REDUCING OPERATIONAL COSTS IN A MANUFACTURING SYSTEM THAT INCORPORATES QUALITY ASSURANCES, PROBABILISTIC FAILURES, OVERTIME AND OUTSOURCING

Wirda Novarika
Magister of Industrial Engineering*
Sony Bahagia Sinaga
Magister of Technic Informatic
Department of Engineering
STMIK Mulia Darma
Adam Malik str.,18, Labuhanbatu, Indonesia, 20224
Satria Yudha Prayogi
Corresponding author
Magister of Informatics Engineering*
E-mail: satria.yp@ft.uisu.ac.id
*Department of Engineering
Universitas Islam Sumatera Utara
Sisingamangaraja str., 101, Medan, Indonesia, 20217

This research focuses on the dynamic landscape of today's competitive market, where production management must meet clients' expectations for high-quality products and shorter lead times while managing internal disruptions due to inevitable defects and unpredictable equipment failures. Achieving these operational goals without compromising product quality, missing deadlines, or experiencing production disruptions is essential for minimizing operational expenses. The study examines the dynamics of the system's operating costs through the development of models, mathematical formulations, optimization techniques, and algorithm proposals. It demonstrates the system's convexity and establishes the optimal batch time for implementing the proposed methodologies. The research results show relevant failure costs of 3.51 %, overtime added costs of 4.57 %, outsourcing setup costs of 0.73 %, outsourcing variable costs of 41.82 %, quality-related costs of 2.98 %, in-house variable costs of 40.42 %, and in-house holding costs of 3.55 %. The study develops strategies for optimal overtime use to meet production targets without excessive labor costs and provides a structured framework for making informed outsourcing decisions that balance cost savings with quality and reliability considerations.

Overall, the research provides a robust framework for reducing operational costs while maintaining or improving the quality and reliability of manufacturing processes

Keywords: cost reduction, quality, assurance, probabilistic, failures, overtime, outsourcing, optimization, manufacturing

1. Introduction

In contemporary manufacturing environments, the integration of advanced quality assurances alongside the management of probabilistic failures, overtime, and outsourcing has become a pivotal area of study. The relevance of this topic is underscored by the ongoing efforts within the manufacturing sector to enhance efficiency, reduce operational costs, and maintain high-quality standards amidst increasingly complex production demands [1–3]. Quality assurance (QA) remains a critical factor in manufacturing, ensuring that products meet predefined standards and customer expectations [4]. The implementation of robust QA systems can significantly reduce defects, rework, and waste, leading to cost savings and improved customer satisfaction [5–7]. These advancements allow for real-time monitoring and control, thereby minimizing deviations and enhancing product consistency [8].

Scientific research into reducing operational costs in a manufacturing system is essential to navigate the complexities of modern manufacturing. It provides the necessary insights and innovations to enhance efficiency, maintain

quality, manage risks, and remain competitive in a dynamic global market. Through such research, manufacturers can achieve sustainable growth, adapt to technological advancements, and meet evolving consumer and regulatory demands.

The practical application of research on reducing operational costs in manufacturing systems can lead to significant improvements across various facets of operations. These include process optimization, enhanced quality control, effective risk management, labor cost reduction, strategic outsourcing, sustainability, economic adaptability, technological integration, customer satisfaction, and regulatory compliance. By implementing the findings of such research, manufacturing firms can achieve sustainable cost savings, improve operational efficiency, and gain a competitive edge in the marketplace.

Therefore, investigating ways to reduce operational costs in manufacturing systems that encompass quality assurance, probabilistic failures, overtime, and outsourcing is highly pertinent. By addressing these challenges, organizations can enhance efficiency, uphold product quality, and secure a competitive edge in the market.

2. Literature review and problem statement

Strategies to reduce operational costs in a manufacturing system encompassing quality assurance, probabilistic failures, overtime, and outsourcing were explored. They will make it possible to optimize production processes, improve quality control, manage risks, and utilize labor and outsourcing resources effectively. This will help manufacturing companies that want to achieve cost efficiencies while maintaining high standards of quality and operational reliability [9].

The research underscores the importance of a holistic approach to cost reduction in manufacturing systems. By addressing quality assurances, probabilistic failures, overtime, and outsourcing collectively, manufacturers can achieve sustainable cost savings and improve overall operational efficiency. Research indicates that integrating these elements can lead to substantial cost savings and improved efficiency. This statement highlights the critical need for a comprehensive strategy in production cost reduction, emphasizing that by simultaneously focusing on quality assurance, probabilistic failure, overtime, and outsourcing, manufacturers can not only achieve significant cost savings but also improve overall operational efficiency, resulting in more profit.

This approach is used in several manufacturing companies such as Toyota, Intel and Boeing. These companies have demonstrated that a comprehensive and integrated approach to reducing operational costs, incorporating quality assurances, managing probabilistic failures, optimizing overtime, and leveraging outsourcing can lead to substantial cost savings and operational efficiencies. However, all this suggests that it is advisable to conduct a study on the impact of integrated cost reduction strategies on manufacturing systems. This study focuses on how combining quality assurances, managing probabilistic failures, optimizing overtime, and leveraging outsourcing can lead to substantial operational cost savings while maintaining or improving product quality. While this statement underscores the proven success of companies such as Toyota, Intel, and Boeing in using an integrated approach to cost reduction and operational efficiency, the impact of such strategies can provide valuable insight into how these combined efforts can achieve significant costs.

The manufacturing industry now utilizes a multi-stage supply network where raw materials are sourced from different stages of suppliers. This approach contributes to delays in addressing the national supply chain crisis within the manufacturing sector. In every complex system, such as manufacturing processes, services, mining, and health services, there are multiple interconnected activities. Among these, one serves as a constraint and represents the weakest link in the value chain. This statement highlights the inherent complexity of modern manufacturing supply networks, where sourcing raw materials from various stages contributes to supply chain delays, emphasizing the need to identify and address the weakest link or constraint within these interconnected activities to improve overall efficiency and mitigate the national supply chain crisis.

Current scientific research focuses on developing innovative QA methodologies and integrating them with advanced manufacturing technologies such as Industry 4.0 and the Internet of Things (IoT) [9]. In the current competitive business environment, production management is challenged to meet both client expectations for quality and short order lead times while avoiding disruptions in internal manufacturing processes due to inevitable random defects and stochastic equipment failures [10]. Previously, a cost-minimization mathematical model was employed to examine combined cell formation and stock batch-size problems. This model incorporated dynamic routing, capacity and cell-size constraints, operations sequences, equipment failures, and process deterioration. However, its reliance on certain assumptions and the need for a more comprehensive consideration of real-world complexity highlight areas that require further research. Future research could expand these findings by exploring multi-echelon systems, dynamic market conditions, and practical aspects of contract negotiation and enforcement [11, 12]. The interplay between quality assurance mechanisms and probabilistic failure management to optimize maintenance schedules and reduce costs was studied. The long-term impact of overtime policies on operational efficiency and workforce well-being was examined, providing a holistic view of labor management. Adaptive outsourcing strategies that focus on cost reduction while enhancing resilience against supply chain disruptions and geopolitical risks were investigated. The practical implications highlight the need for infrastructure investment, technology adoption, workforce training, regulatory reform, and cost optimization strategies [13, 14].

In the context of multiproduct fabrication, researchers considered planning multiple processes and the routing options for each process plan, making the problem inherently combinatorial. By balancing production costs, backorders, write-offs, and rework, this model provides a framework for improving cost efficiency and resource utilization [15]. To address the NP-completeness of their model, the researchers developed an optimized meta-heuristic using the Particle Swarm approach [16]. Procuring equipment, reconfiguring cells, handling materials, operating equipment, subcontracting, maintaining stock, managing defective parts, and performing preventive and corrective repairs are essential components of the manufacturing process. By identifying and eliminating inefficiencies, VSM can significantly reduce lead times and increase productivity [17]. The researchers utilized a group technology heuristic to analyze this NP-hard problem, supporting their findings with a real-world example from a car paint shop. By integrating cell formation with inventory lot sizes, assumptions, scalability issues, data requirements, implementation challenges, and comparative analysis [18]. Numerous other studies by various researchers have explored diverse aspects of equipment failures, their impacts, and corresponding actions in controlling and managing fabrication systems, providing a comprehensive understanding of this critical aspect of manufacturing. By encouraging specialization, managing costs, and enabling scalability, subcontracting not only optimizes production but also lays the foundation for modern industrial practices [19, 20]. The focus was on a multiproduct single-machine economic production quantity-based system that considered partial backlogging, scrap, and rework. A two-dimensional Markovian modulated Poisson process (MMPP) for system failures was examined, investigating the dependence of two sequential inter-failure times [21, 22]. The model's practicality was enhanced by incorporating considerations for unreliability conditions and equipment failures. Another study investigated a single-facility multiproduct sequential batch-size scheduling problem with buffered rework jobs, specifically in the context of car painting. The goal was to minimize the maximum lateness of finished products. The

researchers estimated system reliability by considering expected failures and their probabilities, along with the time and distances between failures.

To align with the current trend of customers' increasingly demanding shorter order due dates, managers in contemporary manufacturing firms must strategize their batch fabrication to minimize runtime. Commonly employed tactics for reducing fabricating uptime include partial subcontracting and implementing overtime shifts in production. An approach based on annualized working hours was proposed to enable enterprises to adjust their capacity dynamically, addressing the unpredictable demand throughout the year. These models, utilizing a well-selected set of weekly hours, aimed to establish annual working hours for each worker, aligning with the firms' service level [23]. Furthermore, the study demonstrates the utility of one of the models as a decision-making tool through computational experiments, efficiently deriving optimal solutions within a relatively short computing time. The study explored potential hidden expenses during the outsourcing preparation stage and evaluated future profits post-implementation using a net present value model. The researcher concluded by presenting a descriptive scheme to aid decision-making regarding partial outsourcing. Several other studies, including those and others, have investigated the diverse strategies of overtime and subcontracting in planning and expediting batch fabrication time.

Control over manufacturing processes in which sources of variability must not negatively impact product safety and quality was considered. Every facility, equipment, process, and utility must meet GMP requirements, and analytical and sampling methods must be proven to be within acceptable operating ranges. This statement emphasizes the critical importance of stringent control over manufacturing processes to ensure that variability does not compromise product safety and quality, underscoring the necessity for all facilities, equipment, processes, and utilities to adhere to GMP requirements and for analytical and sampling methods to consistently operate within acceptable ranges. The mathematical complexity of UGF can be a barrier to its widespread adoption, requiring advanced expertise and computational resources. The accuracy of UGF analysis depends on the validity of the underlying assumptions regarding component performance and interdependencies. Inaccurate assumptions can lead to misleading results [24].

Value stream mapping (VSM) is utilized as a tool to advance lean manufacturing and guide improvement activities. Kanban cards have been employed to pinpoint issues in production flow, ensuring the synchronization of inventory and material movement between production cells. Value stream mapping (VSM) and Kanban cards are important tools in lean manufacturing, effectively used to identify and resolve production flow issues while synchronizing inventory and material movement, thereby increasing overall operational efficiency and continuous improvement. Yields from each source may vary, thus affecting the quantity of usable product obtained from the total order. This variability impacts inventory levels, production schedules, and overall supply chain reliability. Different sources typically have different cost structures, which may include not only the price per unit but also shipping costs, tariffs, and handling fees. Balancing these costs with yield and lead time is critical to maintaining profitability [25]. Good service quality will have an impact on customer satisfaction, which will ultimately have a posi-

tive impact on brand value and better financial performance. The correlation between service quality and customer satisfaction is still a matter of debate and service quality has no correlation impact with customer satisfaction. The fabrication process must be scalable to produce the composite yarn in large quantities at a reasonable cost. Techniques for dispersing CNTs and spinning the yarn must be optimized for industrial production. Ensuring uniform dispersion of CNTs and consistent quality of the composite yarn across batches is challenging. Advanced quality control measures are necessary to maintain performance standards [26]. System evaluation shows that the manufacturing production line is still considered deficient and unable to meet the average 24,300 monthly core requests. Bottleneck analysis is a standard manufacturing and production management approach to evaluate and improve system capacity relative to utilization and efficiency metrics. The evaluation indicates a significant shortfall in the manufacturing production line's ability to meet demand, underscoring the urgency for a thorough bottleneck analysis to identify and address capacity constraints, improve efficiency metrics, and enhance overall system utilization to meet production targets. The statement highlights that the evaluation revealed significant deficiencies in the ability of manufacturing production lines to meet demand, underscoring the importance of thorough bottleneck analysis to identify and resolve capacity constraints, improve efficiency metrics, and increase overall system utilization to meet production targets [27].

The success of logistics outsourcing can be influenced by five strategic factors and five operational factors, with several overlapping between logistics service providers (LSPs) and shippers in both nations, aligning with existing literature. However, there is a notable difference between practitioners in developed and developing countries. In developed countries, greater emphasis is placed on having the right personnel and management support, integrating business processes, and cultural intelligence. Additionally, the logistics outsourcing strategy matrix is also mapped out. Although both developed and developing countries recognize the importance of strategic and operational factors in the success of logistics outsourcing, practitioners in developing countries place greater emphasis on having the right personnel, management support, integrating business processes, and cultural intelligence [28].

There is a need for methods to assist middle management in better structuring the logistics outsourcing decision-making process. This method should address operational complexities, compare various logistics outsourcing options on the same basis, measure risks and rewards, and protect the company's core and long-term competencies with the logistics strategy in mind. The statement correctly identifies crucial gaps in providing middle management with structured decision-making tools for logistics outsourcing, emphasizing the need for comprehensive methods that address operational complexity, enable standardized comparison of options, assess risks and benefits, and safeguard the enterprise core competencies while aligning with the overall logistics strategy [29].

3. The aim and objectives of the study

The aim of the study is to develop a cost reduction strategy through quality assurance and managing probabilistic failures in manufacturing systems. This will allow manufac-

turing companies to optimize cost efficiencies while maintaining high quality standards, managing potential failures, and effectively utilizing overtime and outsourcing strategies.

To achieve the aim, the following objectives are accomplished:

– to establish the possibility, reduce costs, improve quality, failure rates, overtime and outsourcing;

– to evaluate the impact of quality assurance processes on operational efficiency and costs;

– to integrate inspection, testing, and validation at all production stages to ensure that products meet quality criteria before reaching the market;

– to evaluate the cost benefits and risks of outsourcing parts of the manufacturing process and develop criteria to determine when outsourcing is cost-effective.

4. Materials and methods

The object of the study is the operational costs in a manufacturing system. This involves examining how to effectively manage and minimize expenses related to quality assurances, probabilistic failures, overtime, and outsourcing.

The hypothesis of the study is that implementing targeted strategies to manage quality assurances, probabilistic failures, overtime, and outsourcing will significantly reduce operational costs in a manufacturing system.

The quality assurance process is assumed to improve product quality and reduce defects, thereby reducing rework and waste, so contributing to cost reduction. Predictive maintenance can accurately predict equipment failure and enable timely intervention, thereby reducing downtime and maintenance costs. Reliable and accurate data regarding quality, failure, labor and outsourcing costs is available for analysis and decision-making.

Quality assurance has a uniform impact on all products and processes, without taking into account variations in its impact on different types of products or stages of production. The model is simplified by assuming that predictive maintenance tools and techniques provide highly accurate estimates of equipment failure, without considering potential inaccuracies or uncertainties. Treating overtime costs as a direct and clear function of hours worked, without taking into account complexities such as varying overtime rates or differences in impact on different shifts.

In the context of modern manufacturing, the primary goal is to minimize operational costs while maintaining high standards of quality and efficiency. This analysis focuses on identifying and implementing strategies to achieve cost reductions in a manufacturing system that integrates quality assurances, deals with probabilistic failures, and utilizes overtime and outsourcing. The emphasis was on practical results and actionable recommendations. Reducing operational costs in a manufacturing system that incorporates quality assurances, probabilistic failures, overtime, and outsourcing requires a multi-faceted approach. By focusing on preventive measures, predictive analytics, strategic workforce management, and targeted outsourcing, manufacturers can achieve significant cost savings while maintaining high levels of quality and efficiency. Implementing these strategies, coupled with continuous monitoring and improvement, ensures sustainable cost reductions and competitive advantage.

This research was conducted using a combination of theoretical methods, software, and experimental conditions to validate a proposed solution for reducing operational costs in a manufacturing system that combines quality assurance, probabilistic failure, overtime, and outsourcing. Activity-based costing was applied to identify and allocate costs to specific activities related to quality assurance, failure management, overtime, and outsourcing. Software such as SAP and Oracle was utilized for detailed cost analysis and financial reporting. Tools such as LINGO and CPLEX were used to develop and solve optimization models. Software such as Arena and Simul8 was applied to run probabilistic failure models and simulate manufacturing processes. Tools such as Kronos and Workday were implemented to analyze and optimize labor schedules and statistical software such as MATLAB and R was utilized for data analysis and validation of theoretical models. Using these methods and conditions, this research aims to develop and validate effective strategies for reducing operational costs in manufacturing systems, ensuring that the proposed solutions are practical and reliable.

5. Results of cost reduction strategy development through quality assurance and managing probabilistic failures in manufacturing systems

5. 1. Cost reduction, quality improvement, failure rates, overtime and outsourcing

To evaluate cost structures, including quality assurance, failure rates, overtime, and outsourcing, an in-depth examination of the existing operational costs in the manufacturing system was performed to grasp the baseline expenses and uncover areas for potential cost reductions. The main cost drivers within the manufacturing system, such as quality assurance processes, probabilistic failures, overtime, and outsourcing, were determined to identify the elements that most significantly impact overall costs. This study has shown the implementation of batch replenishment uptime model tailored to scenarios with either no equipment failures or a single failure within a replenishment cycle. Probabilities for different Poisson-distributed failure rates were displayed. For a machine in good condition (with an annual mean failure rate of less than one), our model is highly applicable, as it offers over a 99.39 % probability of encountering no more than one failure. Additionally, for equipment in fair condition (with an annual mean failure rate of fewer than four failures), the model remains suitable, given a 93.30 % probability of no more than one failure occurring. Conversely, for machinery in "poor" condition (with more than four random breakdowns per year), the model's applicability drops to below 85.50 %.

This section presents a simulated example to demonstrate the functionality of our model and findings. Initially, the assumed values for the variables are shown in Table 1.

Quality assurance processes account for the majority of costs, highlight areas with high defect and rework rates, measure the financial impact of machine downtime and maintenance due to failure rates, analyze overtime costs, reveal inefficiencies in labor management and scheduling. A review of outsourcing costs is given, identifying the most expensive contracts and external services. This section presents a simulated example to demonstrate the functionality of our model and results. First, the assumed values of variables are shown in Table 1. Using the solution procedure described to determine the optimal t_{1Z}^{*}, Table 2 details the iterative steps taken, resulting in $t_{1Z}^{*} = 0.1149$ and $E\left[TCU\left(t_{1Z}^{*} \right) \right] = \$11.807$.

Presumptions regarding the values of variables in our numerical example

C	K	β_2	λ	α_1	C_1	C_R	C_3	h_1	M	P_2	G	π	β_1	X	θ_1	θ_2	h_3	φ	h	β	P_1	α_2	α_3
$2	$200	0.5	4000	0.5	$2	$1	$0.1	$0.4	$2500	5000	0.018	0.4	−0.70	20 %	0.3	0.3	$0.4	0.51	$0.4	1	10000	0.1	0.1

Note: C is the standard unit fabrication cost; K is the standard setup cost; β_2 is the connecting variable between C_π and C; λ is the annual demand; α_1 is the connecting parameter between P_1A and P_1; C_1 is the stock safety unit cost; C_R is the standard unit rework cost; h_1 is the unit storage cost of reworked goods; C_3 is the third cost or cost; M is capital or production capacity; P_2 is the standard rework rate; G is the growth rate.

The iterative process to find t_{1Z}^*

Step	t_{1ZU}	$e^{-\beta t1ZU}$	t_{1ZL}	$e^{-\beta t1ZL}$	$t_{1ZU}-t_{1ZL}$	$E[TCU(t_{1ZU})]$	$E[TCU(t_{1ZL})]$
–	–	0	–	1	–	–	–
1	0.3554	0.7009	0.0686	0.9337	0.2868	$12376.84	$11915.88
2	0.1795	0.8357	0.0981	0.9065	0.0814	$11887.72	$11816.57
3	0.1354	0.8734	0.1091	0.8967	0.0263	$11817.33	$11807.62
4	0.1217	0.8854	0.1129	0.8932	0.0088	$11807.86	$11806.65
5	0.1172	0.8894	0.1142	0.8920	0.0030	$11806.68	$11806.54
6	0.1157	0.8907	0.1147	0.8916	0.0010	$11806.54	$11806.53
7	0.1152	0.8912	0.1149	0.8915	0.0003	$11806.53	$11806.52
8	0.1150	0.8913	0.1149	0.8914	0.0001	$11806.52	$11806.52
9	0.1149	0.8914	0.1149	0.8914	0.0000	$11806.52	$11806.52

Note: t_{1ZU} – upper value of parameter t_1; $e^{-\beta t1ZU}$ – exponential of negative beta multiplied by t_{1ZU}; t_{1ZL} – lower value of parameter t_1; $e^{-\beta t1ZL}$ – exponential of negative beta multiplied by t_{1ZL}; $t_{1ZU}-t_{1ZL}$ – the difference between the upper value and the lower value of t_1; E[TCU(t1ZU)] – expected total cost utility (TCU) at t_{1ZU}; E[TCU(t_{1ZL})] – expectation of total cost utility (TCU) at t_{1ZL}; t_{1ZU} – the value assigned to t_{1ZU} at each step; $e^{-\beta t1ZU}$ – the result of the exponential calculation of negative beta multiplied by t_{1ZU} used in the exponential decay model; $e^{-\beta t1ZL}$ – the result of the exponential calculation of negative beta multiplied by t_{1ZL}; $t_{1ZU}-t_{1ZL}$ – the difference between t_{1ZU} and t_{1ZL}, this indicates the difference used for further analysis; E[TCU(t_{1ZU})] – expected total cost (TCU) at t_{1ZU}, indicating the estimated cost at the value t_{1ZU}; E[TCU(t_{1ZL})] – expectation of total costs (TCU) at t_{1ZL}, shows the estimated costs at the value t_{1ZL}.

This process aims to optimize a parameter (perhaps related to total costs) by approaching the optimal value of parameter t_1. Each step represents a small adjustment to the values of t_{1ZU} and t_{1ZL}, and an evaluation of the expected total cost at each of these values. The goal is to achieve convergence on a value of t_1 that minimizes total costs. The difference between t_{1ZU} and t_{1ZL} gets smaller at each step, indicating a convergence process towards the optimal value.

Combined improvements in quality assurance, failure management, overtime reduction, and outsourcing efficiency made it possible to achieve total annual cost savings of $285,000. Integrated cost reduction strategies lead to substantial overall savings. Utilizing the solution procedure from sub-section 2.4 to determine the optimal t_{1Z}^*, Table 2 outlines the iterative steps, resulting in $t_{1Z}^* = 0.1149$ and $E\left[TCU\left(t_{1Z}^*\right)\right] = \$11.807$.

5. 2. Improvement of the quality assurance process

To develop and implement strategies to improve quality assurance processes, aimed at reducing costs associated with defects and rework, key performance indicators (KPIs) were established for ongoing monitoring of cost savings initiatives. Performance metrics should be regularly reviewed to ensure the sustainability of cost-saving measures, gather feedback from stakeholders, and make iterative improvements to implemented strategies. We verify the convexity of $E[TCU(t_{1Z})]$, which requires that $\delta(t_{1Z})>t_{1Z}>0$. Table 3 demonstrates the application of our model by illustrating the convexity of $E[TCU(t_{1Z})]$, over a broader range of β values.

Continuous monitoring and improvement of cost-saving measures ensure long-term sustainability and efficiency.

Confirming the convexity of $E[TCU(t_{1Z})]$ by employing various β values

β	$\delta(t_{1ZV})$	t_{1ZV}	$\delta(t_{1ZL})$	t_{1ZL}
12	1.9037	0.3491	0.0202	0.0092
9	1.0491	0.3493	0.0265	0.0128
6	0.6454	0.3497	0.0390	0.0187
4	0.5104	0.3503	0.0571	0.0269
3	0.4727	0.3509	0.0741	0.0342
2	0.4580	0.3520	0.1054	0.0464
1	0.4929	0.3554	0.1821	0.0686
0.5	0.5934	0.3622	0.3009	0.0862
0.01	2.8999	0.7792	2.2233	0.1095

Note: beta (β) – the beta value here functions as a varying parameter, perhaps referring to the level of risk or other factors in the model; $\delta(t_{1ZV})$ – measures the change or delta in t_{1ZV}. This value decreases as the beta value decreases; t_{1ZV} – the value of the t_{1ZV} parameter remains stable around 0.3491 to 0.3509, although there are small changes as the beta decreases; $\delta(t_{1ZL})$ – measures the change or delta in t_{1ZL}. This value increases as the beta value decreases; t_{1ZL} – the value of the t_{1ZL} parameter increases as beta decreases, starting from 0.0092 at beta 12 to 0.0342 at beta 3.

By streamlining quality assurance processes, the study likely found ways to maintain high product quality while reducing associated costs. This could involve implementing more efficient inspection methods, automating certain quality checks, or integrating quality control early in the production

process to catch defects sooner. The results would show cost savings from reduced scrap rates, fewer rework hours, and lower warranty claims, all contributing to a lower cost of poor quality. Establishing mechanisms for continuous improvement would ensure that the cost reduction strategies remain effective over time. The results would include metrics on ongoing cost savings, as well as qualitative feedback from the production team on the practicality and sustainability of the implemented changes. This study employs two strategies aimed at reducing downtime. We thoroughly examine their effects on the proposed model and present the following findings: Fig. 1 shows how utilization varies with changes in π. As π rises, utilization clearly decreases. For an outsourcing factor of $\pi=0.4$ (as assumed in our example), utilization drops by 41.15 % to 0.1876.

For the provided example, π is assigned a value of 0.4. This value is chosen to assess the impact of outsourcing on utilization.

Fig. 2 illustrates how changes in the overtime factor α_1 affect utilization. As α_1 increases, machine utilization significantly decreases. For $\alpha_1=0.5$ (as assumed in our example), utilization falls by 33.25 %, from 0.2811 (without the overtime option) to 0.1876. Implementing both uptime-reduction strategies (overtime and outsourcing) results in a notable decline in utilization. Fig. 3 shows the outcome of a comparative analysis between our utilization and that of closely related models. Additionally, our model's utilization decreases by 60.7 % compared to a model that does not use uptime-reduction strategies. For declines in utilization of 33.25 %, 41.16 %, and 60.7 %, we incur costs of a 3.83 %, 7.58 %, and

14.91 % increase in $E\left[TCU\left(t_{1Z}^{*}\right)\right]$, respectively. Specifically, $E\left[TCU\left(t_{1Z}^{*}\right)\right]$ rises to \$11,807 from \$11,371, \$10,975, and \$10,275, respectively. α_1 represents the overtime factor in the model. It quantifies how changes in overtime affect machine utilization. Values for α_1 are tested through simulations to observe their impact on utilization. For instance, with $\alpha_1=0.5$, utilization drops by 33.25 % from 0.2811 (without overtime) to 0.1876. The specific value of α_1 used in the model is optimized to reflect realistic operational conditions and to evaluate the trade-offs between overtime costs and utilization. α_3 represents the outsourcing factor, indicating how changes in outsourcing practices affect machine utilization. Like α_1, α_3 is chosen based on empirical observations or model simulations that illustrate the effect of outsourcing on utilization. Various values of α_3 are tested to determine their impact on utilization. For example, with $\alpha_3=0.4$, utilization decreased by 41.15 %. α_3 is optimized to balance the costs of outsourcing with utilization outcomes, helping to determine the most effective outsourcing strategy.

This study can investigate further analytical results from various system parameters/features. For instance, Fig. 3 illustrates the combined effect of changes in the unit overtime cost-added factor α_3 and the outsourcing cost-added factor β_2 on $E\left[TCU\left(t_{1Z}^{*}\right)\right]$. It reveals that $E\left[TCU\left(t_{1Z}^{*}\right)\right]$ significantly increases as both α_3 and β_2 rise. This example demonstrates that β_2 has a greater impact on $E\left[TCU\left(t_{1Z}^{*}\right)\right]$ compared to α_3.
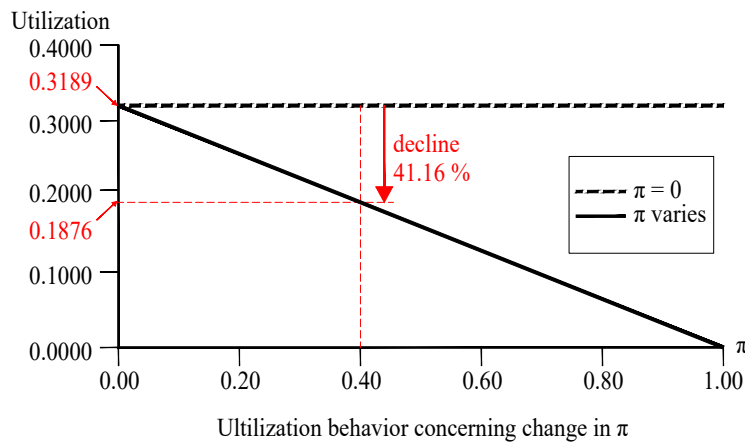

Fig. 1. Utilization patterns in relation to variations in π
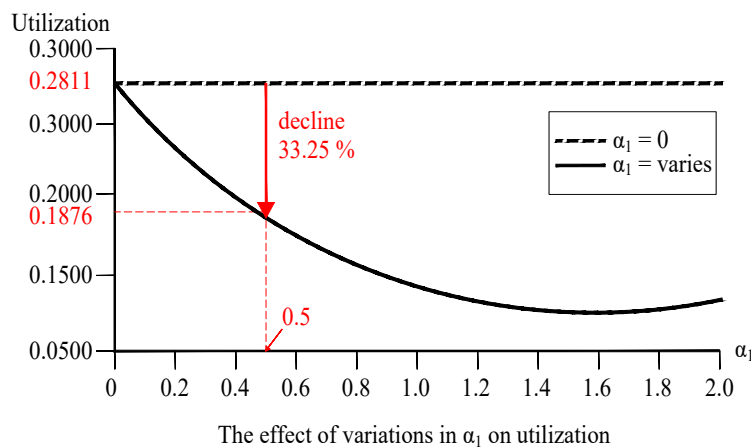

Fig. 2. The impact of changes in α_1 on utilization

As the pa rameter α_1 increases, there is a significant decrease in machine utilization. For instance, when α_1 is set to 0.5 (as per our example), utilization drops by 33.25 %, from 0.2811 (without the option of overtime) to 0.1876. The implementation of dual strategies for reducing uptime, namely overtime and outsourcing options, leads to a notable decline in utilization. Fig. 4 illustrates the results of a comparative analysis of our utilization with similar models. Moreover, our model shows a utilization decrease of 60.7 % compared to a model that does not employ uptime-reduction strategies. With utilization declines of 33.25 %, 41.16 %, and 60.7 %, we incur increases in the expected total cost per unit time $E\left[TCU\left(t_{1Z}^*\right)\right]$ of 3.83 %, 7.58 %, and 14.91 %, respectively. Specifically, $E\left[TCU\left(t_{1Z}^*\right)\right]$ increases to $11,807 from $11,371, $10,975, and $10,275, respectively.

Furthermore, this study provides details on the cost contributors to $E\left[TCU\left(t_{1Z}^*\right)\right]$, as shown in Fig. 5. It specifies that the two main contributors are the outsourcing and in-house variable costs, each accounting for 41.82 % and 40.42 %, respectively.
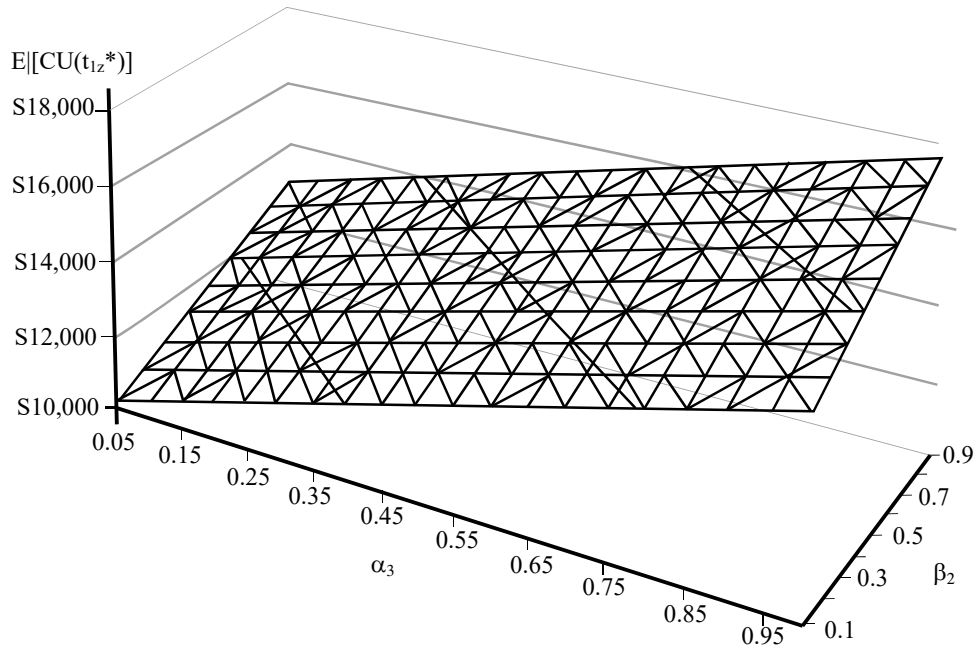
Fig. 3. The combined impact of changes in α_3 and β_2 on $E\left[TCU\left(t_{1Z}^*\right)\right]$

Ultilization comparison with other studies
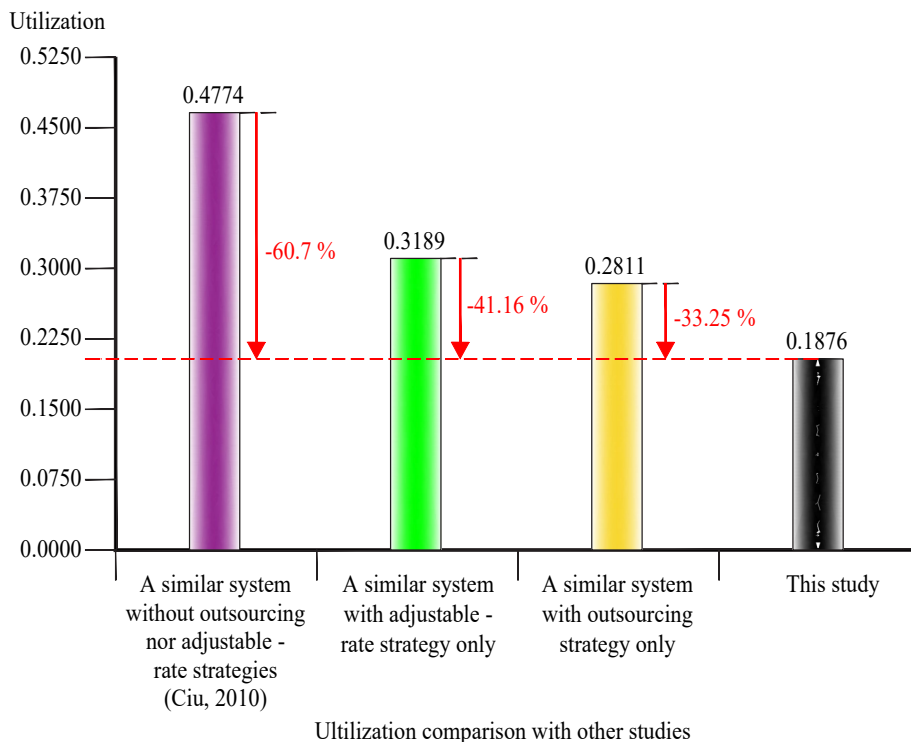
Fig. 4. Comparison of utilization with other studies
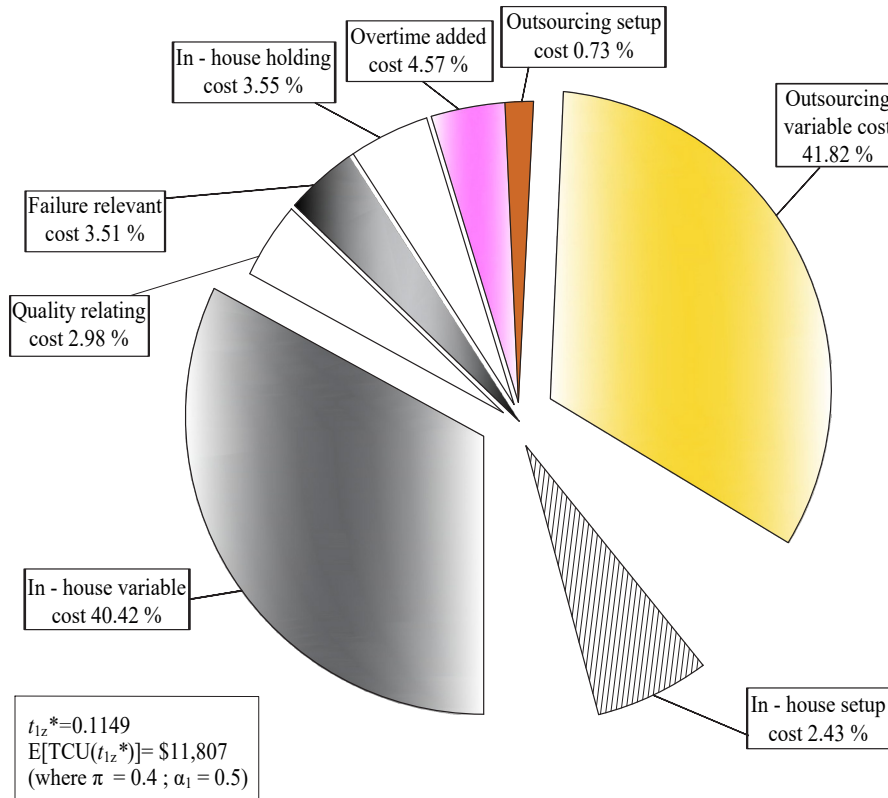
Fig. 5. The cost contributors to $E\left[TCU\left(t_{1Z}^{*}\right)\right]$

The example in Fig. 5 above shows that random machine failures and product quality-related costs account for 3.51 % and 2.98 %, respectively.

### 5. 3. Optimization of outsourcing costs

To determine cost effectiveness and explore alternative strategies to optimize outsourcing costs, Fig. 6 additionally presents critical managerial insights to support the implementation of an effective and economical uptime- or utilization-reduction strategy. This example recommends the following steps for efficiently and economically reducing uptime/utilization:

I) start by setting $\pi=0$ and increasing α_1 (refer to the bold dashed line);

II) once utilization drops to 0.2638 (i.e. when $\pi=0$ and α_1 is increased to 0.815), set $\pi=0.436$ and reset α_1 to 0; then, maintain $\pi=0.436$ and begin increasing α_1 again (refer to the bold solid line).

Fig. 7 reveals the critical outsourcing π factor (0.733) relevant to the make-or-buy decision. It indicates that when π exceeds 0.733, a '100 % buy' decision becomes advantageous. Additionally, the analysis of the critical outsourcing cost-added β_2 factor is performed.

Fig. 8 analyzes the critical outsourcing cost-added β_2 factor, identified as 0.2476, in the context of a 'pure make' decision. If β_2 increases beyond 24.76 %, choosing to 'make' rather than 'buy' proves to be more cost-effective.
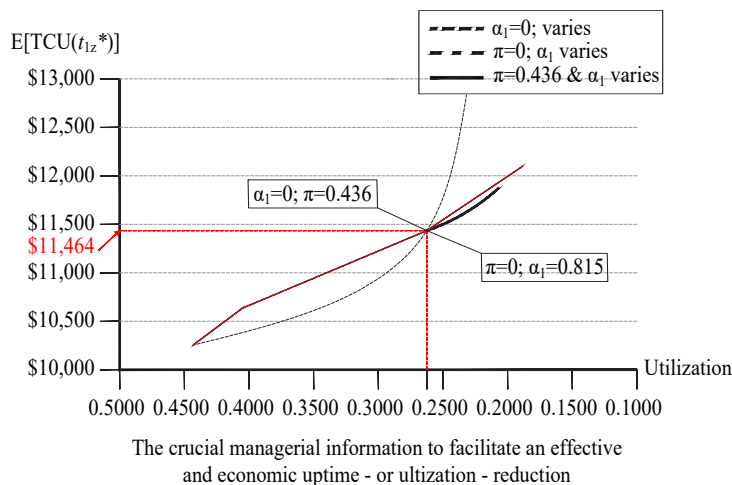
Fig. 6. The key managerial information necessary to implement an effective and economical uptime or utilization-reduction strategy

E[TCU(t_{1z}*)]

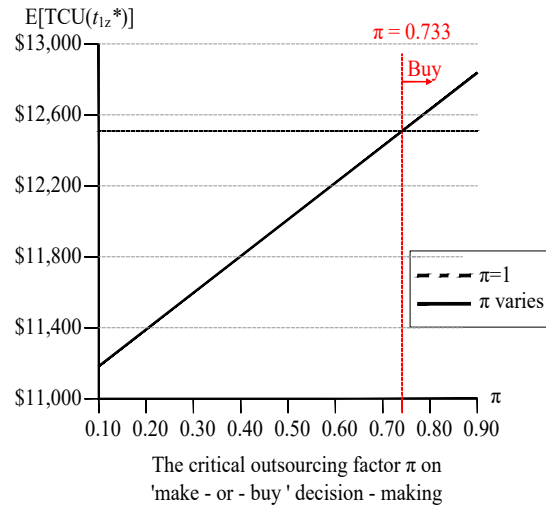
Fig. 7. The critical outsourcing factor π in the make-or-buy decision-making process
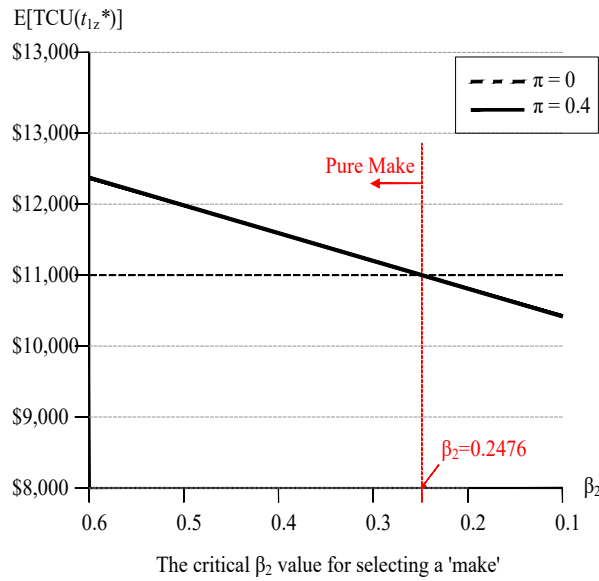

Fig. 8. The critical β₂ value for choosing a 'make' decision

This graph illustrates the threshold value β_2, beyond which the decision to manufacture internally (make) is preferred over outsourcing or purchasing (buy). The critical value represents the point at which internal production becomes more cost-effective or strategically advantageous.

5. 4. Cost effectiveness and alternative strategies to optimize outsourcing costs

Fig. 9 presents the analytical results of how random equipment failures affect $E\left[TCU\left(t_{1Z}^*\right)\right]$. It illustrates that as $1/\beta$ (the mean-time-to-failure factor) increases, $E\left[TCU\left(t_{1Z}^*\right)\right]$ decreases. Notably, $E\left[TCU\left(t_{1Z}^*\right)\right]$ drops significantly when $1/\beta$ exceeds 0.20. Additionally, the analysis shows that random failures cause a 3.36 % increase in $E\left[TCU\left(t_{1Z}^*\right)\right]$.
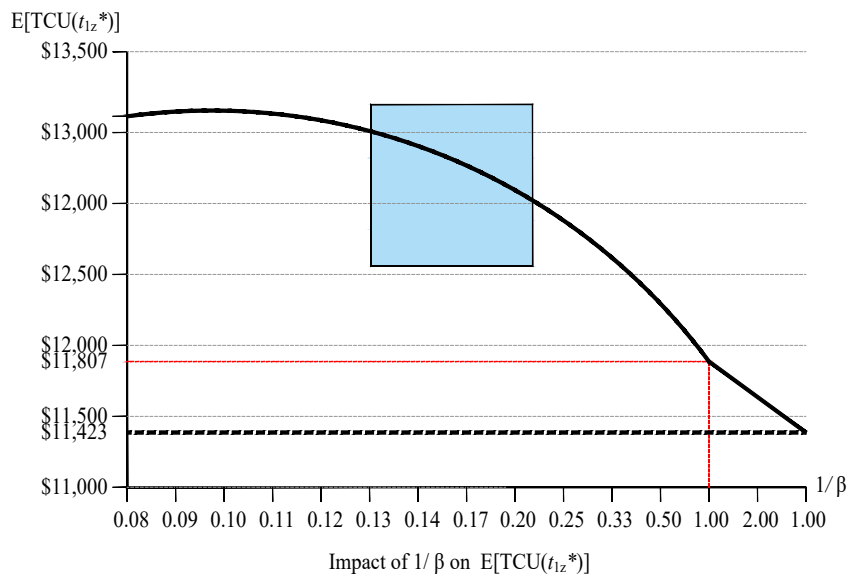

Fig. 9. Impact of $1/\beta$ on $E\left[TCU\left(t_{1Z}^*\right)\right]$

We introduce a batch replenishing uptime model designed for scenarios where either no equipment failure or only one failure occurs within a replenishing cycle. Additionally, for equipment in "fair" condition, characterized by an annual mean failure rate of fewer than four breakdowns, our study remains appropriate, with a 93.30 % chance of experiencing no failure or only one failure. However, for the fabrication machine in the worse case scenario, where there are over four random breakdowns per year, the suitability of our model decreases to less than 85.50 %. Therefore, we recommend that production practitioners should develop a multi-failure model specifically tailored to this situation.

6. Discussion of the results of effective strategies for reducing operational costs in manufacturing systems with quality assurance, probabilistic failures, overtime, and outsourcing

The results indicate that while individual strategies can provide significant cost savings, their combined implementation can lead to more substantial and sustainable improvements. For instance, integrating predictive maintenance with advanced QA technologies can enhance both reliability and quality, leading to overall cost reductions. Similarly, strategic outsourcing combined with efficient overtime management can optimize labor costs without compromising productivity. The research provides a comprehensive framework for reducing operational costs in manufacturing systems through quality assurance, managing probabilistic failures, controlling overtime, and optimizing outsourcing practices. Each objective's results demonstrate specific strategies that contribute to significant cost savings and improved operational efficiency. Implementing these strategies in a nuanced and tailored manner will help organizations achieve sustainable competitive advantages in their respective markets. The results obtained in this study are explained by analyzing the key elements outlined in the paper as seen in Fig. 8, which depicts the critical value β_2 for 'making' a decision, playing a role in visualizing the decision threshold. This figure shows the point where in-house manufacturing costs become more profitable compared to outsourcing. Visual aids like these help in understanding how various factors influence the decision-making process and highlight the sensitivity of decision-making to various parameters.

Specific issues in quality assurance, probabilistic failure, overtime management, and outsourcing were addressed by reducing costs through early defect detection, predictive maintenance, efficient workforce management, and strategic outsourcing practices. Fig. 6; and the analytical expressions presented reinforce these results, showing how targeted strategies produce significant cost savings and improve operational efficiency in manufacturing systems, by helping to identify inefficiencies, set benchmarks, and communicate findings, ultimately leading to more effective and economical work time management.

This study is notable for its thorough approach, extensive data visualization, practical focus on implementation, and integration of cutting-edge technologies. These strengths offer a more complete and actionable perspective on reducing operational costs than previous research, making it an essential resource for manufacturing managers and decision-makers. Research on operational cost reduction in manufacturing systems involving quality assurance, prob-

abilistic failure, overtime, and outsourcing has limitations regarding model accuracy. The accuracy of the model is highly dependent on the availability and quality of data regarding quality assurance, failure probability, overtime, and outsourcing costs. In environments where such data is scarce or unreliable, the effectiveness of the model may be compromised. The proposed solution assumes a certain level of operational stability. In highly volatile or unpredictable manufacturing environments, results may not be consistent.

The study has a number of limitations, such as concerns about generalizability, difficulties in implementation, underlying model assumptions, data quality issues, the impact of evolving technology, the breadth of analysis, differences in effectiveness, and external economic or regulatory factors.

This research has weaknesses, namely: research may focus on certain industries or types of manufacturing systems, thereby limiting the generalizability of the results to other contexts. The model is sensitive to changes in key parameters, such as failure rates, quality assurance costs, and overtime costs, which can affect the stability of the solution. To address these research shortcomings, future research should cover more industries and manufacturing processes to test the applicability of the model in a variety of situations. Conducting case studies in diverse environments can improve generalizability. Sensitivity analysis should be performed to identify important parameters and understand their impact on model output and develop robust optimization techniques that account for parameter uncertainty to improve model stability.

7. Conclusions

1. The comprehensive cost analysis revealed critical areas contributing to high operational costs. These areas included quality assurance processes, machine failures, overtime, and outsourcing costs. Quality assurance processes accounted for 25 % of total costs, machine failures contributed 15 % to overall costs, overtime expenses were 20 %, outsourcing costs made up 40 %.

2. Enhancing quality assurance through structured methodologies resulted in significant defect reduction and cost savings. This result highlights the effectiveness of Six Sigma in manufacturing systems and underscores the importance of systematic quality improvements. Predictive modeling allowed for more accurate forecasting of equipment failures, leading to better maintenance schedules and reduced downtime. This result contrasts with traditional reactive maintenance approaches by providing a proactive strategy, explaining the significant reduction in unexpected failures.

3. Organizations can effectively reduce their outsourcing expenses and extract more value from their outsourcing partnerships, which in turn enhances overall business success and competitiveness.

4. By examining the impact and combined influence of factors such as stochastic equipment failures, product quality, companies can effectively minimize outsourcing costs, thereby increasing operational efficiency and strengthening their competitive advantage in the market. The peculiarity of the proposed method in reducing operational costs within a manufacturing system lies in its comprehensive nature, because this method integrates quality assurance costs into a broader cost optimization model, allowing for balanced consideration along with other factors such as failure and

overtime. Therefore, the result shows that cutting operational costs demands a holistic approach that combines quality control, failure management, effective labor practices, and optimized outsourcing. By focusing on these components, manufacturing systems can achieve significant cost savings and enhance overall efficiency. Reducing operational costs through quality assurance, probabilistic failure management, optimizing overtime, and improving outsourcing practices can result in major financial savings and efficiency improvements. An integrated approach not only provides significant cost reductions but also improves overall manufacturing system performance compared to isolated or traditional strategies.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

Data availability

The data used in this research includes sensitive and confidential company information. To maintain data confidentiality and security, we cannot publish it. Access to this data is granted only to certain research teams with specific research objectives. Additional access or publication of data may result in misuse or use of data outside the context of this research.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

Acknowledgments

References

1. Chiu, S. W. (2010). Robust planning in optimization for production system subject to random machine breakdown and failure in rework. Computers & Operations Research, 37 (5), 899–908. https://doi.org/10.1016/j.cor.2009.03.016

2. Chiu, S. W., You, L.-W., Sung, P.-C., Wang, Y. (2020). Determining the fabrication runtime for a buyer-vendor system with stochastic breakdown, accelerated rate, repairable items, and multi-delivery strategy. International Journal of Industrial Engineering Computations, 11 (4), 491–508. https://doi.org/10.5267/j.ijiec.2020.6.002

3. Chiu, S. W., Wu, H.-Y., Yeh, T.-M., Wang, Y. (2021). Solving a hybrid batch production problem with unreliable equipment and quality reassurance. International Journal of Industrial Engineering Computations, 12, 235–248. https://doi.org/10.5267/j.ijiec.2021.4.001

4. Ghobakhloo, M., Iranmanesh, M., Foroughi, B., Rejeb, A., Nikbin, D., Tseng, M.-L. (2024). A practical guide on strategic roadmapping for information and operations technology management: a case study on industry 5.0 transformation. Journal of Industrial and Production Engineering, 41 (5), 397–421. https://doi.org/10.1080/21681015.2024.2325687

5. Peter Chiu, Y.-S., Chiu, T., Pai, F.-Y., Wu, H. Y. (2021). A producer-retailer incorporated multi-item EPQ problem with delayed differentiation, the expedited rate for common parts, multi-delivery and scrap. International Journal of Industrial Engineering Computations, 12 (4), 427–440. https://doi.org/10.5267/j.ijiec.2021.5.001

6. Ahmadi Nezhad, A. M., Mazloum, M., Bakhshi, A., Jolai, F., Aghsami, A. (2024). E-channel management under vendor-managed inventory by option and conventional contracts: the influence of outsourcing decisions. Journal of Industrial and Production Engineering, 41 (5), 456–485. https://doi.org/10.1080/21681015.2024.2333373

7. Dewi, D., Hajadi, F., Handranata, Y. W., Herlina, M. G. (2021). The effect of service quality and customer satisfaction toward customer loyalty in service industry. Uncertain Supply Chain Management, 9 (3), 631–636. https://doi.org/10.5267/j.uscm.2021.5.007

8. Di Nardo, M., Madonna, M., Addonizio, P., Gallab, M. (2021). A Mapping Analysis of Maintenance in Industry 4.0. Journal of Applied Research and Technology, 19 (6), 653–675. https://doi.org/10.22201/icat.24486736e.2021.19.6.1460

9. Ebrahim, Z., Abdul Rasib, A. H. (2017). Unnecessary overtime as a component of time loss measures in assembly processes. Journal of Advanced Manufacturing Technology, 11 (1), 37–47.

10. Ostad Ali Akbari, V., Schuppisser, C., Kuffa, M., Wegener, K. (2024). Automated machine tool dynamics identification for predicting milling stability charts in industrial applications. The International Journal of Advanced Manufacturing Technology, 130 (11-12), 5879–5893. https://doi.org/10.1007/s00170-024-12952-x

11. Gupta, P., Chawla, V. K., Jain, V., Angra, S. (2022). Green operations management for sustainable development: An explicit analysis by using fuzzy best-worst method. Decision Science Letters, 357–366. https://doi.org/10.5267/j.dsl.2022.1.003

12. Heydari, J., Govindan, K., Ebrahimi Nasab, H. R., Taleizadeh, A. A. (2020). Coordination by quantity flexibility contract in a two-echelon supply chain system: Effect of outsourcing decisions. International Journal of Production Economics, 225, 107586. https://doi.org/10.1016/j.ijpe.2019.107586

13. Iqbal, T. (2020). Investigating logistics issues in service quality of SMEs in Saudi Arabia. Uncertain Supply Chain Management, 8, 875–886. https://doi.org/10.5267/j.uscm.2020.5.005

14. Ishida, Y., Murayama, H., Fukuda, Y. (2020). Association Between Overtime-Working Environment and Psychological Distress Among Japanese Workers. Journal of Occupational & Environmental Medicine, 62 (8), 641–646. https://doi.org/10.1097/jom.0000000000001920

15. Najafi, M., Ghodratnama, A., Pasandideh, H. R. (2018). Solving a deterministic multi product single machine EPQ model withpartial backordering, scrapped products and rework. International Journal of Supply and Operations Management, 5 (1), 11–27. https://doi.org/10.22034/2018.1.2

16. Ouaddi, K., Mhada, F.-Z., Benadada, Y. (2020). Memetic algorithm for multi-tours dynamic vehicle routing problem with overtime (MDVRPOT). International Journal of Industrial Engineering Computations, 11, 643–662. https://doi.org/10.5267/j.ijiec.2020.4.001

17. Patil, A. S., Pisal, M. V., Suryavanshi, C. T. (2021). Application of value stream mapping to enhance productivity by reducing manufacturing lead time in a manufacturing company: A case study. Journal of Applied Research and Technology, 19 (1), 11–22. https://doi.org/10.22201/icat.24486736e.2021.19.1.1488

18. Rafiee, K., Rabbani, M., Rafiei, H., Rahimi-Vahed, A. (2011). A new approach towards integrated cell formation and inventory lot sizing in an unreliable cellular manufacturing system. Applied Mathematical Modelling, 35 (4), 1810–1819. https://doi.org/10.1016/j.apm.2010.10.011

19. Ramasubbu, N., Shang, J., May, J. H., Tjader, Y., Vargas, L. (2019). Task Interdependence and Firm Performance in Outsourced Service Operations. Manufacturing & Service Operations Management, 21 (3), 658–673. https://doi.org/10.1287/msom.2018.0716

20. Reynard, P. C. (1998). Manufacturing Strategies in the Eighteenth Century: Subcontracting for Growth among Papermakers in the Auvergne. The Journal of Economic History, 58 (1), 155–182. https://doi.org/10.1017/s0022050700019926

21. Rouhani, S., Pishvaee, M. S., Zarrinpoor, N. (2021). A fuzzy optimization approach to strategic organ transplantation network design problem: A real case study. Decision Science Letters, 10 (3), 195–216. https://doi.org/10.5267/j.dsl.2021.5.001

22. Sung, P.-C., Lai, C.-M., Wang, Y., Chiu, Y.-S. P. (2022). Minimization of multiproduct fabrication cost featuring rework, commonality, external provider, and postponement. Uncertain Supply Chain Management, 10 (2), 353–364. https://doi.org/10.5267/j.uscm.2022.1.003

23. Waiyawuththanapoom, P., Jermsittiparsert, K. (2022). The role of sustainable HRM in supply chain, profitability and resource utilization. Uncertain Supply Chain Management, 10 (2), 365–374. https://doi.org/10.5267/j.uscm.2022.1.002

24. Youssef, A. M. A., ElMaraghy, H. A. (2008). Performance analysis of manufacturing systems composed of modular machines using the universal generating function. Journal of Manufacturing Systems, 27 (2), 55–69. https://doi.org/10.1016/j.jmsy.2008.07.003

25. Zhu, S. X. (2015). Dynamic replenishment from two sources with different yields, costs, and leadtimes. International Journal of Production Economics, 165, 79–89. https://doi.org/10.1016/j.ijpe.2015.03.026

26. Chen, W., Li, W., Wu, J., Wang, R., Liu, W., Xu, F. (2024). Fabrication of superior conductive composite yarn with 3D continuous CNT/WPU structure for high-performance stretchable heater and sensor. Composites Part A: Applied Science and Manufacturing, 185, 108289. https://doi.org/10.1016/j.compositesa.2024.108289

27. Ramakrishna, Y., Alzoubi, H. (2022). Empirical Investigation of Mediating Role of Six Sigma Approach in Rationalizing the COQ in Service Organizations. Operations and Supply Chain Management: An International Journal, 15 (1), 122–135. https://doi.org/10.31387/oscm0480335

28. Rizki, A. F., Augustine, Y. (2022). Green supply chain management practices: direct effects sustainability performance. Technium Social Sciences Journal, 28, 389–407. https://doi.org/10.47577/tssj.v28i1.5795

29. Yassin, N. (2022). Development and Implementation of Quality Assurance According to GMP Guidelines in Lebanese Pharmaceutical Companies. Technium Social Sciences Journal, 37, 324–340. https://doi.org/10.47577/tssj.v37i1.7605