is notable that the optimal scenario still shows significant waiting time for many stations while Mach5 is fully utilized (in either setup or working states). This indicates that if the system were meant to be enhanced even further, Mach5 would potentially receive further investments. While future cost-benefit analyses will quantify ROI, the 50% resource expansion is the catalyst for competitive mass production from constrained job-shop and can strategically be justified by the operational transformations, i.e., scalability

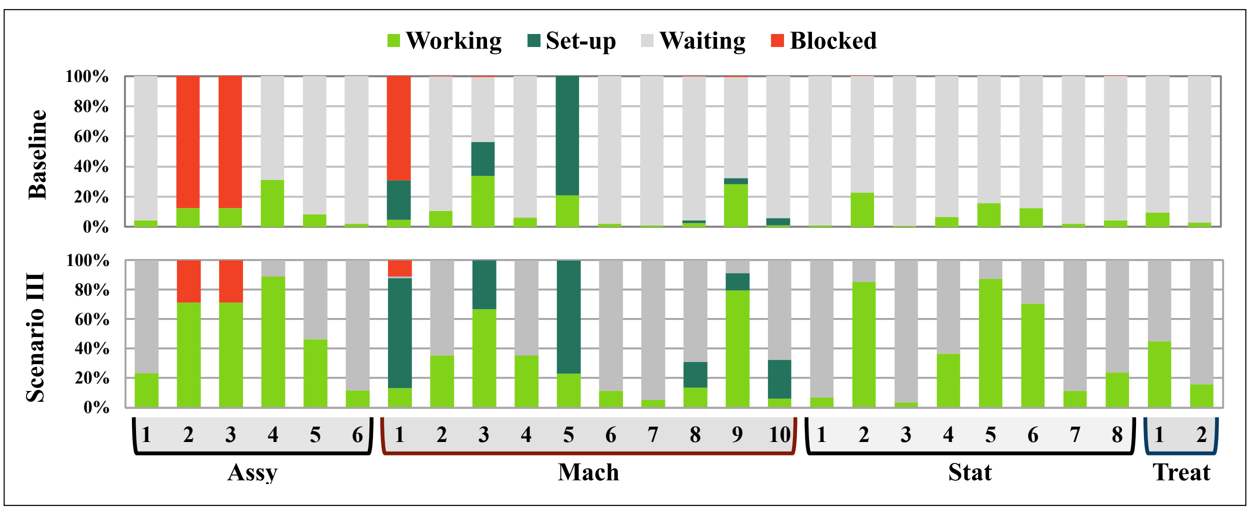

Figure 5: Station status charts and utilization for the baseline and the best proposed scenario.

payoff and dynamic flexibility. This investment unlocks mass-production economies of scale, turning high upfront costs into long-term margin growth with 82% higher throughput and no lost sales.

4 CONCLUSIONS

The increasing demand for pumping equipment in the offshore and marine industry has introduced new challenges for key players in this market. This study investigated the utilization of simulation-based digital twins for optimizing the process of capacity expansion and mass production in this industry to mitigate these new demand patterns. To achieve an optimal expansion plan for such manufacturing systems, this study proposes a hybrid approach involving redundancy allocation, pull order batch sizing, and buffer inventory policy optimization using metaheuristic algorithms. All combinations of these methods were explored numerically as separate scenarios to examine the individual effectiveness of each method on the overall performance of the system. The reported results showed a significant improvement of up to 82.7% for the hybrid scenario that applies all of the above-mentioned optimization workarounds.

Based on our improved results, this company is now able to meet the annual projected demand in just 214 days, and the cycle time for the pumps has experienced a drastic decrease from 6.18 days to as low as one day. This has led to the system achieving the goal of not having lost sales while it was suffering from over 80% lost sales in the initial setup. The promising results achieved in this study underscore the applicability of the proposed framework in maritime equipment manufacturing industries and pave the way for more acceptance of digital twin-based analysis among the stakeholders of this sector of the maritime industry. Applying this framework in other manufacturing case studies and investigating its effectiveness in other contexts can be an interesting extension to this study. In this study, we ignored prolonged machine maintenance and considered one work shift. Another potential avenue for future research can involve sensitivity analysis and resiliency studies of such systems against various types of failures in the comprising processes, as well as investigating the effect of multi-shift work schedules on the throughput.

ACKNOWLEDGMENTS

The first author wishes to express his sincere gratitude to FRAMO for their generous financial support in the form of a stipend to conduct the research.

REFERENCES

Alfas, M., Y. Tian, A. Attar, M. Luis and V. I. Sucala. 2025. "A DES-Based Online Digital Twin Framework for Festo's Cyber-physical System: Industry 4.0". In *Simulation Workshop 2025 (SW25)*. March 31st-April 2nd, Exeter, UK, 249-257.

Attar, A., C. A. Irawan, A. A. Akbari, S. Zhong and M. Luis. 2024. "Multi-Disruption Resilient Hub Location–Allocation Network Design for Less-than-Truckload Logistics". *Transportation Research Part A: Policy and Practice* 190:104260.

Attar, A., Y. Jin, M. Luis, S. Zhong and V. I. Sucala. 2023. "Simulation-Based Analyses and Improvements of the Smart Line Management System in Canned Beverage Industry: A Case Study in Europe". In *2023 Winter Simulation Conference (WSC)*, 2124–2135 https://doi.org/10.1109/WSC60868.2023.10407288.

Attar, A., S. Raissi, and K. Khalili-Damghani. 2015. "Multi-Objective Reliability-Redundancy Allocation for Non-exponential Multi-State Repairable Components". In *IIEC2015*. January 7th-8th, Tehran, Iran, 1-6.

Attar, A., S. Raissi, and K. Khalili-Damghani. 2016. "Simulation–Optimization Approach for a Continuous-Review, Base-Stock Inventory Model with General Compound Demands, Random Lead Times, and Lost Sales". *Simulation* 92(6):547–564.

Attar, A., S. Raissi, and K. Khalili-Damghani. 2017. "A Simulation-Based Optimization Approach for Free Distributed Repairable Multi-State Availability-Redundancy Allocation Problems". *Reliability Engineering & System Safety* 157:177–191.

Boj'ic, S., M. Maslaric, D. Mircetic, S. Nikolicic and S. Todorovic. 2023. "Simulation and Genetic Algorithm-Based Approach for Multi-Objective Optimization of Production Planning: A Case Study in Industry". *Advances in Production Engineering & Management* 18(2):250–262.

Cheng, F., M. Ettl, Y. Lu, and D. D. Yao. 2012. "A Production–Inventory Model for a Push–Pull Manufacturing System with Capacity and Service Level Constraints". *Production and Operations Management* 21(4):668–681.

de Groot, L. R. and A. Hübl. 2021. "Developing a Calibrated Discrete Event Simulation Model of Shops of a Dutch Phone and Subscription Retailer During COVID-19 to Evaluate Shift Plans to Reduce Waiting Times". In *2021 Winter Simulation Conference (WSC)*, 1–12 https://doi.org/10.1109/WSC52266.2021.9715306.

Edh Mirzaei, N., P. Hilletofth, and R. Pal. 2021. "Challenges to Competitive Manufacturing in High-Cost Environments: Checklist and Insights from Swedish Manufacturing Firms". *Operations Management Research* 14(3):272–292.

Gola, A., Z. Pastuszak, M. Relich, Ł. Sobaszek and E. Szwarc. 2021. "Scalability Analysis of Selected Structures of a Reconfigurable Manufacturing System Taking Into Account a Reduction in Machine Tools Reliability". *Eksploatacja i Niezawodność* 23(2):242–252.

Grznár, P., M. Krajčovič, A. Gola, L. Dulina, B. Furmannová, Š. Mozol, *et al*. 2021. "The Use of a Genetic Algorithm for Sorting Warehouse Optimisation". *Processes* 9(7):1197.

Heshmat, M., M. El-Sharief, and M. El-Sebaie. 2013. "Simulation Modeling of Production Lines: A Case Study of Cement Production Line". *Journal of Engineering Sciences* 41(3):1045–1053.

Hung, K.-T. and J. K. Liker. 2007. "A Simulation Study of Pull System Responsiveness Considering Production Condition Influences". *International Journal of Industrial and Systems Engineering* 2(2):123–136.

Jung, W.-K., H. Kim, Y.-C. Park, J.-W. Lee and E. S. Suh. 2022. "Real-Time Data-Driven Discrete-Event Simulation for Garment Production Lines". *Production Planning & Control* 33(5):480–491.

Kliment, M., J. Kronová, M. Pekarčíková, P. Trebuňa and M. Baluch. 2025. "The Implementation of Simulation in Designing Production Expansion". *Processes* 13(2):299.

Kovbasiuk, K., K. Židek, M. Balog, and L. Dobrovolska. 2021. "Analysis of the Selected Simulation Software Packages: A Study". *Acta Tecnología* 7(4):111–120.

Kuncova, M. and M. Zajoncova. 2018. "Discrete Event Simulation Usage to Model and Optimize the Production Line". *MM Science Journal* 3(3):2325–2332.

Mehra, S., R. Inman, and G. Tuite. 2006. "A Simulation-Based Comparison of Batch Sizes in a Continuous Processing Industry". *Production Planning & Control* 17(1):54–66.

Mohan, J., K. Lanka, N. A. Rao, and V. K. Manupati. 2021. "Sustainable Flexible Job Shop Scheduling: A Systematic Literature Review". In *15th Global Congress on Manufacturing and Management*. June 7th-9th, Liverpool, UK, 227–246.

Pekarcikova, M., P. Trebuna, M. Kliment, and M. Dic. 2021. "Solution of Bottlenecks in the Logistics Flow by Applying the Kanban Module in the Tecnomatix Plant Simulation Software". *Sustainability* 13(14):7989.

Ugheoke, I. B., A. H. Nurudeen, I. M. Dagwa, and I. D. Muhammad. 2024. "Facility Layout Design, Simulation, and Optimization for Kaolin Beneficiation Plant Using Flexsim". *Mechanical Technology and Engineering Insights* 1(1):15–28.

Xu, G., J. Feng, F. Chen, H. Wang and Z. Wang. 2019. "Simulation-Based Optimization of Control Policy on Multi-Echelon Inventory System for Fresh Agricultural Products". *Agricultural and Biological Engineering* 12(2):184–194.

Zupan, H. and N. Herakovic. 2015. "Production Line Balancing with Discrete Event Simulation: A Case Study". *IFAC-PapersOnLine* 48(3):2305–2311.

AUTHOR BIOGRAPHIES

SEBASTIAN PIHL is an Operations Engineer at FRAMO in Bergen, Norway. He holds an M.Eng. degree in Engineering and Management from the University of Exeter, United Kingdom. His professional and research interests focus on the integration of emerging technologies into manufacturing environments, with a particular emphasis on high-level simulation and the development of data-driven production systems. His email address is sapi@framo.no.

AHMAD ATTAR is a postgraduate teaching associate with the Department of Engineering, University of Exeter, UK, delivering System Modelling, Simulation, and Mathematical Programming. With about a decade of experience in the industry, Ahmad joined Exeter in 2022 as a Ph.D. student in Engineering, focusing on the simulation of resilient, sustainable, cost-efficient systems, and their special applications to offshore wind energy and the general industry. His email address is a.attar@exeter.ac.uk.

MARTINO LUIS is a Senior Lecturer at the Department of Engineering, University of Exeter, UK. He holds a Ph.D. in Operations Research from Kent Business School, University of Kent, UK, and co-leads the Exeter Digital Enterprise Systems (ExDES) laboratory with Professor Sucala. His research interests are the applications of optimization and simulation modeling in facility location, supply chain design, and inventory routing with a focus on sustainable operations. His e-mail address is m.luis@exeter.ac.uk.

ØYSTEIN HAUGEN is the Production Engineering Manager at FRAMO, a leading manufacturer of pumping systems. He holds an M.Sc. in Mechanical Engineering from the Norwegian University of Science and Technology (NTNU). With over a decade of experience in the industry, his professional background includes extensive work in manufacturing process development, production system optimization, and industrial automation. He currently leads initiatives focused on advancing digitalization and operational efficiency in high-mix, low-volume manufacturing environments. His email address is oyha@framo.no.