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Integrated Systemic Modeling of Production Scheduling, Maintenance, and Quality Control in Closed-Loop Supply Chains

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ABSTRACT

Closed-loop supply chains (CLSCs) are increasingly recognized as essential frameworks for achieving operational efficiency and sustainability in modern industries. This study focuses on optimizing production scheduling, maintenance strategies, and quality control within CLSCs, specifically tailored for the home appliances industry. The proposed model integrates preventive and corrective maintenance policies, scheduling, and quality management into a unified system that minimizes costs while enhancing reliability and sustainability. The Strategic Choice Approach (SCA) was employed to structure complex decision-making processes, leveraging the expertise of industry professionals to identify key uncertainties and variables. A Genetic Algorithm (GA) was utilized to optimize decision variables, including sample size, sampling intervals, control limits, and maintenance schedules, ensuring robust solutions under real-world constraints. The model categorizes machine failures into immediate and delayed modes, providing tailored strategies for each to maintain system performance. Comparative analyses highlight the integrated model's superior cost-effectiveness and operational benefits over traditional independent approaches. Sensitivity analyses further demonstrate the robustness of the model under varying operational conditions, validating its adaptability and scalability. By addressing the interconnected challenges of maintenance, scheduling, and quality control, this research offers a practical and holistic solution for CLSCs, contributing to improved operational resilience, customer satisfaction, and alignment with sustainability objectives. The decision-making process provides valuable insights and confident recommendations for future research.

Keywords

Integrated system, Production scheduling, Maintenance, Closed-loop supply chain, Strategic choice approach.

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1. Introduction

Supply chains are the lifelines of modern industries (Taghipour et al., 2023b), underpinning the processes that deliver goods and services efficiently and sustainably. In recent years, the concept of closed-loop supply chains (CLSCs) (Foukolaei et al., 2024) has gained significant attention as industries recognize the importance of integrating forward and reverse logistics to manage resources more effectively (Gholian-Jouybari et al., 2024). CLSCs are particularly valuable in sectors such as the home appliances industry, where product lifecycles demand robust mechanisms for recycling (Ghaedi et al., 2024), remanufacturing, and waste reduction (Ramezani et al., 2024). This approach minimizes environmental impact and creates opportunities for cost savings and enhanced customer satisfaction (Taghipour et al., 2024), aligning with global sustainability goals (Taghipouret al., 2023). Scheduling and production planning are critical elements within supply chains, influencing resource allocation, production efficiency, and customer fulfillment (Shambayati et al., 2023). Effective scheduling ensures that production meets demand while minimizing delays and costs, whereas robust planning aligns operational strategies with long-term business goals (Scheller et al., 2023). These factors are even more complex in CLSCs, where production planning must accommodate uncertainties in reverse logistics, such as the timing and quality of returned products (Gholizadeh et al., 2023). Moreover, integrating maintenance strategies and quality control into scheduling processes becomes essential to ensure operational reliability and product integrity (Corsini et al., 2024). Balancing these interdependencies for industries like home appliances is key to maintaining competitiveness in increasingly dynamic markets (Bhattacharya et al., 2024).

Systems thinking provides a practical framework for addressing these complexities by emphasizing the interconnectedness of various elements in CLSC operations (Coenen et al., 2018). By viewing production scheduling, maintenance, and quality control as parts of a unified system, systems thinking enables organizations to identify feedback loops, dependencies, and potential trade-offs (León & Calvo-Amodio, 2017). This perspective is particularly valuable for CLSCs, where the flow of materials, information, and resources must be optimized across multiple stages (MahmoumGonbadi et al., 2021). Industries can move away from siloed approaches through systems thinking and develop integrated strategies that enhance overall performance, resilience, and sustainability (Jaaron & Backhouse, 2019).

This study is motivated by addressing these challenges in CLSC operations. Specifically, it focuses on developing an integrated model for production scheduling, preventive and corrective maintenance, and quality control in the home appliances industry. Using the Strategic Choice

Approach (SCA) to identify key decision variables and mathematical modeling to optimize them (Antweiler & Schlund, 2023), the study aims to provide a comprehensive solution that minimizes costs and enhances system performance. By bridging theoretical advancements with practical applications, this research contributes to the ongoing discourse on CLSC optimization and demonstrates the value of holistic decision-making frameworks.

The remainder of this paper is organized as follows. The literature review examines previous studies on CLSCs, production scheduling, and integrated maintenance strategies, highlighting existing gaps and opportunities. The methodology section details the use of SCA and the development of the mathematical model. The results section presents the findings, illustrating the effectiveness of the proposed model with numerical examples. The discussion provides insights into managerial implications, highlighting the advantages of integrated approaches over independent models. Finally, the conclusion summarizes the study's contributions and outlines directions for future research in advancing CLSC strategies.

2. Literature review

Recent advancements in closed-loop supply chains (CLSCs) have emphasized the importance of integrating innovative optimization methods to enhance efficiency and sustainability. Recent studies in the field of closed-loop supply chains are listed in the Table 1. Aliahmadi et al. (2023) developed a multi-echelon CLSC model that incorporated pricing decisions and queuing systems under uncertainty. Their approach utilized Flexible Robust-Fuzzy Optimization (FRFO) and meta-heuristic algorithms, such as G-HHO and PSO, to maximize net present value (NPV). Results showed that increasing the number of production lines reduced queue lengths and enhanced profitability, with the G-HHO algorithm performing best for large-scale problems. Similarly, Gholizadeh et al. (2023) proposed a closed-loop green supply chain network incorporating redundancy strategies for reliability and eco-friendliness. Their model, which applied hybrid heuristics and meta-goal programming, achieved notable cost reductions, increased eco-friendly part usage, and improved system reliability through active standby strategies. Scheller et al. (2023) analyzed CLSCs for lithium-ion batteries using a multi-stage, multi-product, multi-period production planning approach in the context of network structures. The study compared centralized, decentralized, and circular factory setups, demonstrating that circular factories outperformed others in reducing transportation costs and enhancing material flow in the short term. Corsini et al. (2024) extended the focus to production capacity and control policies, evaluating four production control strategies in CLSCs. Their findings highlighted the Adaptive Hedging Corridor Policy as a practical approach for enhancing customer service levels and minimizing the bullwhip effect, with return flows and manufacturing operations playing critical roles in supply chain performance.

Multi-objective optimization models have also been pivotal in addressing CLSC challenges under uncertainty. Yousefi et al. (2021) presented a model for aggregate production planning, optimizing costs, customer satisfaction, and product quality through LP-metric and LINGO software. Applied to military industry data, the model effectively balanced conflicting objectives. Roshani et al. (2023) tackled capacitated lot-sizing and scheduling in CLSCs, incorporating sequence-dependent setup times. By leveraging large-bucket mixed-integer programming and Grey Wolf optimization algorithms, their model minimized costs across manufacturing, remanufacturing, inventory holding, and energy utilization, demonstrating the effectiveness of these algorithms in solving NP-hard problems. Emerging technologies like IoT and artificial intelligence (AI) are transforming CLSC operations. Shambayati et al. (2023) and Shambayati et al. (2022) explored IoT-enabled virtual CLSCs, revealing significant improvements in profitability and efficiency through advanced tracking and defect management systems. Meanwhile, Bhattacharya et al. (2024) provided a comprehensive review of AI applications in CLSCs, identifying ten popular techniques and proposing a framework with fifteen research questions for future exploration. Hussaini et al. (2023) contributed to CLSC viability by proposing a multi-period, multi-season model to manage fluctuations in demand and costs, emphasizing the importance of accurate cost forecasting and capacity adjustments.

Table 1. Summary of the related recent studies

Author(s)	Aim	Methods	Findings
(Aliahmadi et al., 2023)	To model a multi-echelon closed-loop supply chain with pricing decisions and queuing systems under uncertainty.	Flexible Robust-Fuzzy Optimization (FRFO) and meta-heuristic algorithms (G-HHO, PSO, ALO, GWO)	Maximized net present value (NPV), reduced queue lengths, and improved NPV with increased production lines. G-HHO algorithm provided the best performance for large sample problems.
(Gholizadeh et al., 2023)	To design a closed-loop green supply chain network with a redundancy strategy for eco-friendly parts and maximum reliability.	Multi-objective mixed-integer program with a hybrid heuristics algorithm and multi-choice meta-goal programming	Achieved a 15.3% decrease in total cost, 2.83% increase in eco-friendly parts, and 11.25% increase in reliability with active standby strategy.
(Scheller et al., 2023)	To develop a production planning model for closed-loop supply chains in lithium-ion batteries, analyzing different network structures.	Multi-stage, multi-product, multi-period production planning approach	Circular factories outperformed centralized and decentralized networks in the short term, improving material flow and reducing transportation costs.
(Corsini et al., 2024)	To analyze how production capacity and production control policies impact the performance of closed-loop supply chains.	Comparison of four production control policies using simulation	Adaptive Hedging Corridor Policy enhanced customer service levels and reduced the bullwhip effect. Sensitivity analysis highlighted the importance of return flows and manufacturing operations.

Author(s)	Aim	Methods	Findings
(Yousefi-Babadi et al., 2021)	To present a multi-objective model for aggregate production planning in a closed-loop supply chain under uncertain conditions.	LP-metric and LINGO software for multi-objective optimization	Optimized costs, customer satisfaction, supplier satisfaction, and product quality; solved through numerical examples and actual data in military industry.
(Roshani et al., 2023)	To address capacitated lot-sizing and scheduling with sequence-dependent setup times in a closed-loop supply chain.	Large-bucket mixed-integer programming, matheuristic, and grey wolf optimization algorithms	Minimized manufacturing, remanufacturing, setup, inventory holding, backlogging, and energy costs. The proposed algorithms demonstrated effectiveness in solving the problem.
(Shambayati et al., 2023)	To optimize a virtual closed-loop supply chain (VCLSC) using IoT under uncertainty.	Grey Wolf algorithm and Firefly algorithm for optimization	The Firefly algorithm outperformed others, leading to higher profit for the VCLSC. The use of IoT significantly increased profits by tracking defective parts and improving chain efficiency.
(Bhattacharya et al., 2024)	To review the applications of Artificial Intelligence (AI) in closed-loop supply chains (CLSC) and propose future research directions.	Systematic literature review of 303 peer-reviewed articles	Identified 10 popular AI techniques and 7 CLSC subfields where AI could bring significant benefits. Proposed a framework with 15 research questions for future research.
(Hussaini et al., 2023)	To develop a multi-period, multi-season model for ensuring supply chain viability under fluctuations.	Mixed-integer mathematical model solved with CPLEX solver	Highlighted seasonal supplier layoffs, capacity adjustments, and accurate cost forecasting as critical strategies for maintaining supply chain viability.
(Shambayati et al., 2022)	To optimize virtualization in closed-loop supply chains using IoT.	Grey Wolf and Firefly algorithms for optimization; sensitivity analysis	IoT integration significantly enhanced efficiency and profitability of the virtual supply chain by improving tracking, product delivery, and defect management.

While significant advancements have been made in optimizing closed-loop supply chains (CLSCs), gaps remain in fully integrating key aspects such as production scheduling, maintenance strategies, and quality control under uncertainty. Existing studies primarily focus on isolated components, such as pricing decisions (Aliahmadi et al., 2023), green supply chain design (Gholizadeh et al., 2023), or specific network structures (Scheller et al., 2023). However, the interplay between these elements, particularly in real-world constraints like fluctuating demand, multi-objective trade-offs, and operational disruptions, is less explored. The novelty of the current study lies in its holistic approach to optimizing CLSCs by integrating production, maintenance, and quality management using advanced optimization techniques. By addressing these interdependencies and incorporating dynamic factors such as machine reliability and system efficiency, the study bridges existing gaps. It offers a unified framework that enhances cost-effectiveness, sustainability, and decision-making robustness in complex supply chain environments.

3. Methodology

The study employed the Strategic Choice Approach (SCA) (Khazaei et al., 2021b) to design an optimized closed-loop supply chain model tailored for the home appliances industry. SCA, a methodology from the soft operational research category (Dehghan Nayeri et al., 2018), is a collaborative decision-making framework that emphasizes the incremental management of uncertainties and involves participants with diverse expertise (Khazaei et al., 2021a). For this research, nine home appliance industry experts were convened in structured workshops (Paucar-Caceres et al., 2020). These experts represented various domains: production, logistics, quality control, and sustainability. The workshops were designed to systematically identify the key decision areas, uncertainties, and comparison criteria essential for designing an effective closed-loop supply chain. The SCA process unfolded through its four strategic modes—shaping, designing, comparing, and choosing—enabling the group to build a commitment package for decisions to be implemented incrementally (Franco, 2007). The discussions focused on defining uncertainty boundaries, such as the working environment, guiding values, and interrelated choices, specific to the home appliances sector (DeCarolis et al., 2017). For example, uncertainties about product lifecycle, recycling processes, and customer return behaviors were identified and categorized. By navigating these uncertainties, the group collaboratively formulated assumptions about the structure and functionality of the supply chain, ensuring that the proposed model addressed practical challenges and aligned with industry needs.

The assumptions derived from the SCA workshops (Figure 1) were systematically converted into a mathematical model for optimization, which will be elaborated on in subsequent sections. This conversion involved translating qualitative insights into quantitative parameters, enabling precise modeling of production scheduling, maintenance strategies, and reverse logistics flows. The mathematical formulation integrated these assumptions into a robust framework to minimize costs and improve efficiency across the closed-loop supply chain. This integration of SCA with mathematical modeling provides a unique methodological approach, bridging expert-driven decision-making with quantitative optimization for practical implementation (Awasthi et al., 2018). Therefore, our model in this paper categorizes machine failures into two distinct modes (Bektur, 2020): 1) The first type of breakdown mode (FM_1): The breakdown of the machine is determined immediately. 2) The second type of failure mode (FM_2): Machine failure after production is determined by transferring the process average in the discussion of process quality.

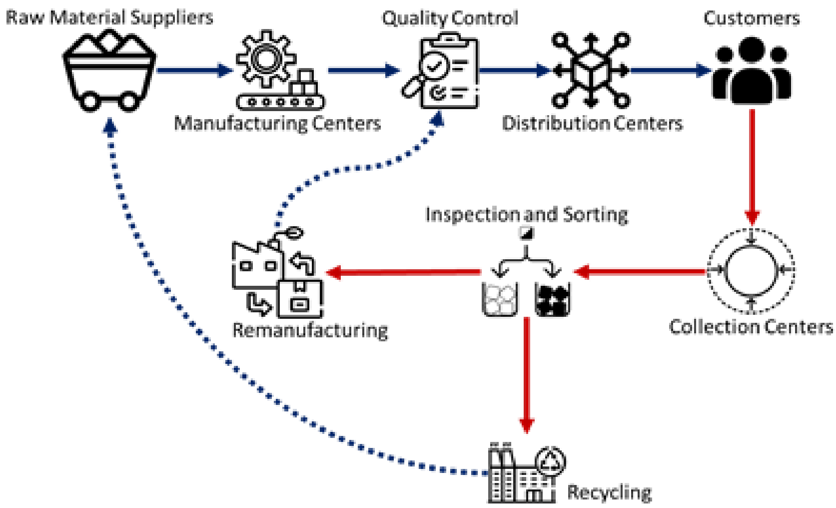

Figure 1. The designed flow of CLSC model after SCA employment

3.1. Assumptions and descriptions

Here are the assumptions the authors will examine:

1) Corrective maintenance and repairs are fundamentally minimal. Post-correction, the equipment's lifespan remains unchanged, and the duration of the corrective activity is included in its operational life.
2) Maintenance and repairs are inherently partial; they only partially address the issue, leading to potential recurring problems.
3) For quality control, the authors consider only one characteristic: CTQ[1].
4) The production process starts from the state under control. The mean and standard deviation of CTQ are μ and σ as follows.
5) A specific error that happens randomly and causes the process average to σ when it remains constant. It transfers from μ_0 to $\delta+\mu_0$ μ_1
6) The control chart monitors the process $\bar{x}$.

Table 2 shows the variables and parameters of the CLSC model.

Table 2. Variables and parameters

Variables / Parameters	Definition
$ARL2_E$	The average sample length is when the process is out of control for external and environmental reasons.
$ARL2_{M/C}$	The average sample length when the process is out of control due to machine wear.
ARL1	The average sample length when the process is under control.
K	Coefficient of control limit.
C_{lp}	The cost of stopping production.
C_{Rej}	The cost of returning the product.
$C_{resetting}$	The cost of restoring the process to the first state.
prd_E	Overall evaluated time.
$[C_{CM}]_{FM_1}$	Expected cost of maintenance and corrective repairs due to the first mode error.
C_{PM}	Expected cost of preventive maintenance and repairs.

[1] Critical to Quality

Variables / Parameters	Definition
$E\ [T_{Cycle}]$	Duration of the process.
T_1	The time required to determine the occurrence of the specified reason.
$E\ [T_{restore}]$	The time required to restore the process to the first state or to repair the machine if the process has gone out of control due to the environment or machine depreciation.
$[TCQ]_{process-failure}$	The cost of quality degradation due to process defects.
λ_1	Process failure rate due to environmental and external reasons.
λ_2	The machine breakdown rate due to machine depreciation.
C_{FCCM}	Fixed cost of maintenance operations and corrective repairs.
C_{FCPM}	Fixed cost of preventive maintenance and repairs.
LC	Cost of labor for maintenance and repairs.
MT_{CM}	Average time required for maintenance and corrective repairs.
MT_{PM}	Average time required for preventive maintenance and repairs.
N_f	Average number of failures.
t_{PM}	Interval of maintenance and repair activities.
β_E	The possibility of a second type of error due to an external reason.
$\beta_{M/C}$	The possibility of the second type of error due to the depreciation of the machine.
P_{FM_1}	Probability of occurrence of the first failure mode.
P_{FM_2}	Probability of occurrence of the second failure mode.
λ	Process failure rate.
PR	Production rate.
N	Sample size.
T_s	Sampling time.
α	First type error.
H	Time interval between sampling.

3.2. Model description

If FM_1 occurs, the machine stops immediately. Corrective operations are applied to repair it. Therefore, the cost of maintenance and corrective repairs ($[C_{CM}]_{FM_1}$) consists of the cost of idle time, the cost of repairing and restoring the machine to its original state (Bocken et al., 2019). The machine's condition influences the effects of FM_2 and results in an increased product return rate. In other words, FM_2 impacts the process's return rate. It is assumed that the process halts immediately upon detecting FM_2, and corrective measures are implemented to restore normal operating conditions. Additionally, the process may deteriorate due to external factors (E), such as environmental conditions, operator errors, or improper tool usage (Calabrese et al., 2019). The process transitions to an out-of-control state if an external event (E) occurs. Process monitoring accomplishes detection of FM2 or an external cause (E). In this article, a control chart mechanism is used for monitoring. The control chart design parameters include sample size (n), sampling interval (h), and coefficient (k) to determine the distance from the central line to the control limit. Therefore, the total cost of process failure due to E and FM_2, i.e., $[TCQ]_{process-failure}$, include the cost of machine idleness, product return due to process transfer, repair cost, sampling and inspection cost, and the deviation cost of CTQ target values (Centobelli et al., 2020).

The authors need to account that both parameters, FM_1 and FM_2, are flawed and diminished. Reducing FM_2 leads to increased costs due to out-of-control operations and quality issues. However, preventive maintenance requires resources and time that could be used for production. The cost of preventive maintenance (PM) includes the expense of process downtime (C_{PM}) and the costs associated with maintenance and repairs. This article discusses the problem of determining the optimal values of the decision variables (n, h, k, t_{PM}) to minimize the total cost per time unit ($[TCT]_{Maintenance*Quality}$) (Chaturvedi et al., 2017). It should be noted that the life of the equipment is reduced after preventive maintenance and repair according to the repair and return factor. The total cost per unit of time for maintenance and preventive repairs and control chart policy ($[TCT]_{Maintenance*Quality}$) is the ratio of the total cost of quality control ($[TCQ]_{process-failure}$), the total cost of preventive maintenance and repairs (C_{PM}), and the total cost of machine breakdown ($[C_{CM}]_{FM_1}$), to the evaluation time. The cost incurred due to FM_2 includes the cost of process quality control. Therefore, the total cost is as follows per unit of time for the integrated model (Chen et al., 2023) in Equation 1:

$$[TCT]_{Maintenance*Quality} = \frac{1}{prdE}([C_{CM}]FM_1 + C_{PM} + [TCQ]_{process\text{-}failure}) \quad (1)$$

Where $[TCT]_{Maintenance*Quality}$ = (n, h, k, t_{PM}) and prd_E. The time is planned and evaluated according to the analysis of what will be done. Therefore, the optimization problem can be Equation 2:

$$\begin{aligned}
&\text{Minimize } [TCT]_{Maintenance*Quality}\\
&\text{Subject to}\\
&a_1 \le n \le b_1\\
&a_2 \le h \le b_2\\
&a_3 \le k \le b_3\\
&a_4 \le t_{PM} \le b_4\\
&n, h, k, t_{PM} \ge 0
\end{aligned} \quad (2)$$

Where α_i and b_i are decision variables and upper and lower limit values. Next, the authors will describe the three cost functions within the objective function. For the specified evaluation period, expected cost models are derived for preventive and corrective maintenance related to FM_1 and the cost of process failures due to external factors associated with FM_2. To calculate the costs associated with corrective and preventive maintenance for FM_1, the analyst needs the following information (Chen et al., 2018): The amount of time required for corrective maintenance (CM) and preventive maintenance (PM) operations encompasses not only the actual maintenance and repair activities but also reasonable delays, such as waiting for labor, materials, or other necessary resources. These operations incur costs, including machine downtime, labor expenses, required materials, and associated fees. Additionally, equipment failure is always possible due to specific failure modes, highlighting the critical need for a comprehensive and proactive maintenance and repair strategy to ensure system reliability and operational efficiency (Chihambakwe et al., 2021). For the cost of maintenance and corrective repairs, the authors must have the following factors:

1) Average duration needed for maintenance and corrective repairs: MT_{CM}
2) System production rate: PR
3) The cost of stopping production during maintenance and corrective repairs: C_{lp}
4) Cost of labor for maintenance and corrective repairs: LC
5) Fixed cost of maintenance operations and corrective repairs: C_{FCCM}
6) The possibility of the first mode failure: P_{FM_1}
7) Average number of failures: N_f

The cost of maintenance and corrective repairs on FM_1 is calculated as Equation 3:

$$[C_{CM}]_{FM_1} = [[PR.C_{lp}+LC] + C_{FCCM}] \times P_{FM_1} \times N_f \quad (3)$$

where $[MT_{CM}$.[PR.C_{lp}+LC] + $C_{FCCM}]$ is the cost of machine failure due to maintenance and corrective repairs. The variable is t_{PM} in Equation 2-3 where N_f is a function that lies in it, discussed in the following.

The following should be considered to obtain a cost model for preventive maintenance and repairs:

1) Average time required for preventive maintenance and repairs: MT_{PM}
2) System production rate: PR
3) The cost of stopping production during preventive maintenance and repairs: C_{lp}
4) Cost of labor for preventive maintenance and repairs: LC
5) Fixed cost of preventive maintenance and repairs: C_{FCPM}
6) The possibility of the second mode failure: P_{FM_2}
7) Time of the entire evaluated course: prd_E

The expected total cost of preventive maintenance and repairs will be as Equation 4:

$$C_{PM} = [MT_{PM} \,.\, [PR.\, C_{lp}+LC] + C_{FCPM}] \times \frac{prd_E}{t_{PM}} \quad (4)$$

where $[MT_{PM}$. [PR. C_{lp}+LC] + $C_{FCPM}]$ is the cost of machine downtime is due to preventive maintenance and repairs and $\frac{prd_E}{t_{PM}} = N_{PM}$. The number of preventive maintenance and repairs is rounded to a smaller integer. Building on the work of Govindan et al. (2016), the authors have developed a novel model that optimizes product return costs, a unique approach to maintenance and repair costs. In new studies, the number of maintenance and corrective repairs is obtained by simulating machine defects for the given evaluation period, explained in the next section.

Next, the total cost of the process defect of $[TCQ]_{process-failure}$ is calculated. Then, the authors calculate the length of the period E$[T_{Cycle}]$. The period length refers to the anticipated duration between successive controlled intervals. During these intervals, costs arise from process sampling, product defects, and false alarms. If the process deviates from control, it is presumed that it cannot revert to a controlled state without external intervention. There are costs such as upgrading the level of the produced product, sampling, repair and return, searching for the reason, and stopping the process to return to the controlled state. After this, one period ends, and the successive periods begin. This section breaks down the expected cost of process quality control into costs. These costs include:

1) Expected cost to find the specific cause,
2) Sampling cost,
3) Expected cost for out-of-control operations.
4) The expected cost of restoring the process in a state that goes out of control due to machine wear or external and environmental reasons.

It is assumed that C_F is the fixed cost of sampling and C_V is the cost of variable sampling. Therefore, the expected cost of sampling in one period, the sum of fixed and variable costs per unit of time, is as Equation 5:

$$E[C_{sampling}]=(C_F + C_V.n) \times \left(ARL2_{M/C} \times {}^{\lambda_2}/_{\lambda} + ARL2_E \times {}^{\lambda_2}/_{\lambda}\right) \tag{5}$$

Now, the authors calculate the expected cost due to the lack of quality in the out-of-control state, and in fact, the authors get the cost of the defective products produced when the process is in the out-of-control state. The cost of returning the product when the process is out of control due to machine failure is Equation 6:

$$E[c_o]_{M/C}=(PR\times P_{M/C} \times C_{Rej})\times [\,(h+n.T_s) \times (ARL2_{M/c} \times {}^{\lambda_2}/_{\lambda} + ARL2_E \times {}^{\lambda_1}/_{\lambda}) - \tau+T_1)]\times ({}^{\lambda_2}/_{\lambda}) \tag{6}$$

Moreover, when the process goes out of control due to an external and environmental factor, the return cost is Equation 7:

$$E[c_o]_{E}=(PR\times P_{E} \times C_{Rej})\times [\,(h+ n.T_s) \times (ARL2_{M/c} \times {}^{\lambda_2}/_{\lambda} + ARL2_E \times {}^{\lambda_1}/_{\lambda}) - \tau+T_1)]\times ({}^{\lambda_1}/_{\lambda}) \tag{7}$$

$P_{M/C}$ and P_E are the probability of producing a defective product due to machine depreciation, external and environmental reasons, respectively. It is obtained from the Equation 8 and 9:

$$P_{M/C}=1-Pr(LSL\leq X\leq USL)=1-Pr(\frac{LSL-(\mu+\delta_{M/C})}{\sigma}\leq N(0,1)\leq\frac{USL-(\mu+\delta_{M/C})}{\sigma}) \quad (8)$$

$$P_E=1-Pr(LSL\leq X\leq USL)=1-Pr(\frac{LSL-(\mu+\delta_E)}{\sigma}\leq N(0,1)\leq\frac{USL-(\mu+\delta_E)}{\sigma}) \quad (9)$$

where USL and LSL are high and low-quality specification limits (tolerance). It is assumed that $C_{resetting}$ is the cost of finding and restoring the original state. The expected cost amount is calculated for $C_{resetting}$ in Equation 10:

$$E[C_{resetting}]=[C_{resetting}\times T_{resetting}]\times({}^{\lambda_1}/_{\lambda}) \quad (10)$$

The expected cost of the maintenance activity and corrective repairs due to the error, finding, and repairing the specific reason for the cause of the machine failure are show in Equation 11:

$$E[c_{Repair}]_{FM_2}=[(MT_{CM}).[PR.C_{lp}+LC]+C_{FCCM}]\times({}^{\lambda_2}/_{\lambda}) \quad (11)$$

This cost includes stoppage of production, cost of labor, and fixed cost of maintenance and corrective repairs. Therefore, the expected cost of process failure in the desired period is according to Equation 12:

$$E[C_{process}]=E[C_{sampling}]+E[c_o]_{M/C}+E[c_o]_E+E[C_{resetting}]+E[c_{Repair}]_{FM_2} \quad (12)$$

It is assumed that the failure of the process is repeated naturally. The period will be the same whenever the process is transferred from the state under control to the state out of control and back to the first state. (The duration of the course will be fixed). If the authors have M periods of process failure in an evaluated time, the total cost is according to Equation 13:

$$[TCQ]_{process-failure}=[E(C_{process})]\times M \quad (13)$$

In Equation 14, M is:

$$M=\frac{prd_E}{E[T_{cycle}]} \quad (14)$$

The expected course time is the sum of the following terms:

1) the desired period for the specific cause to occur,
2) the desired duration for analyzing and examining a sample and the graph of the results,
3) the desired period until the chart gives us a sign of leaving the controlled state,
4) the desired period to discover and analyze the specific reason that occurred,
5) The desired period to return the process to the first state if the defect of FM_2 is due to an external reason or to repair the process if the defect is due to the reason.

It is assumed that the time of the controlled state follows an exponential distribution with a mean of $1/\lambda$. The failure rate value is independent in the statistical discussion. Therefore:

$$\text{ARL1}= 1/\alpha \tag{15}$$

In Equation 16, α is α = Pr $(out\ of\ control\ signal|process\ is\ in\ control)$ and it is based on the calculations in quality control:

$$\alpha = 2\,\text{F(-k)} \tag{16}$$

where F will be the cumulative normal distribution, Process failure rate: λ, Coefficient of control limit: k, and Sampling period: h. It is supposed that τ is the expected time of occurrence and a specific reason. When the specified reason occurs between the i and i+1 samples. Therefore:

$$\tau = = h/2 \tag{17}$$

Hence, is τ the independent of i. where ARL2 is the average length of the period when the process has moved to an out-of-control state. According to the quality control discussion, if the taken samples are independent, therefore:

$$\text{ARL2}_{\text{M/C}}={}^{1}/1 - \beta_{\text{M/C}} \tag{18}$$

$$\text{ARL2}_{\text{E}}={}^{1}/1 - \beta_{\text{E}} \tag{19}$$

$$\beta\text{= Pr}(in\ control\ signal \mid process\ is\ out\ of\ control\,) \tag{20}$$

$$\beta_{M/C}\text{=Pr}\left(LCL \le \bar{x} \le UCL\middle|\mu = \mu_1 = \mu_0 + \delta_{M/C}\sigma_p\right) \tag{21}$$

$$\beta_{E}\text{=Pr}\left(LCL \le \bar{x} \le UCL\middle|\mu = \mu_1 = \mu_0 + \delta_{E}\sigma_p\right) \tag{22}$$

Since it is $\bar{\text{X}} \sim \text{N}(\mu, \sigma_{\text{P}}^2/\text{n})$ and the upper and lower control limits are equal to Equation 22 and 24 :

$$\text{UCL}=\mu_0 + k\sigma_p/\sqrt{n} \tag{23}$$

$$\text{LCL}=\mu_0 - k\sigma_p/\sqrt{n} \tag{24}$$

Then we will have:

$$\beta_{M/C}\text{=F}\left(\frac{UCL-(\mu_0+\delta_{M/C}\sigma_p)}{\sigma_p/\sqrt{n}}\right) - \text{F}\left(\frac{LCL-(\mu_0+\delta_{M/C}\sigma_p)}{\sigma_p/\sqrt{n}}\right) \tag{25}$$

$$\beta_{E}\text{=F}\left(\frac{UCL-(\mu_0+\delta_{E}\sigma_p)}{\sigma_p/\sqrt{n}}\right) - \text{F}\left(\frac{LCL-(\mu_0+\delta_{E}\sigma_p)}{\sigma_p/\sqrt{n}}\right) \tag{26}$$

Where F is the indicator and the standard normal cumulative distribution function. The equation 25 and 26 can be simplified as Equation 27 and 28:

$$\beta_{M/C}=\mathrm{F}(k-\delta_{M/C}\sqrt{n})\ -\mathrm{F}(-k-\delta_{\frac{M}{C}}\sqrt{n}) \quad (27)$$

$$\beta_{E}=\mathrm{F}(k-\delta_{E}\sqrt{n})\ -\mathrm{F}(-k-\delta_{E}\sqrt{n}\ ) \quad (28)$$

For an n sample, the time is equal to n. T_s to analyze the samples and the graph result, where T_s is the sampling time. The expected time is out of control from the occurrence of a specific reason until the process. As described in Equation 29:

$$[\ (\mathrm{h}+\ \mathrm{n}.T_s)\times(ARL2_{M/c}\times{}^{\lambda_2}/_{\lambda}+ARL2_E\ \times{}^{\lambda_1}/_{\lambda}\ )]-\tau \quad (29)$$

Failure rate due to external and environmental reasons: λ_1

Breakdown rate due to machine depreciation: λ_2

The authors suppose that T_1 is the expected time to find specific a cause and E[$T_{restore}$] is the expected time to restore the process to the first state due to external reasons or machine failure in an out-of-control state. A specific cause is searched for restoring the process. It depends on the type of error that occurred. For example, the process may have problems due to machine depreciation or external and environmental reasons. (E[$T_{restore}$]) is the expected time for return or repair. As described in Equation 30::

$$\mathrm{E}[T_{restore}]=(T_{resetting}\times{}^{\lambda_1}/_{\lambda}+MT_{CM}\times{}^{\lambda_2}/_{\lambda} \quad (30)$$

Therefore, the time of a period becomes Equation 31:

$$\mathrm{E}[T_{Cycle}]=[(\ \mathrm{h}+\mathrm{n}.T_s)\times(ARL2_{M/c}\times{}^{\lambda_2}/_{\lambda}+ARL2_E\ \times{}^{\lambda_1}/_{\lambda}\ )]-\tau+T_1+\mathrm{E}[T_{restore}] \quad (31)$$

3.3. Process and machine failure rate

A model for integrating and consolidating maintenance repairs and quality control has been presented. Now, the relationship between these two issues should be addressed. Maintenance, repairs, and quality control relationships can be related, and the total cost function can be integrated. Therefore, these two issues can be related to the objective function by obtaining a mathematical relationship for the process failure rate (λ). In this research, machine breakdowns are considered in two ways. One type is that the machine's performance is gradually depreciated, and the other is immediately affected. The probability of machine breakdowns is taken from previous information. Similarly, the process may fail due to machine wear or external and environmental reasons. The failure rate is supposed to be due to the machine's depreciation (λ_2), erosion, and external and ecological reasons (λ_1). Therefore, the failure rate of the process (λ) will be the sum of the failure rate due to the machine's wear and tear and the failure rate due to external and environmental reasons (Equation 32).

$$\lambda = \lambda_1 + \lambda_2 \tag{32}$$

The authors consider the breakdown rate due to machine tear as Equation 33:

$$\lambda_1 = \frac{1}{prd_E}(N_f) \tag{33}$$

And the failure rate will be determined due to external and environmental reasons:

$$\lambda_2 = \frac{1}{MTTF} \tag{34}$$

Where MTTF is the mean time between failures. N_f and MTTF are calculated based on the data for each problem. The MTTF will be calculated by the data of each problem, information about the time intervals of maintenance operations and preventive repairs, and the number of failures occurring between intervals. Obtaining $\mathbf{N_f}$ is the number of failures analytically and accurately for a short impossible planning period. Different ways and models have been proposed to do this, but they have often been time-consuming and complicated. $\mathbf{N_f}$ is known as t_{PM} function. The regression approximation method is used. The authors obtain according to the equation 35 an approximate amount by having the time intervals of preventive maintenance and repairs and the number of breakdowns in each interval in different intervals of a period.

$$N_f = \text{a } (t_{PM})^b \tag{35}$$

N_f and t_{PM} are predicted by regression, and the values a and b. To solve the mathematical model derived from the SCA, the authors employed a Genetic Algorithm (GA), a widely used meta-heuristic optimization technique suitable for addressing complex, multi-objective problems. GA was chosen for its robustness in exploring large solution spaces and its ability to find near-optimal solutions efficiently through evolutionary processes, such as selection, crossover, and mutation. The algorithm was configured to optimize decision variables—including production scheduling parameters, preventive maintenance intervals, and quality control thresholds—to minimize the total cost and enhance overall supply chain performance.

4. Implementing and results

Recently, the use of integrated models compared to independent models has attracted the attention of many researchers. Researchers engage in integrated and consolidated modeling by studying and examining the characteristics of different subjects because this type of modeling has shown better results than independent modeling of subjects. The critical point is whether the proposed model will be more efficient and suitable than the independent model. Based on this, the integrated model is compared with two independent models of maintenance and repairs and quality control, and using a numerical example in both models will determine which model provides a better answer. For this purpose, the authors must first analyze the problem into two independent models of quality control and maintenance and repairs and then compare the performance of two integrated and independent models with a numerical example to see which model will provide a more optimal solution. Article model is specifically designed to address the critical areas of maintenance and repairs within a system. The primary goal is establishing an optimal time interval for implementing preventive maintenance and repairs directly influenced by the associated costs.

In this model, quality control is not considered. The possibility that the quality of the produced products may decrease is ignored. Therefore, the cost of maintenance and corrective repairs is considered in Equation 36:

$$C_{CM}=[MT_{CM}.\ [\mathrm{PR}.C_{lp}+\mathrm{LC}]+C_{FCCM}]\times N_f \tag{36}$$

Also, the cost of preventive maintenance and repairs is according to equation 37.

$$\mathrm{C_{PM}}=[\mathrm{MT_{PM}}.\ [\mathrm{PR}.\mathrm{C_{lp}}+\mathrm{LC}]+\mathrm{C_{FCPM}}]\times\frac{\mathrm{prd_E}}{\mathrm{t_{PM}}} \tag{37}$$

The cost of maintenance and repairs in a planned period will be the total cost of corrective and preventive maintenance and repairs (Equation 38).

$$\mathrm{C_{MP}}=\frac{1}{\mathrm{prd_E}}(\mathrm{C_{CM}}+\mathrm{C_{PM}}) \tag{38}$$

The optimal time interval for preventive maintenance and repairs ($\mathrm{t_{PM}}$) is obtained by minimization of C_{MP}. In this model, only the aspect of quality control in the existing system is considered, and maintenance and repairs are ignored. Therefore, the model has a different period. That is E[T_{cycle}] changes to compare to the integrated model. The reason for these changes is apparent. In this model, the issue of machine tear and breakdowns related to the machine requiring repairs is no longer discussed, and the breakdown rate depends only on external and environmental reasons. If the issue of machine maintenance and repairs is not considered, the only things that affect the quality of the produced products are external and environmental factors. The length of the period obtained in the quality control model is almost similar to the size of the period in the integrated model. The failure rate is only specific to external and environmental factors, which is shown by λ_E.So the length of the period in the quality control model is according to Equation 39:

$$E[T_{cycle}]_{SPC}={}^{1}/_{\lambda_E}+[(\mathrm{h}+\mathrm{n}T_S)\ \times(ARL2)_E]-\tau+T_1+T_{reset} \quad (39)$$

The cost function of quality control is equation 41 considering maintenance and repairs.

$$C_{SPC}=\frac{(C_F+C_V.n).({}^{1}/_{\lambda_E}+T_0\times\frac{S}{ARL_1})+[h\times(ARL2)_E]-\tau+nT_S}{h}+(\alpha.\ PR.C_{Rej}).({}^{1}/_{\lambda_E}+(PR\times\frac{(R_\delta)_E}{1-\beta_E}\times C_{Rej}).\ (h.\ (ARL2)_E)-\tau+nT_S+(C_{resetting}\times T_{resetting}) \quad (41)$$

Therefore, the total cost of quality control per time unit is according to Equation 42:

$$CPUT_{SPC}=\frac{C_{SPC}}{E[T_{cycle}]_{SPC}} \quad (42)$$

4.1. *Numerical data*

This part implements a numerical example of the model to obtain optimal decision variables. First, a single-component device is considered part of a single-machine system. Let's assume the machine works three seven-hour shifts six days a week. The time for preventive maintenance and repairs is 7 times units, and the time for maintenance and corrective repairs is 12 times. Suppose the process is under control. The value of the parameters of the given problem is shown in Table 3.

Table 3. The value of the parameters of the given problem

Data	C_v	C_F	$\mathbf{T_{resetting}}$	T_1	T_0	T_s	$\delta_{M/C}$	δ_E
value	50	100	2	1	1	$\frac{20}{60}$	0.6	1.5
data	PR	C_{reset}	LC	C_{Lp}	C_{FCPM}	C_{FCCM}	$C_{false-Alare}$	C_{Rej}
value	10	5000	500	400	1000	10000	1200	2500

Based on the data related to the problem, the authors implement this data in our model, and the proposed model is solved using MATLAB 2021 software. The optimal variables were obtained as follows:

$(\mathrm{n}^*, \mathrm{k}^*, \mathrm{h}^*, \mathrm{t_{PM}}^*)$=(11,1.90,5.8,643)

f^*(11.8,1.76,5.73,648) =112

In this part of paper two increments of 10 and 20 percent for each of the data C_V, C_F C_{rej}, $\mathrm{T}_{resetting}$, T_0, T_1, δ_E,$\delta_{M/C}$ are implemented.

Table 4. The amount of changes in some problem parameters at +(10%) and +(20%) levels

Data	First value	+(%10)	+(%20)
δ_E	1/5	1/65	1/8
$\delta_{M/C}$	0/6	0/66	0/72
T_0	1	1/1	1/2
T_1	1	1/1	1/2
$T_{resetting}$	2	2/2	2/4
C_{Rej}	2500	2750	3000
C_v	50	55	60
C_F	100	110	120

Table 5. The proposed method objective functions

Data	N	h	k	t_{pm}	$f(n,h,k,t_{pm})$
$\delta_E = 1/65$	11	7	1/90	653	118
$\delta_E = 1/8$	10	6	1/92	655/5	120/5
$\delta_{M/C} = 0/66$	12	8	1/85	654	119
$\delta_{M/C} = 0/72$	11	8	1/9	654	117
$T_0 = 1/1$	12	6	1/8	652	112
$T_0 = 1/2$	12	6	1/8	652	112
$T_1 = 1/1$	12	6	1/8	652	112
$T_1 = 1/2$	12	6	1/8	652	112
$T_{resetting} = 2/2$	12	6	1/95	651	113
$T_{resetting} = 2/2$	12	6	1/9	652	114
$C_{Rej} = 2750$	13	6	1/85	650	113
$C_{Rej} = 3000$	13	5/5	1/85	651	115
$C_F = 110$	12	6	1/8	652	112/5
$C_F = 120$	13	8	1/85	652	114/5
$C_v = 550$	11	9	1/8	651	113
$C_v = 600$	11	9	1/8	650	114

Table 4-5, shows that when δ_E and $\delta_{M/C}$ increase by 10 and 20 percent of the data. The values of the objective function and decision variables exhibit significant changes, yet our model remains largely unaffected by variations in other data. It underscores the critical importance of maintaining process control. Additionally, changes in the average standard deviation of the key qualitative characteristic are highly significant.

4.2. More analysis

Now, the question is raised: If the independent model is not used and the integrated model is not used, what difference will occur in the value of the optimal objective function? For this purpose, the data is put into the independent quality control cost function and solved by MATLAB software using GA. The result is as follows:

(n^*, k^*, h^*)=(11,3.44,9)

f^*(11 ,3.44 ,9) =359.8

As can be seen, the value of the cost function in the quality control department alone is higher than the total cost in the integrated model, where maintenance, repairs, and quality control are considered together. Monitoring the production equipment and machines is essential, considering the maintenance and repairs of a quality control model. The manufactured products are produced according to acceptable quality with the maintenance and repairs of the equipment and machines. Production of products with the expected quality reduces the costs related to quality control. In this model, implementing preventive maintenance and repairs reduces the number of out-of-control states in the system, resulting in a higher percentage of products within control limits. By optimizing the intervals for preventive maintenance, repairs, and quality parameters, the total cost function can be minimized. The example illustrates that this approach significantly lowers the cost function compared to scenarios where maintenance and repairs are neglected. Therefore, integrating preventive maintenance and repairs with quality control proves to be much more effective.

5. Discussion

This study underscores the significance of integrating production scheduling, maintenance strategies, and quality control within CLSC. By addressing the interconnectedness of these elements, the proposed model aims to achieve both cost efficiency and operational sustainability. Leveraging the SCA in tandem with mathematical modeling, the study navigates the complexities of real-world systems, particularly in the home appliances industry. Categorizing machine failures into two modes and utilizing a GA for optimization, the model provides a robust framework for decision-making that accounts for uncertainties and variable constraints. Integrating maintenance and quality control highlights the importance of managing interdependencies to minimize production downtime and enhance system reliability. Decision variables such as sample size, control limits, and maintenance intervals emerge as critical factors in balancing operational costs with system performance. Preventive and corrective maintenance integration reduces costs while aligning operations with sustainability objectives, positioning the model as a valuable tool for industries aiming for eco-friendly practices and long-term resilience. Managers can leverage the integrated model to establish cost-effective maintenance schedules and elevate product quality, improving customer satisfaction and reducing return rates. By embedding sustainability into the supply chain framework, organizations can bolster their competitive edge while adhering to eco-friendly practices. The model’s adaptability, supported by its capacity to handle uncertainties, ensures its relevance across diverse manufacturing contexts that demand precise quality and maintenance management. This discussion underscores the study's contribution to advancing supply chain strategies and offers actionable insights for optimizing operations.

6. Conclusion

The challenge of production scheduling has long been a critical focus for engineers and researchers, with considerable advancements aimed at optimizing the process. Scheduling in single-machine systems has emerged as a particularly significant subfield involving the precise allocation of resources to ensure production efficiency. Concurrently, preventive maintenance (PM) and corrective maintenance (CM) have gained prominence as researchers aim to determine the optimal timing for such activities to reduce costs and prevent operational disruptions. In parallel, quality control has become a central concern, ensuring that products meet expected standards and that the production system remains within control limits. When deviations occur, identifying root causes and implementing corrective measures becomes essential to restoring order and maintaining productivity.

Production managers are pivotal in aligning maintenance and quality control efforts to minimize costs and optimize system performance. The integration of these two aspects is critical, as failure to do so can lead to machine depreciation, increased product return rates, and customer dissatisfaction. Numerous models have been proposed to address these challenges, focusing on determining optimal intervals for maintenance and repairs while designing effective control charts to manage quality. These efforts aim to mitigate costs related to machine downtime, workforce repairs, and deviations from quality standards. The significance of these interconnected processes underscores the need for integrated approaches that consider the dependencies between maintenance and quality control rather than treating them in isolation.

Recent studies have highlighted the synergistic benefits of combining maintenance, repairs, production scheduling, and quality control into integrated models. Integrated approaches consistently outperform independent models by addressing the dependencies between these elements, resulting in reduced costs and improved operational outcomes. The model presented in this study exemplifies this integration, encompassing maintenance, repairs, and quality control in a unified system. By optimizing four key decision variables—sample size, sampling interval time, control limit coefficient, and preventive maintenance intervals—, the model minimizes total costs while maintaining high standards of reliability and quality reliability and quality standards. A comparative analysis with independent models demonstrated the superiority of the integrated approach, with significant cost reductions validating its effectiveness.

Future research could explore extending the proposed integrated model to account for dynamic and stochastic variations in real-time production environments. Advanced technologies such as machine learning and IoT could enhance the model's adaptability, allowing for predictive maintenance and real-time quality monitoring. Additionally, the model could be applied to more complex, multi-machine systems and diverse industries to evaluate its scalability and versatility. Investigating the environmental and sustainability impacts of such integrations, particularly in closed-loop supply chains, could also yield valuable insights for industries aiming to align operational efficiency with eco-friendly practices. Future studies can further refine integrated models and provide comprehensive solutions for modern manufacturing challenges by addressing these areas.

Disclosure statement

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