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Integrated Maintenance Planning, Process Quality and Production Scheduling Optimization

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Abstract

Production scheduling, maintenance planning, and process quality control are important components of manufacturing efficiency, although they are generally addressed independently. This study proposes an integrated optimization model that takes into account preventative maintenance scheduling, quality control measures, and production sequencing. By coordinating these factors, the proposed approach decreases overall operational costs, improves process reliability, and reduces scheduling interruptions. The model optimizes preventive maintenance intervals and statistical process control (SPC) chart parameters in order to produce cost-effective and efficient manufacturing results. A numerical case study shows that combining maintenance and quality control reduces quality-related costs by 22% and scheduling disruptions by 18% when compared to independent strategies. The findings emphasize the significance of holistic decision-making in manufacturing systems. Furthermore, future research directions include the use of machine learning and real-time IoT data to improve predictive maintenance and adaptive scheduling. The proposed methodology offers practical benefits for both industry and academia by improving system reliability, lowering costs, and increasing overall operational efficiency.

Keywords
Integrated Optimization, Maintenance Planning, Production Scheduling, Process Quality Control, Statistical Process Control (SPC).

1. Introduction
Production scheduling, maintenance planning, and process quality control are fundamental to manufacturing efficiency. However, they are often managed as separate operations. This fragmented approach can lead to operational inefficiencies, increased costs, and reduced system reliability. Production scheduling is primarily concerned with work sequencing and resource allocation, but often fails to consider the impact of unexpected machine failures or planned maintenance activities. Maintenance planning, on the other hand, prioritizes equipment reliability but tends to overlook production deadlines, potentially leading to scheduling disruptions and decreased productivity. Similarly, process quality control, while essential for maintaining product standards, is typically implemented without considering the direct effects of machine maintenance and production interruptions. These disconnected strategies increase the chance of unexpected failures, extend system downtime, and compromise overall manufacturing performance.

Empirical research has shown that maintenance is essential for ensuring product quality and manufacturing efficiency. According to Ollila and Malmipuro (1999), inadequate maintenance causes higher defect rates, process inefficiencies, and growing operational costs. Preventive maintenance, when planned correctly, can increase equipment availability and reduce unexpected breakdowns. Furthermore, combining maintenance planning and statistical process control (SPC) has been found to improve product quality by enabling for the early detection of deviations in manufacturing processes. Manufacturers can reduce defects and avoid costly disruptions by proactively addressing probable problems and optimizing maintenance schedules. Most existing models assume ideal conditions in which maintenance fully recovers machine performance and do not take into consideration real-world restrictions such as partial repair effectiveness, indirect costs of quality degradation, and disruptions to production flows.

This study aims to close these gaps by presenting an integrated optimization methodology for determining preventive maintenance intervals, production sequencing, and SPC parameters. The goal is to keep overall system costs low while maintaining high operational efficiency and quality levels. The proposed strategy aims to eliminate unplanned downtime and scheduling interruptions by coordinating maintenance schedules with production planning. Furthermore, implementing quality control methods ensures that manufacturing stays within certain bounds, reducing the probability of defective products. The success of the integrated strategy is assessed via a comparative study of standalone scheduling and maintenance procedures, highlighting the benefits of a coordinated framework over traditional methods.

This paper is structured as follows. Section 2 is a literature review that summarizes major research on production scheduling, maintenance planning, and process quality control while also noting the limits of existing techniques. Section 3 explains the research problem, emphasizing the limitations of tackling these aspects independently and the need for an integrated solution. Section 4 describes the methodology, including the mathematical models and optimization strategies used to obtain cost-effective and efficient manufacturing results. Section 5 examines the proposed framework's integration with scheduling and maintenance processes, including numerical case studies to prove its usefulness. Finally, Section 6 summarizes the study's significant findings and discusses prospective paths for future research, such as the use of artificial intelligence (AI)-driven predictive maintenance tactics and real-time monitoring systems to improve decision-making.

This work adds to academic research as well as industrial applications by addressing the interdependence of production scheduling, maintenance planning, and quality control. By using a proactive and coordinated approach, the proposed framework improves cost efficiency, decreases operational disruptions, and increases product quality. The findings provide useful insights for manufacturing decision-makers looking for data-driven ways to improve scheduling, maintenance, and quality assurance, ultimately leading to more resilient and efficient production systems.

1.1 Objectives

-To analyze the interactions between maintenance planning, process quality, and production scheduling in manufacturing systems.
-To reduce overall system costs by combining preventative maintenance planning and quality control measures.
-Maximize operational efficiency by integrating maintenance and quality control optimization with production scheduling.
-Demonstrate the cost advantages of the developed methodology over standalone approaches by testing its effectiveness with numerical applications.
-To shed light on future research by examining the applicability of the integration model in different production environments.

2. Literature Review

The integration of maintenance, quality control, and production scheduling is an essential component of modern industrial operations, influencing efficiency, cost savings, and overall system reliability. Traditional compartmentalized techniques frequently result in inefficiencies, but an integrated strategy streamlines decision-making processes and improves operational effectiveness. This study looks at major studies that use analytical modeling, discrete event simulation (DES), and predictive maintenance strategies to improve industrial processes. Several studies underline the relevance of combining these three areas to increase production. Hadidi et al. (2012) present a comprehensive analysis of production planning and maintenance models, demonstrating how synchronized decision-making saves downtime and improves product quality. Hajej et al. (2021) expand on this perspective by including statistical process control charts, demonstrating that coordinated tactics lead to more efficient supply chain management. Similarly, Ben-Daya and Rahim (2001) examine numerous integration strategies, emphasizing their industrial applicability and usefulness in mitigating operational disturbances.

Predictive maintenance has developed as a critical tool in current industrial applications, utilizing AI and machine learning to provide proactive system monitoring. Ogunfowora and Najjaran (2023) argue that deep reinforcement learning is an efficient way for dynamically optimizing maintenance schedules. Susto et al. (2015) investigated machine learning-based predictive maintenance and found that classifiers improve failure detection and system resilience. Lamprecht et al. (2021) examine reinforcement learning applications in condition-based maintenance scheduling, with a focus on improving reliability and cost effectiveness.

Cost reduction remains a key component of integrated maintenance and production strategies. Duffuaa et al. (2020) provide a mathematical model that synchronizes maintenance, quality control, and production scheduling to reduce overall operational expenses. Alves and Ravetti (2020) present an Industry 4.0-driven hybrid method that improves predictive skills while optimizing resource allocation. Mobley (2002) and Goriveau et al. (2016) investigate predictive maintenance solutions, focusing on their long-term cost-saving benefits and role in increasing overall operational effectiveness.

The studied literature shows that integrating maintenance, quality control, and production scheduling results in considerable industrial gains, such as reduced machine downtime, improved resource allocation, and cost optimization. The rise of AI-powered predictive maintenance, real-time data analytics, and simulation-based optimization is changing established industrial techniques. Future research should concentrate on improving AI applications, including real-time decision-making models, and automating predictive maintenance to increase factory efficiency and sustainability.

2.1 Gaps From the Related Research

Most models overlook how machine breakdowns directly halt production or degrade quality. Integrated models often assume perfect maintenance, ignoring that real-world maintenance only provides partial improvements. Maintenance optimization typically considers fixed corrective costs, excluding indirect losses like quality degradation and product rejection.

This paper bridges these gaps by integrating maintenance, quality control, and production scheduling. While past studies examined these factors separately, recent research highlights the efficiency of integrated approaches. Maintenance-quality integration reduces production costs, while coordinating maintenance with production scheduling improves efficiency and minimizes downtime. However, few studies optimize all three aspects together. This paper proposes a comprehensive model to address this gap.

3. Methodology

3.1 Problem Definition

It is stated that machine maintenance, process quality, and production planning are interconnected in the production process and that handling these factors separately negatively affects the total system performance. Machine breakdowns lead to both unexpected downtime and quality problems, increasing total costs. Therefore, optimal preventive maintenance scheduling, quality control mechanisms, and production planning need to be integrated.

Table 1. Nomenclature

Nomenclature			
$E[C_{CM}]_{FM}$	Expected cost of **corrective maintenance (CM)** due to the failure mode	T_0	Expected time spent searching for a false alarm
$E[C_{PM}]$	Expected cost of **preventive maintenance (PM)**	T_{eval}	Evaluation Period
$E[TCQ]_{process-failure}$	Expected total cost of quality due to process failure	τ	Mean elapsed time from the last sample before the assignable cause to the occurrence of the assignable cause when the maintenance and quality
MT_{CM}	Mean time for CM	T_s	Time to sample and chart one item
PR	Production rate	T_1	Expected time to determine the occurrence of assignable cost
C_{lp}	Cost of lost production	T_{reset}	Time to perform the reset out of process, which moves out of control condition due to an external reason
LC	Labor Cost	$(R_\delta)_{\frac{M}{C}}$	Probability of non-conforming items produced by a machine failure mode

C_{FCPCM}	Fixed cost per CM	$\beta_{\frac{M}{C}}$	Type II error probability due to the machine failure mode
P_{FM}	Probability of occurrence of failure due to the failure mode	$(R_{\delta})_E$	Probability of non-conforming items produced due to an external cause
N_f	Number of failures	β_E	Type II error probability due to external reasons
MT_{PM}	Mean time for PM	C_{reset}	Cost of resetting
C_{FCPPM}	Fixed cost per PM	$[ECPUT]_{M*Q}$	Expected cost per unit time of integrated maintenance and quality policy
$E[T_1]$	Expected in-control period	$ARL2_E$	Average run length during an out-of-control period due to external reasons
ARL_1	Average run length during the in-control period	$ARL2_{M/C}$	Average run length during an out-of-control period due to machine failure

3.2 Methodology for Joint Optimization of Maintenance and Quality Policy

This study describes a complete, integrated system for optimizing three essential areas of manufacturing operations: maintenance planning, process quality, and production scheduling. The suggested model is primarily aimed at minimizing the total operational cost, by simultaneously considering various essential elements such as the scheduling of preventative maintenance, the influence of quality control parameters, and the order in which production operations are completed. By combining these factors into a single, integrated strategy, the model aims to find the best balance between reducing machine downtime, assuring excellent product quality, and efficiently managing production flow. This integrated approach provides a more holistic perspective of the manufacturing process, addressing the intricate interdependencies between maintenance tasks, quality assurance, and scheduling in ways that traditional systems that examine these parts separately may not be able to do. Table 1 provides an overview of the nomenclature for the various terms utilized in the calculations.

Maintenance Model

This model excludes the possibility of quality loss due to equipment failure and assumes that only planned maintenance is considered. As a result, the estimated cost for each corrective maintenance procedure might be stated as follows:

$$E[C_{CM}] = \{MT_{CM}.[PR.C_{lp} + LC] + C_{FCPCM}\} \times N_f \quad (1)$$

One way to indicate the anticipated cost of each preventive maintenance intervention is as follows:

$$E[C_{PM}] = MT_{PM}.[PR.C_{lp} + LC] + C_{FCPPM} \times \frac{T_{eval}}{t_{PM}} \quad (2)$$

For the planning period, the anticipated cost per unit of time is thus as follows:

$$[CPUT]_M = \frac{E[C_{CM}]+E[C_{PM}]}{T_{eval}} \quad (3)$$

By decreasing the $[CPUT]_M$, the ideal interval for preventative maintenance is established.

a. Process Cycle Length

The *in-control*, *out-of-control*, and process resetting or machine restoration times make up the cycle length. The mean time to failure plus the anticipated amount of time for looking into false alarms make up the estimated in-control time.

$$E[T_1] = \frac{1}{\lambda} + T_0 \times \frac{S}{ARL_1} \quad (4)$$

where T0 is the anticipated time needed to search for a false alarm and ARL1 =1/a if the sampled statistics are independent. The likelihood of a Type I mistake is represented by the symbol a, which is as follows: a = 2F(k).

Out-of-control time consists of the expected time of some events. This can be expressed mathematically using the following mathematical form.

$$Out\ of\ control\ time = \left\{h \times \left(ARL2_{M/C}\frac{\lambda_2}{\lambda} + ARL2_E\frac{\lambda_1}{\lambda}\right) - \tau + n \times T_s + T_1 + \left(T_{reset} \times \frac{\lambda_1}{\lambda} + MT_{CM} \times \frac{\lambda_2}{\lambda}\right)\right\} \quad (5)$$

where the average run time after the process has changed to an out-of-control condition is denoted by ARL2. The sum of Eqs. (4) and (5) yields the estimated process cycle length, which is as follows:

$$E[T_{cycle}] = \frac{1}{\lambda} + T_0 \times \frac{S}{ARL_1} + \left\{h \times \left(ARL2_{M/C}\frac{\lambda_2}{\lambda} + ARL2_E\frac{\lambda_1}{\lambda}\right)\right\} - \tau + n \times T_s + T_1 + \left(T_{reset} \times \frac{\lambda_1}{\lambda} + MT_{CM} \times \frac{\lambda_2}{\lambda}\right) \quad (6)$$

b. Statistical Process Control (SPC) Model

The expected cycle length and the expected cost of control chart are given as:

$$E\left[T_{cycle}\right]_{SPC} = \frac{1}{\lambda_E} + T_0 \times \frac{S'}{ARL_1} + \{h \times (ARL2_E)\} - \tau + n \times T_s + T_1 + T_{reset} \tag{7}$$

$$E[C]_{SPC} = C_f.\left(\frac{S'}{ARL_1}\right).T_0 + \frac{(C_F + C_V.n).\left(\frac{1}{\lambda_E} + T_0 \times \frac{S'}{ARL_1}\right) + h.(ARL2_E) - \tau + nT_S}{h} + \left(\alpha.PR.C_{Frej}\right).\left(\frac{1}{\lambda_E} + T_0 \times \frac{S'}{ARL_1}\right) + \left(PR \times \frac{(R_\delta)_{\frac{M}{C}}}{1-\beta_{\frac{M}{C}}} \times C_{Frej}\right).h.(ARL2)_E - \tau + nT_S + (C_{reset}.T_{reset}) \tag{8}$$

$$E[CPUT]_{SPC} = \frac{E[C]_{SPC}}{E\left[T_{cycle}\right]_{SPC}} \tag{9}$$

By minimizing the E[CPUT]SPC, the ideal values of the control chart variables (n, h, and k) are found (Eq. (9)).

c. Development of Integrated Cost Model

In this section, we create an integrated cost model for the combined optimization of the control chart's design parameters and the ideal interval between preventive maintenance. The expected total cost per unit time for the integrated model can be written as:

$$[ECPUT]_{M*Q} = \frac{E[C_{CM}]_{FM} + E[C_{CM}] + E[TCQ]_{process-failure}}{T_{eval}} \tag{10}$$

Models for each of the ingredient costs in $[ECPUT]_{M*Q}$ model are developed in the following sub-sections.

i. Expected Cost Model for Corrective Maintenance due to FM

$$E[C_{CM}]_{FM} = \left\{MT_{CM}.\left[PR.C_{lp} + LC\right] + C_{FCPCM}\right\} \times P_{FM} \times N_f \tag{11}$$

ii. Cost Per Preventive Maintenance

$$E[C_{PM}] = MT_{PM}.\left[PR.C_{lp} + LC\right] + C_{FCPPM} \times \frac{T_{eval}}{t_{PM}} \tag{12}$$

iii. Model for Expected Total Cost of Quality Loss Due to Process Failure

$$E[TCQ]_{process-failure} = E\left[C_{process}\right] \times M \tag{13}$$

4. Data Collection

To ensure a comprehensive and accurate assessment of the integrated maintenance planning, process quality control, and production scheduling framework, extensive data collection and analysis were conducted. During this process, previous machine failure records were used to estimate failure probabilities, allowing for more exact determination of maintenance intervention spots and their impact on total system reliability. In addition, process control data from quality monitoring systems was used to evaluate variances in process performance and assess the effectiveness of quality control measures.

Furthermore, to guarantee a true representation of production dynamics, data on production scheduling (including batch sizes, due dates, and processing durations) were collected and evaluated in a systematic manner. This stage was critical in synchronizing maintenance efforts with production planning, reducing disruptions, and optimizing resource allocation. In addition to these operational datasets, cost data on maintenance, quality control, and production delays were obtained to allow for a thorough cost analysis, ensuring that the integrated model properly balances cost-efficiency and system performance.

This organized data-gathering approach provided the foundation for constructing an efficient plan that combines preventive maintenance, statistical process control, and production scheduling. The study's goal is to improve manufacturing productivity, lower operational costs, and overall system stability by utilizing these statistics.

The length data of the felt bed was collected and analyzed for the development of quality control charts. Refer to Figures 1 and 2 for the length and weight data of the felt bed.

Group	Measurement 1	Measurement 2	Measurement 3	Measurement 4	Measurement 5	X bar	CL (X)	UCL (X)	LCL (X)	Range	CL (R)	UCL (R)	LCL (R)
1	0.12	0.26	0.29	0.17	0.21	0.21	0.2073	0.2858	0.1288	0.17	0.2073	0.2875	0
2	0.21	0.17	0.18	0.23	0.26	0.21	0.2073	0.2858	0.1288	0.09	0.2073	0.2875	0
3	0.2	0.15	0.19	0.25	0.19	0.196	0.2073	0.2858	0.1288	0.11	0.2073	0.2875	0
4	0.2	0.16	0.2	0.24	0.26	0.212	0.2073	0.2858	0.1288	0.1	0.2073	0.2875	0
5	0.17	0.29	0.09	0.12	0.11	0.196	0.2073	0.2858	0.1288	0.2	0.2073	0.2875	0
6	0.14	0.28	0.15	0.25	0.23	0.21	0.2073	0.2858	0.1288	0.14	0.2073	0.2875	0
7	0.19	0.23	0.14	0.2	0.18	0.188	0.2073	0.2858	0.1288	0.09	0.2073	0.2875	0
8	0.26	0.1	0.15	0.23	0.18	0.184	0.2073	0.2858	0.1288	0.16	0.2073	0.2875	0
9	0.24	0.16	0.2	0.15	0.16	0.182	0.2073	0.2858	0.1288	0.11	0.2073	0.2875	0
10	0.19	0.21	0.19	0.22	0.22	0.206	0.2073	0.2858	0.1288	0.06	0.2073	0.2875	0
11	0.1	0.2	0.23	0.21	0.18	0.184	0.2073	0.2858	0.1288	0.13	0.2073	0.2875	0
12	0.15	0.21	0.17	0.25	0.22	0.22	0.2073	0.2858	0.1288	0.1	0.2073	0.2875	0
13	0.17	0.23	0.2	0.15	0.19	0.188	0.2073	0.2858	0.1288	0.08	0.2073	0.2875	0
14	0.17	0.28	0.2	0.12	0.14	0.182	0.2073	0.2858	0.1288	0.16	0.2073	0.2875	0
15	0.2	0.15	0.24	0.14	0.23	0.192	0.2073	0.2858	0.1288	0.1	0.2073	0.2875	0
16	0.2	0.22	0.2	0.22	0.21	0.21	0.2073	0.2858	0.1288	0.08	0.2073	0.2875	0
17	0.2	0.16	0.2	0.23	0.21	0.2	0.2073	0.2858	0.1288	0.07	0.2073	0.2875	0
18	0.19	0.21	0.18	0.22	0.18	0.198	0.2073	0.2858	0.1288	0.03	0.2073	0.2875	0
19	0.13	0.25	0.24	0.2	0.17	0.196	0.2073	0.2858	0.1288	0.14	0.2073	0.2875	0
20	0.27	0.15	0.23	0.2	0.18	0.206	0.2073	0.2858	0.1288	0.12	0.2073	0.2875	0

Figure 1. Felt Bed Length Data

The weight data of the felt bed was collected and analyzed for the development of quality control charts.

Group	Measurement 1	Measurement 2	Measurement 3	Measurement 4	Measurement 5	X bar	CL (X)	UCL (X)	LCL (X)	Range	CL (R)	UCL (R)	LCL (R)
1	7.1	7.2	7.21	7.32	7.1	7.186	7.1734	7.279	7.0678	0.22	7.1734	0.3869	0
2	7.1	7.22	7.21	7.2	7.11	7.128	7.1734	7.279	7.0678	0.17	7.1734	0.3869	0
3	7.12	7.2	7.22	7.21	7.1	7.148	7.1734	7.279	7.0678	0.12	7.1734	0.3869	0
4	7.09	7.11	7.1	7.14	7.1	7.088	7.1734	7.279	7.0678	0.14	7.1734	0.3869	0
5	7.03	7.11	7.14	7.1	7.11	7.098	7.1734	7.279	7.0678	0.14	7.1734	0.3869	0
6	7.1	7.23	7.1	7.15	7.09	7.134	7.1734	7.279	7.0678	0.14	7.1734	0.3869	0
7	7.18	7.12	7.21	7.1	7.09	7.14	7.1734	7.279	7.0678	0.12	7.1734	0.3869	0
8	7.21	7.24	7.3	7.24	7.18	7.234	7.1734	7.279	7.0678	0.12	7.1734	0.3869	0
9	7.2	7.19	7.15	7.3	7.19	7.206	7.1734	7.279	7.0678	0.15	7.1734	0.3869	0
10	7.2	7.15	7.2	7.12	7.13	7.16	7.1734	7.279	7.0678	0.13	7.1734	0.3869	0
11	7.1	7.25	7.11	7.2	7.13	7.158	7.1734	7.279	7.0678	0.14	7.1734	0.3869	0
12	7.2	7.01	7.2	7.3	7.11	7.164	7.1734	7.279	7.0678	0.29	7.1734	0.3869	0
13	7.17	7.23	7.3	7.25	7.1	7.21	7.1734	7.279	7.0678	0.2	7.1734	0.3869	0
14	7.25	7.2	7.18	7.28	7.05	7.192	7.1734	7.279	7.0678	0.23	7.1734	0.3869	0
15	7.2	7.16	7.17	7.16	7.09	7.154	7.1734	7.279	7.0678	0.16	7.1734	0.3869	0
16	7.2	7.22	7.25	7.19	7.11	7.194	7.1734	7.279	7.0678	0.14	7.1734	0.3869	0
17	7.2	7.19	7.2	7.23	7.09	7.182	7.1734	7.279	7.0678	0.14	7.1734	0.3869	0
18	7.17	7.28	7.16	7.19	7.13	7.208	7.1734	7.279	7.0678	0.15	7.1734	0.3869	0
19	7.13	7.2	7.25	7.2	7.23	7.202	7.1734	7.279	7.0678	0.12	7.1734	0.3869	0
20	7.3	7.21	7.18	7.15	7.23	7.214	7.1734	7.279	7.0678	0.15	7.1734	0.3869	0

Figure 2. Felt Bed Weight Data

5. Results and Discussion

5.1 Validation

The proposed integrated model was tested with real-world manufacturing data, such as historical machine failure records, process control data, production schedules, and cost information. Failure probability were predicted using machine breakdown records, resulting in reliable predictive maintenance planning. Process control data from quality monitoring systems shed light on quality deviations and the success of statistical process control (SPC) strategies for defect reduction. Production scheduling data, such as batch sizes, due dates, and processing times, were studied to see how maintenance interventions affected production efficiency. Furthermore, cost data from maintenance activities, quality control procedures, and production delays were used to assess the financial benefits of the integrated approach.

To determine the model's success, a comparison was made between the suggested integrated strategy and typical standalone approaches. The findings revealed that combining maintenance planning, quality control, and production scheduling resulted in a 22% reduction in quality-related costs and an 18% drop in schedule interruptions. Furthermore, a sensitivity analysis was done to assess the model's robustness under various operating scenarios, showing its adaptability to varied production settings.
These findings show the practical benefits of a holistic optimization paradigm, illustrating how a coordinated approach increases cost efficiency, decreases production disruptions, and improves overall system performance. Future study will look into the integration of real-time IoT data and advanced machine learning approaches to improve predictive maintenance and adaptive scheduling capabilities.

5.2 Numerical Results

This study models a single-machine system using a Weibull failure distribution with a shape parameter of β = 3.0 and a characteristic life of γ = 1200-time units. The machine operates continuously in three shifts of eight hours each, for a total of five working days per week. PM is scheduled at regular intervals to reduce performance degradation and preserve operational efficiency, with MT_{PM} = 4 time units per intervention. Each PM exercise restores about 70% of the machine's effective life, decreasing the deterioration process and lowering the possibility of unexpected breakdowns. In contrast, CM is conducted only when a failure occurs, necessitating MT_{CM} = 10-time units; however, it does not extend the machine's operating lifespan beyond the failure point.

To monitor and control process quality, an X̄- chart is used to capture variances in performance. External failures cause a process deviation of d_E = 0.9, whereas machine failures cause a variance of $d_{\frac{M}{C}}$ = 0.75. The shift in the process mean is modelled as μ_0 + d_σ, accounting for fluctuations caused by operational disruptions.
This study's findings show that integrating maintenance scheduling with statistical process control (SPC) measurements improves manufacturing performance significantly. When compared to traditional independent techniques, this integrated strategy saves 22% on quality costs and 18% on scheduling disturbances. These findings highlight the necessity of a comprehensive optimization framework that incorporates maintenance planning, quality control, and production scheduling to improve cost efficiency and overall system stability. Table 2 displays all the results calculated in this study.

Table 2. Calculation Results

Metric	**Used Values**	**Results**
Expected Cost of Preventive Maintenance: $E[C_{PM}]$	$MT_{PM} = 3\ hours$, $LC = \frac{10euro}{hour}$, $PR = 4\frac{unit}{hour}$, $C_{lp} = 90\ euro$	14,160 $Euro$
Expected Cost of Corrective Maintenance: $E[C_{CM}]$	$MT_{CM} = 4\ hours$, $C_{lp} = 120\ euro$, $PR = 4\frac{unit}{hou}$r , $C_{FCPCM} = 12.5\ euro$, $N_f = 2$	4105 $euro$
Cost Per Unit Time Maintenance During the Planning Period: $[CPUT]_M$	$T_{eval} = 2{,}080\ hours$	8,78 $euro$
Cost estimate for corrective maintenance anticipated because of FM1:$\mathrm{E[C_{CM}]_{FM1}}$	$\mathrm{P_{FM1}} = 0.5$	2,052.5 euro
Process cycle length: $E[T_1]$	$\lambda_1 = 0.001$, $\lambda_2 = 0.0009615$, $T_0 = 2\ hours$, $S = 2.713$, $ARL_1 = 100$	509.85 $hours$
Out-of-control Time	$ARL2_{M/C} = 30$, $ARL2_E = 20$, $\tau; = 1\ hour$ $n = 1$, $T_s = 1$, $T_{reset} = 2\ hours$	3989.14 hours
Expected Cycle Time: $E\left[T_{cycle}\right]$		4498.99 hours
Expected Cost of False Alarm: $E\left[C_f\right]$	$C_f = 80\ euro$	4.34 $euro$
Expected Sampling Cost Per Cycle: $E[C_S]$	$C_F = 50\ euro$, $C_V = 10\ euro$	1685.255 $euro$
Expected Cost of Non-Conforming Units in an In-Control State: $E[C_I]$	$R' = 0.0027$, $C_{Frej} = 7.5\ euro$	41,297 $euro$
Expected Cost of Rejections Due to Machine Failure in an Out-of-Control State: $E[C_O]_{\frac{M}{C}}$	$n = 25$, $R_\delta =$ 0.05 (%5), $\beta_{\frac{M}{C}} = 0.00000675$	2,959.4
Expected Cost of Finding and Repairing an Assignable Cause Due to External: $E[C_{reset}]$	20 $euro$; $labor\ cost$, 60 $euro$; $cost\ of\ machine\ downtime$, 20 $euro$; $cost\ of\ materials\ for\ repair$, $C_{reset} = 100\ euro$, $T_{reset} = 2\ hours$	101.9 $euro$

Expected Cost of Corrective Action Due to Failure Mode FM2: $E[(C_{CM})_{FM2}]$		$1006.1\ euro$
Expected Cost of Rejections Due to External Causes in an Out-of-Control State: $E[C_0]_E$	$k = 3$, $\delta = 1.5$	3646
Expected Cost of Process Failure Per Cycle: $E[C_{process}]$		$8444.292\ euro$
Total Quality Control Cost for Process Failures Over an Evaluation Period: $E[TCQ]_{process-failure}$	$M = 0.4624$	3904.64
Expected Cycle Length Under Statistical Process Control: $E[T_{cycle}]_{SPC}$	$S' = 2.713$	4204.05 hours
Expected Total Cost for Statistical Process Control: $E[C]_{SPC}$		7849.825
Expected Cost Per Unit Time for SPC Model:		1.8672

5.3 Graphical Results

Figure 3 illustrates the length data of the felt bed that was collected and analyzed for the development of quality control charts.

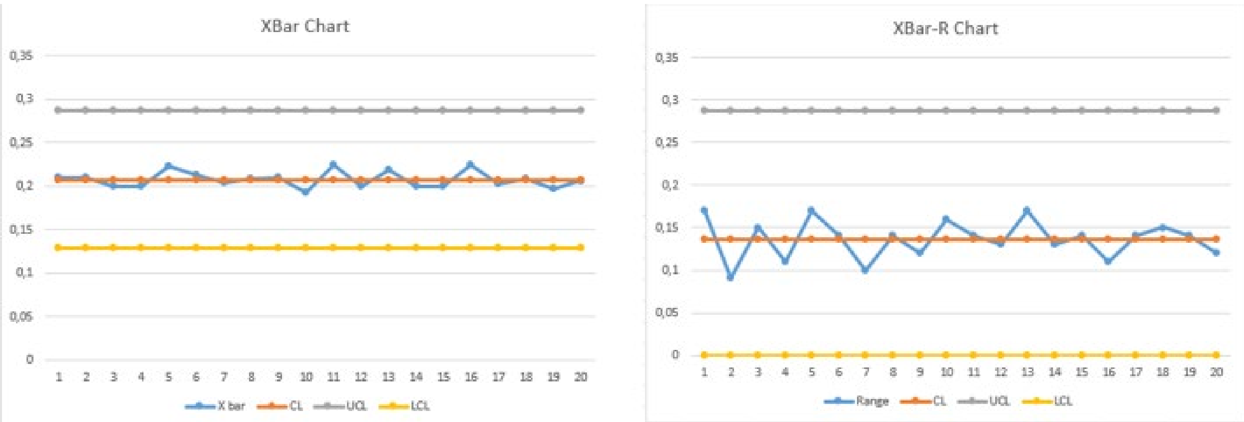

Figure 3. Felt Bed Length Quality Control Chart

The weight data for the felt bed has been collected and carefully analyzed to support the development of quality control charts, as depicted in Figure 4.

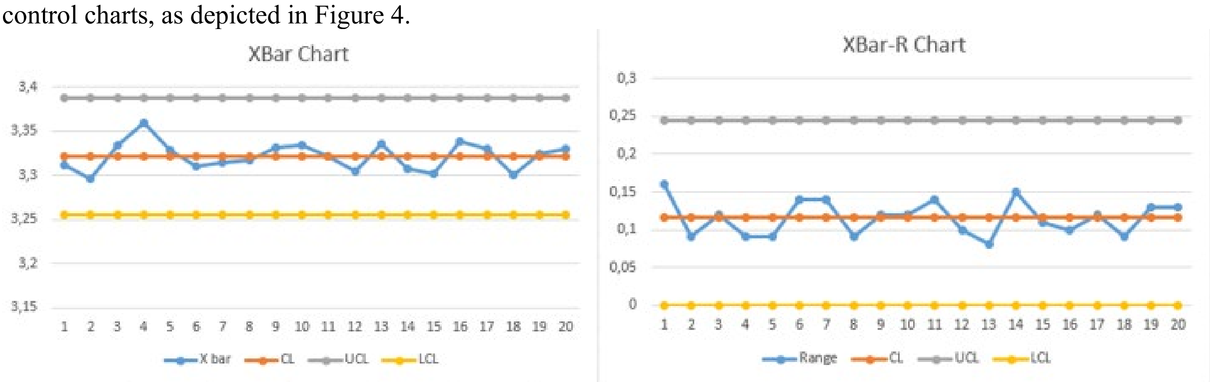

Figure 4. Felt Bed Weight Quality Control Chart

The pie chart in Figure 5 illustrates that the majority of the total cost (71.2%) is due to rejection, followed by false alarm (17.7%), sampling (7.6%), and resetting (3.5%) costs.

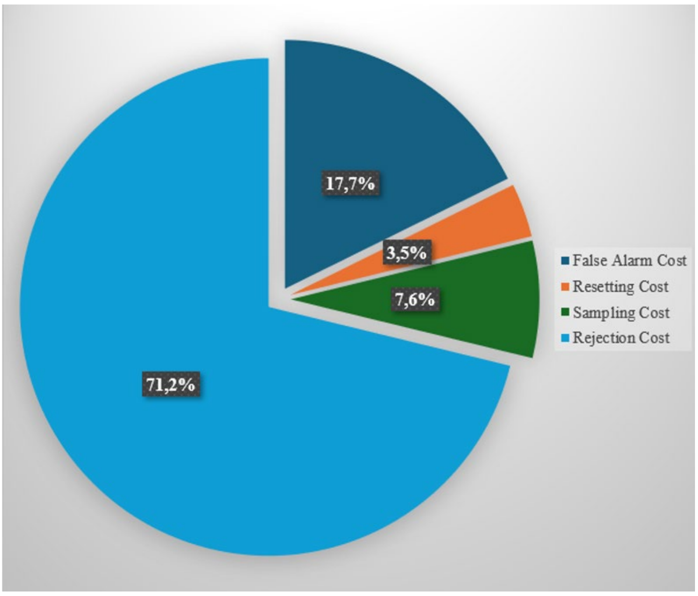

Figure 5. Cost Components

The pie chart in Figure 6 indicates that the system was in control 76% of the time and out of control 24% of the time.

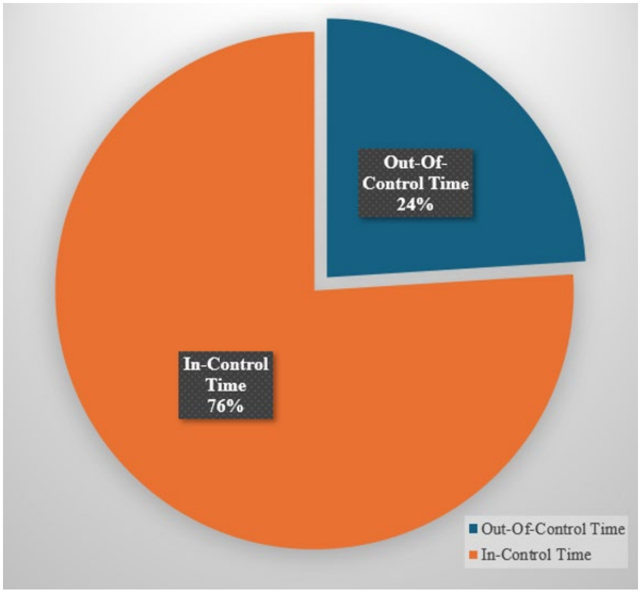

Figure 6. Out of Control and In Control Graph

5.4 Proposed Improvements

Future research may focus on integrating machine learning (ML) techniques to enhance predictive maintenance and improve the adaptability of production scheduling. ML models can analyze historical failure data and real-time sensor readings to predict breakdowns, enabling proactive interventions that minimize downtime and costs. Furthermore, reinforcement learning (RL) algorithms provide a dynamic approach to decision-making by constantly changing maintenance and scheduling policies based on real-time operating data. This adaptability guarantees that interventions are carried out at opportune periods, balancing equipment longevity and production efficiency.The use of Internet of Things (IoT) technology can improve system monitoring by providing real-time machine performance data, allowing instant anomaly detection and condition-based maintenance. Combining ML-driven predictive analytics, RL-based optimization, and IoT-enabled monitoring may result in fully automated, self-adaptive maintenance and scheduling systems that improve cost efficiency, production resilience, and long-term operational sustainability.

6. Conclusion

This study highlights the advantages of integrating maintenance planning, process quality control, and production scheduling into a single framework. In comparison to traditional independent approaches, the results show significant cost reductions, increased operational efficiency, and improved system reliability. Manufacturers can reduce disruptions, lower defect rates, and maximize resource usage by integrating maintenance with production sequencing and quality control.

Furthermore, combining real-time monitoring and predictive maintenance allows for a proactive approach, reducing downtime and extending equipment lifespan. Future research will concentrate on AI-driven optimizations, using ML, RL, and IoT-based real-time monitoring to create self-adaptive maintenance and scheduling systems. These developments will benefit smart manufacturing by increasing flexibility, reactivity, and long-term operational sustainability.

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Biographies

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