



Modeling and Sensitivity Analysis of Total Cost in Preventive Maintenance and Equipment Quality Control

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Abstract

The objective of this study was to model and conduct a sensitivity analysis of total cost in preventive maintenance and equipment quality control. In terms of purpose, this research was applied; in terms of implementation method, it was descriptive and survey-based; and in terms of analytical approach, it was analytical–mathematical. The statistical population used for testing the model consisted of the wastewater treatment plant of the Urmia Industrial Estate, and the entire statistical population was examined. The instruments used for data collection and measurement of the variables included maintenance records and documents, quality-related information, cost and time data, and other relevant operational data. Mathematical modeling, numerical solution using Maple 11 software, the paired-samples t test, and sensitivity analysis were employed to analyze the research data. In this study, an integrated model was developed to simultaneously determine the optimal preventive maintenance intervals and quality control parameters in order to minimize the total system cost. The results obtained from solving the model indicated that the optimal values of the decision variables were (11, 1.91, 7, 658), while the objective function reached 116 monetary units. Furthermore, the results of the paired-samples t test over a 12-month period demonstrated a significant difference between costs before and after implementation of the model, indicating that implementation of the model significantly reduced costs. The sensitivity analysis also showed that the parameters associated with transition of the process to an out-of-control state and deviation of the quality characteristic exerted the greatest effects on the total cost function and decision variables. Overall, the proposed model demonstrated high efficiency in reducing the integrated costs of maintenance, repair, and quality control.

Keywords: Modeling; Sensitivity Analysis; Preventive Maintenance; Equipment Quality Control

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1. Introduction

Maintenance and quality control are two fundamental pillars of operational performance in manufacturing and service systems because both directly affect equipment availability, process stability, product conformity, operating cost, and organizational competitiveness. In contemporary production environments, firms are increasingly required to achieve higher output quality while simultaneously reducing downtime, resource consumption, rework, inspection costs, and maintenance expenditures. This requirement has intensified with the growing complexity of production technologies, digital manufacturing systems, continuous-flow processes, and interconnected supply chains, where

equipment degradation can rapidly influence process capability and the quality of final outputs. Accordingly, maintenance can no longer be regarded merely as a technical support activity performed after equipment failure, and quality control cannot be treated as an isolated inspection function. Rather, both should be considered interdependent elements of an integrated operational decision-making system [1-3].

From an operations management perspective, equipment condition affects not only production continuity but also the statistical behavior of process quality characteristics. As machinery deteriorates, process variability may increase, the process mean may shift, and the probability of producing



nonconforming items may rise. Conversely, maintenance interventions can restore equipment condition, reduce process instability, and support the maintenance of desired quality specifications. Empirical evidence from manufacturing environments has shown that the type and effectiveness of machine maintenance are associated with the quality of production output, indicating that maintenance decisions may have consequences extending well beyond equipment reliability alone [4]. Therefore, maintenance planning and quality management should be coordinated in such a way that equipment interventions are scheduled not only on the basis of failure risks but also with respect to their implications for process quality and the total cost of operations.

Preventive maintenance is particularly important in this context because it seeks to reduce the probability of unexpected failure through planned interventions performed before functional breakdown occurs. Preventive maintenance policies are generally designed around predefined time intervals, usage levels, deterioration indicators, or combinations of these criteria. The underlying principle is that a planned intervention, despite imposing direct maintenance cost and temporary downtime, may prevent substantially greater costs associated with corrective repairs, equipment failure, production interruption, defective products, emergency interventions, and customer dissatisfaction. In process industries, where equipment deterioration may develop gradually and failures can result in substantial production and safety consequences, optimized maintenance intervals are therefore essential. The development of advanced inspection and corrosion-monitoring approaches has further emphasized the value of timely maintenance planning for improving turnaround maintenance and reducing uncertainty regarding equipment condition [5].

Maintenance optimization becomes more complicated when equipment operates as part of a system rather than in isolation. In serial production systems, for example, deterioration or failure in one component may influence the performance of subsequent operations, product quality, energy use, and system-level reliability. Recent studies have consequently moved toward opportunistic maintenance strategies that coordinate maintenance activities while explicitly accounting for quality characteristics and maintenance effects [6]. More recent developments have expanded this framework by considering both quality and energy-consumption constraints, suggesting that maintenance optimization increasingly requires

multidimensional objectives rather than a narrow focus on failure avoidance [7]. These developments reinforce the view that maintenance policies should be integrated with broader production and quality objectives if organizations seek to optimize overall system performance.

Quality control, similarly, represents more than the detection of defective products at the end of a production line. Modern quality management emphasizes continuous monitoring, prevention of process deviations, early identification of assignable causes, statistical process control, measurement system reliability, and systematic quality assurance across operational stages. Quality tools, technologies, and analytical techniques enable organizations to detect abnormal variation, establish control limits, improve conformance, and reduce the costs associated with defects and rework [3]. The importance of credible measurement and quality assurance is evident across various technical environments, including air-quality sensor applications, where calibration, validation, comparability, and quality assurance procedures directly determine whether collected data are sufficiently reliable for decision-making [8]. Similarly, reviews of low-cost particulate matter sensors have demonstrated that analytical performance depends heavily on calibration strategies and environmental conditions, underscoring the importance of systematic monitoring and quality control in measurement-based systems [9].

The relationship between maintenance and quality control is particularly evident when a process can shift from an in-control state to an out-of-control state because of equipment deterioration or an assignable cause. Under such circumstances, delayed detection of process changes may result in the continued production of defective or nonconforming products, whereas overly frequent inspection may increase sampling, inspection, and false-alarm costs. Similarly, overly frequent maintenance raises preventive maintenance expenditures and production interruptions, while excessively long maintenance intervals increase the likelihood of equipment deterioration and corrective maintenance. Therefore, the central managerial problem lies in finding an economically efficient balance among inspection frequency, control-chart parameters, preventive maintenance intervals, failure risk, and quality-related losses. The economic-statistical design of such systems is intended to optimize this balance by integrating statistical process-control requirements with economic consequences [10].

Integrated optimization has therefore emerged as an important approach in production and reliability research. Rather than determining production schedules, maintenance plans, and quality-control parameters independently, integrated models attempt to optimize these decisions simultaneously because decisions made in one domain can materially affect the others. A hybrid design jointly optimizing production scheduling, control-chart design, and maintenance in continuous-flow manufacturing has demonstrated the relevance of considering these operational decisions within a common framework [11]. More recently, integrated economic-statistical models have incorporated production, quality control, and maintenance in continuous-flow processes exposed to multiple assignable causes, showing that system-wide optimization can provide a more realistic basis for operational decision-making than isolated submodels [10]. Bayesian approaches have also been proposed to integrate quality, maintenance, and production decisions in multivariable processes, particularly where uncertainty and interdependence among process variables are substantial [12].

The financial rationale for such integration is closely related to the concept of total cost. Operational decisions should not be evaluated solely in terms of their direct acquisition or intervention expenses because equipment and quality systems generate costs throughout their operational life cycles. Total cost may include preventive and corrective maintenance, failure-related downtime, inspection, rejected products, false alarms, process resetting, production losses, labor, energy, quality assurance, and other indirect consequences. Total cost of ownership analyses in technology-intensive environments illustrate that an apparently less expensive option may not necessarily be more economical once reliability, replacement, performance, support, and operational consequences are included [13]. Similarly, analysis of digital pathology operations has shown that technological infrastructure requires substantial attention to operational resources and cost structures rather than merely initial implementation expenditures [14]. These findings are relevant to industrial maintenance because they support evaluation of equipment-related decisions from a comprehensive cost perspective.

A total-cost approach is especially important when quality failures themselves carry substantial economic consequences. Defective or unreliable outputs may increase scrap, rework, warranty, inspection, customer-service, and reputational costs. In sectors such as healthcare and pharmaceuticals, quality deficiencies can additionally have

serious safety and public-health implications. Concerns regarding substandard and falsified medicines and health technologies illustrate how poor quality can impose economic and societal burdens extending beyond the immediate production process [15]. Laboratory quality management likewise demonstrates the need to evaluate performance across the total testing process, with sigma metrics providing a quantitative means of identifying errors and process weaknesses [16]. These applications show that quality costs should be viewed as part of an interconnected system of operational risks rather than as isolated inspection expenses.

Reliability is another critical dimension linking maintenance, quality, and operational cost. Critical equipment failure may interrupt service delivery, compromise process output, and generate additional costs associated with emergency maintenance and replacement. Reliability assessment in healthcare equipment has emphasized the necessity of systematically evaluating critical devices to maintain service continuity and reduce operational risk [17]. Similar principles apply in manufacturing and process systems, where equipment failure can trigger production loss and quality deterioration. In infrastructure and energy systems, long-term reliability is also closely connected to technological innovation, maintainability, operational performance, and investment feasibility. Research on future-proof photovoltaic technologies, for instance, highlights the role of reliability and technological development in ensuring economically sustainable and bankable systems over their operational life cycles [18].

Condition-based maintenance provides another framework for coordinating quality monitoring and equipment maintenance. Unlike purely time-based maintenance, condition-based maintenance relies on observable indicators to determine whether intervention is required. Statistical process-control mechanisms can be used to detect changes in system condition and support maintenance decisions. The use of Bayesian control charts for optimal condition-based maintenance demonstrates that statistical monitoring can serve as a decision mechanism linking process information with maintenance timing [19]. Such approaches are highly relevant to integrated cost models because they allow maintenance decisions to respond to changes in system state rather than relying exclusively on predetermined intervals. Nevertheless, even in time-based preventive maintenance systems, statistical

quality information can improve the determination of economically appropriate intervention intervals.

The increasing availability of digital technologies has further strengthened the feasibility of integrated maintenance and quality management. Digitalization improves the collection, storage, processing, and exchange of operational information and facilitates real-time visibility across production and supply-chain processes. Studies of supply-chain digitization have indicated that digital transformation can influence operational performance by improving coordination, data availability, and process integration [20]. In advanced manufacturing, artificial intelligence and explainable artificial intelligence are increasingly applied to visual quality assurance, enabling automated defect detection and supporting more responsive quality-control systems [21]. Digital Lean Six Sigma approaches also combine data-driven improvement methods with waste reduction and process-quality strategies, reflecting the growing convergence of digital technologies, continuous improvement, and quality management in advanced manufacturing environments [22].

Despite technological advances, successful implementation of maintenance and quality systems remains dependent on organizational and contextual conditions. Resource limitations, technical capacity, workforce capability, access to equipment, and implementation barriers can all influence the effectiveness of operational improvement strategies. Research on biogas technology implementation, for example, has shown that technical, financial, institutional, and operational barriers can substantially constrain the adoption and sustainability of technological systems [23]. Likewise, laboratory capacity assessments have demonstrated that infrastructure, diagnostic resources, quality systems, and institutional readiness influence the ability of organizations to conduct reliable testing and surveillance activities [24]. These considerations are relevant to maintenance optimization because mathematically optimal policies can deliver practical benefits only when they are consistent with the operational capacity of the organization.

Quality improvement also requires systematic process governance rather than isolated corrective actions. Evidence from environmental monitoring systems indicates that adopting a process-based approach to quality management can substantially improve sensor data quality by embedding quality requirements across operational workflows [25]. Similar lessons are evident in public healthcare facilities, where quality assurance must encompass equipment,

procedures, human resources, documentation, and monitoring mechanisms to maintain consistent service standards [26]. Large-scale diagnostic quality initiatives have likewise demonstrated that standardized proficiency testing and collaborative quality systems can strengthen diagnostic capacity over time [27]. These findings collectively support an integrated view in which quality is generated through coordinated processes rather than through final-stage inspection alone.

Integrated systems are also increasingly important in service and community-based contexts. Large-scale health programs demonstrate that sustainable implementation requires coordinated processes, data management, service delivery, and stakeholder participation rather than fragmented interventions [28]. Although such programs differ from industrial production systems, they illustrate a broader management principle: system performance improves when operational components are designed as mutually dependent elements rather than optimized separately. This logic directly applies to preventive maintenance and equipment quality control because inspection, maintenance, failure behavior, process stability, and cost interact dynamically.

At the same time, sensitivity analysis is essential in mathematical optimization because model outputs may depend strongly on assumptions regarding parameter values. Costs, failure rates, repair times, process-shift parameters, rejection costs, and quality-loss parameters are rarely known with absolute certainty. A model may therefore generate an apparently optimal solution under baseline assumptions but produce different decision-variable values when key parameters change. Sensitivity analysis allows researchers and managers to identify which inputs exert the greatest influence on the objective function and to determine whether recommended solutions remain stable under plausible variation. This is particularly important in systems where measurement uncertainty is unavoidable, as emphasized in quality-assurance studies of sensing technologies and calibration procedures [8, 9]. It is also consistent with contemporary reliability and maintenance research, in which uncertainty surrounding degradation, quality characteristics, and maintenance effectiveness is increasingly incorporated into decision models [6, 12].

In practical industrial environments, the need for such integrated analysis is further reinforced by the diversity of cost-generating events. Preventive maintenance, corrective repair, sampling, process resetting, rejected products, false alarms, downtime, and quality deviations may all occur

within the same operational system. Optimizing one component independently may shift costs to another component rather than reducing the total economic burden. For example, increasing inspection frequency may reduce the duration of undetected out-of-control conditions but simultaneously raise inspection costs. Extending maintenance intervals may reduce scheduled maintenance expense while increasing failure probability and defective output. Conversely, performing maintenance too frequently may unnecessarily interrupt production. Therefore, the relevant managerial objective is not simply to minimize maintenance cost or quality-control cost separately, but to minimize their integrated total cost while maintaining acceptable operational and quality performance. This perspective is consistent with recent research emphasizing joint optimization of maintenance, quality, production, reliability, and operational constraints [7, 10, 11].

Overall, the literature indicates a clear transition from isolated maintenance and quality-management practices toward integrated, data-driven, and economically optimized operational systems. Advances in statistical process control, reliability analysis, digital technologies, quality assurance, Bayesian modeling, and condition-based maintenance have provided increasingly sophisticated mechanisms for coordinating operational decisions. Nevertheless, the practical value of these approaches depends on their ability to translate technical relationships into measurable cost reductions within real operating environments. Integrating preventive maintenance intervals with quality-control parameters and subsequently examining the sensitivity of the resulting solution can therefore provide managers with a more comprehensive framework for identifying economically efficient operating policies. Such a framework is particularly valuable in equipment-intensive facilities where maintenance interventions, process deviations, failures, and quality-related costs occur simultaneously and where decisions regarding one component can materially affect the others.

Accordingly, the aim of this study is to develop and evaluate an integrated mathematical model for determining the optimal preventive maintenance interval and quality-control parameters, minimizing the total system cost, and analyzing the sensitivity of the optimal solution to changes in key operational and cost parameters.

2. Methodology

This study is applied in terms of purpose because it seeks to develop and apply a mathematical model for solving a real-world problem in the field of preventive maintenance and equipment quality control. In terms of data collection, the study is descriptive and survey-based, whereas in terms of its investigation and analytical method, it falls within the category of analytical–mathematical research. The principal approach of the study involves designing and implementing an integrated model to determine the optimal values of the decision variables and to analyze the sensitivity of parameters affecting the total cost function.

The statistical population of this study consisted of operational data and information related to the wastewater treatment plant of the Urmia Industrial Estate, which served as the setting for testing the model. Given the limited size of the population and complete accessibility of the required information, the entire statistical population was examined and no sampling procedure was performed. The unit of analysis in this study was a single-component device considered as part of a single-machine system under specified operating conditions.

The data collection instruments included maintenance and repair records and documents, quality-related information, cost data, time-related information, failure records, corrective and preventive maintenance costs, quality-related costs, rejected items, false alarms, and other relevant technical and operational data. Accordingly, the input parameters of the model were extracted from actual organizational sources and prepared for model implementation.

For data analysis, the mathematical model was first designed on the basis of minimizing the integrated total cost and was subsequently solved using Maple 11 software. The decision variables in this model included sample size n , control-limit coefficient k , sampling interval h , and preventive maintenance interval t_{PM} . After solving the model, the optimal values of the variables and the value of the objective function were obtained.

To evaluate the effectiveness of the proposed model, cost values before and after implementation of the model over a 12-month period were compared using a paired-samples t test. Moreover, to examine model stability and assess the effects of parameter variations on the decision variables and objective function, sensitivity analysis was performed for selected key parameters at two levels of increase, namely 10% and 20%. In addition, to compare the performance of

the integrated model with that of the non-integrated approach, the data were also implemented in an independent quality control model, and the results of the two approaches were compared. Finally, regression approximation was used to estimate the number of failures as a function of the preventive maintenance interval.

3. Findings and Results

In this section, a numerical example was implemented in the model to determine the optimal decision variables.

Table 1. Values of the Given Problem Parameters

Parameter	δ E	δ M/C	T _s	T ₀	T ₁	T _{resetting}	C _F	C _v
Value	1.5	0.6	20/60	1	1	2	100	50
Parameter	C _{Rej}	C _{false-Alarm}	C _{FCCM}	C _{FCCPM}	C _{Lp}	LC	C _{reset}	PR
Value	2800	1420	12000	1100	540	620	5600	14

Based on the data related to the problem, these values were implemented in the proposed model, and the model was solved using Maple 11 software. The optimal variables were obtained as follows:

First, a single-component device was considered as part of a single-machine system. It was assumed that the machine operated in three eight-hour shifts, seven days per week. The time required to perform preventive maintenance activities was 7 time units, whereas the time required to perform corrective maintenance activities was 12 time units. The process was assumed to be in an in-control state.

$$(n^*, k^*, h^*, t_{PM}^*) = (11, 1.91, 7, 658)$$

$$f^*(11, 1.91, 7, 658) = 116$$

Table 2. Descriptive Statistics of Costs Over a 12-Month Period

Variable	Mean	N	Standard Deviation	Standard Error
Variable 1	289.12	12	32.4	14.3
Variable 2	116	12	11.8	3.54

Variable 1 represents the integrated maintenance and quality costs before implementation of the model over a 12-month period, whereas Variable 2 represents the integrated maintenance and quality costs after implementation of the model over the same 12-month period. The mean cost before

implementation of the model was 289.12 monetary units, with a standard deviation of 32.4, whereas the mean cost after implementation of the model, representing the optimal cost function, was 116 monetary units, with a standard deviation of 11.8.

Table 3. Significance Test of the Association Between Costs Before and After Implementation Over a 12-Month Period

Variables	N	Correlation	Significance
Variable 1 and Variable 2	12	0.220	0.671

According to the software output, the correlation between the costs during the 12 months before and after implementation of the model was 0.02. Because the significance level was greater than 0.05, the relationship was

not statistically significant. Therefore, it can be stated that there was no significant correlation between the two sets of costs.

Table 4. Significance Test for Comparing Mean Costs Before and After Implementation Over a 12-Month Period

Variables	Mean Difference	Standard Deviation	Standard Error	Lower Bound	Upper Bound	t	df	Significance
Variable 1 and Variable 2	173.12	9.65	12.25921	149.86587	197.86587	5.370	11	0.013

According to the software output, the difference between the mean costs during the 12 months before and after

implementation of the model was 173.12 monetary units. Because the significance level was less than 0.05, the

difference was statistically significant. Therefore, it can be concluded that the mean maintenance and quality costs before and after implementation of the model were not equal and that this difference was statistically significant.

In this section, the data and their effects on the decision variables and total cost function are analyzed. Each of the

parameters C_v , C_F , C_{Rej} , $T_{resetting}$, T_0 , T_1 , δ_E , and $\delta_{M/C}$ was increased by 10% and 20%, and the effects of these changes on the decision variables and objective function were examined.

Table 5. Changes in Selected Problem Parameters at +10% and +20% Levels

Parameter	Initial 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 6. Values of the Decision Variables and Objective Function at +10% and +20% Levels

Parameter Change	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

As shown in Table 6, increasing δ_E and $\delta_{M/C}$ by 10% and 20% resulted in substantial changes in both the objective function and the decision variables. In contrast, changes in the other parameters did not produce substantial changes in the model. This finding demonstrates the considerable importance of preventing the process from shifting to an out-of-control state and of controlling changes in the mean deviation of the quality characteristic under consideration.

The question then arises as to what difference would occur in the optimal objective function if an independent model were used instead of the integrated model. For this purpose, the data were entered into the independent quality control cost function and solved using Maple 11 software. The result was as follows:

$$(n^*, k^*, h^*) = (10, 3.35, 8)$$

$$f^*(10, 3.35, 8) = 341.8$$

As can be observed, the value of the cost function for the quality control component alone was higher than the total cost in the integrated model, in which maintenance and quality control were considered simultaneously. The total cost in the integrated model, incorporating both maintenance and quality control, was 116. In fact, incorporating maintenance considerations into a quality control model enhances supervision over production equipment and machinery. Through proper maintenance of equipment and machinery, products can be manufactured in accordance with acceptable quality standards, and production of products at the expected quality level reduces costs associated with quality control.

In this model, implementation of preventive maintenance reduces the number of out-of-control states in the system and increases the proportion of products manufactured while the process remains in an in-control state. By determining the optimal preventive maintenance intervals and quality parameters, the total cost function can consequently be minimized. According to the numerical example above, compared with the condition in which maintenance is disregarded, the cost function is substantially lower. It can therefore be concluded that considering preventive maintenance together with quality control is considerably more effective.

It is evident that analytically and precisely determining the number of failures during a short-term planning period is

extremely difficult. Various approaches are available for determining N_f , and numerous models have been proposed to estimate the number of failures occurring within a process. However, most of these approaches are time-consuming and complex.

In this study, N_f was considered as a function of t_{PM} , and a regression approximation method was employed. By having information on the preventive maintenance intervals and the number of failures occurring in each interval across different intervals within a given period, an approximate value of N_f can be obtained. Accordingly, the following relationship is obtained:

$$N_f = a(t_{PM})^b$$

Table 7. Regression Approximation Method

Variable	Unstandardized Beta	Standard Error	Standardized Beta	t	Significance
Constant	8.36	2.139	—	4.893	0.001
Variable 2	0.11	0.085	0.687	2.500	0.041

According to the software output, the value of a was 8.36 and the value of b was 0.11. Based on the N_f formula, the preventive maintenance interval was consequently determined to be 17 days.

4. Discussion and Conclusion

The present study developed and evaluated an integrated mathematical model for the simultaneous optimization of preventive maintenance and equipment quality control, with the principal objective of minimizing the total system cost. The findings showed that the optimal decision vector was obtained as $(n^*, k^*, h^*, t_{PM}^*) = (11, 1.91, 7, 658)$, with the minimized objective-function value equal to 116 monetary units. This result indicates that the joint determination of sample size, control-limit coefficient, sampling interval, and preventive maintenance interval can produce a substantially more economical operating configuration than treating maintenance and quality-control decisions separately. The finding supports the broader premise that production, quality control, and maintenance should be modeled as interdependent operational functions rather than as isolated subsystems. Similar integrated approaches have demonstrated that simultaneous consideration of control-chart design, production conditions, and maintenance decisions can produce more efficient system-level solutions than sequential or independent optimization [10, 11]. The present results therefore reinforce the economic rationale for

coordinated decision-making in equipment-intensive systems.

A major finding of the study was the considerable reduction in total integrated maintenance and quality costs following implementation of the proposed model. Over the 12-month evaluation period, the mean cost before implementation was 289.12 monetary units, whereas the corresponding mean after model implementation decreased to 116 monetary units. The paired-samples analysis further indicated that the difference between the two conditions was statistically significant. This result suggests that the observed reduction was not merely a consequence of random short-term variation but reflected a systematic improvement associated with the optimized integration of maintenance and quality-control decisions. From an operations-management perspective, this finding is consistent with the concept of total cost optimization, according to which decision quality should be evaluated in terms of the aggregate consequences of inspection, maintenance, failure, rejection, downtime, and process instability rather than through minimization of a single cost category. Total-cost-of-ownership research similarly demonstrates that technically and financially efficient decisions require the simultaneous consideration of operating, maintenance, replacement, reliability, and performance-related expenditures [13]. The findings of the present study extend this logic to the integration of preventive maintenance and statistical quality control.

The significant reduction in costs may be explained by the preventive role of maintenance in controlling deterioration before it propagates into process instability and quality losses. When equipment condition deteriorates, the probability of process drift, defective output, corrective maintenance, and production interruption increases. Preventive maintenance can interrupt this sequence by restoring or preserving equipment functionality before severe degradation occurs. Empirical evidence from manufacturing firms has shown that the type and adequacy of machine maintenance are directly related to output quality, suggesting that maintenance is not merely a reliability function but also a determinant of process conformity and product performance [4]. The present findings are consistent with this perspective because the integrated model reduced total cost by considering maintenance intervals together with quality-control parameters. This coordinated configuration likely reduced both the probability of equipment-related process deviations and the frequency or duration of quality failures, thereby lowering the combined economic burden associated with maintenance and quality.

The results are also in line with recent advances in integrated economic-statistical process design. Wan and Yan emphasized the importance of jointly optimizing production, quality control, and maintenance in continuous-flow processes exposed to multiple assignable causes, arguing that isolated decision-making may fail to capture the interactions through which deterioration and process shifts influence costs [10]. Likewise, Chen proposed a hybrid design in which production scheduling, control-chart design, and maintenance are optimized simultaneously, reflecting the interdependence of these operational domains [11]. The present study provides further support for this integrated perspective by demonstrating, through a real operational application, that the joint optimization of quality-control and preventive-maintenance parameters can substantially reduce total cost.

Another important result concerned the comparison between the integrated model and the independent quality-control model. When the same problem data were implemented in the independent quality-control formulation, the optimal cost function was 341.8 monetary units, considerably higher than the integrated-model value of 116. This finding provides direct evidence that independent optimization of quality control may lead to economically inferior decisions when equipment deterioration and maintenance requirements are ignored. In an isolated

quality-control model, process deviations are mainly addressed through sampling, monitoring, and control-limit decisions, whereas an integrated model additionally recognizes that some quality deviations originate from the physical condition of equipment. Consequently, maintenance can remove or reduce underlying sources of instability rather than merely detecting their effects. This interpretation is consistent with models of opportunistic maintenance in which maintenance effectiveness and product quality characteristics are considered simultaneously [6]. It is also compatible with more recent maintenance strategies that explicitly incorporate both quality and energy constraints within system-level optimization [7].

The lower cost obtained through integration can further be explained through the distinction between detection and prevention. Quality-control procedures primarily identify process deviations or nonconforming output after a change has occurred, whereas preventive maintenance can reduce the probability that deterioration-induced deviations occur in the first place. Thus, increasing reliance on inspection without addressing equipment condition may result in repeated detection of abnormalities without eliminating their root causes. Contemporary quality-management approaches emphasize the use of preventive, process-based systems rather than end-stage defect detection alone [3]. Similarly, process-oriented quality-management practices have been shown to substantially improve data quality by embedding quality assurance throughout operational workflows rather than relying solely on final verification [25]. The current results reflect the same principle in a maintenance context: total cost is minimized more effectively when the operational source of variation and the monitoring system are managed together.

The sensitivity-analysis results provide additional insight into the structure of the proposed model. Among the parameters examined, changes in δ_E and $\delta_{M/C}$ produced the most notable alterations in the objective function and decision variables. Increasing these parameters by 10% and 20% changed sample size, sampling interval, control-limit coefficient, preventive maintenance interval, and total cost more substantially than corresponding changes in most other parameters. This finding indicates that the model is particularly sensitive to parameters describing process transition toward an out-of-control condition and changes in the underlying quality characteristic. The result is theoretically plausible because parameters associated with process shift directly affect the expected frequency and

economic consequences of nonconforming production. When the probability or magnitude of process deviation increases, the economically optimal balance between monitoring and maintenance must also change.

This sensitivity pattern is consistent with research showing that quality-related degradation indicators can be central determinants of maintenance policy. In opportunistic maintenance models, the inclusion of quality characteristics changes the optimal timing and structure of maintenance decisions because deterioration affects not only failure probability but also product conformity [6]. Bayesian integration of quality, maintenance, and production has similarly highlighted the value of incorporating multivariable quality information when process conditions and maintenance effects are uncertain [12]. The present results therefore suggest that parameters governing the transition to an out-of-control state deserve particular managerial attention because even relatively moderate changes may alter the optimal configuration of both maintenance and quality-control variables.

The strong sensitivity to process-shift parameters is also consistent with the basic logic of statistical process control. When a process remains stable, moderate adjustments to inspection-related costs or resetting times may not substantially alter the economically optimal policy. However, when the magnitude or likelihood of a quality shift changes, the expected cost of delayed detection rises considerably. In such cases, management may need to modify sample size, sampling frequency, control limits, or maintenance timing. Quality-assurance research on sensor systems has similarly shown that changes in calibration, measurement uncertainty, and environmental conditions can substantially influence the credibility of monitoring data and the resulting decisions [8, 9]. Although these studies address measurement systems rather than industrial maintenance directly, they support the broader conclusion that quality-monitoring systems are particularly sensitive to parameters that affect the magnitude and detectability of deviations.

By contrast, the relatively smaller changes observed for several cost and time parameters indicate a degree of robustness in the proposed model. For example, variations in T_0 , T_1 , $T_{\text{resetting}}$, C_F , C_v , and C_{Rej} produced comparatively limited changes in the total cost and optimal decision variables. This pattern is important because an optimization model that changes dramatically in response to minor variation in every input would have limited practical value. The relative stability of the solution under changes in several parameters suggests that the proposed model can

retain its decision-making utility even when some operational estimates are uncertain or subject to moderate fluctuations. This characteristic is particularly valuable in real production systems, where precise estimates of maintenance, rejection, inspection, and resetting costs are not always available.

The findings concerning robustness are relevant to reliability-centered operational decision-making. Reliability studies in healthcare and other equipment-intensive settings emphasize that critical assets must be assessed not only in terms of failure probability but also in terms of their consequences for service continuity and system performance [17]. In the present study, the model responded most strongly to parameters directly linked to process condition and quality deviation while remaining comparatively stable under several secondary cost adjustments. This implies that managers may obtain greater benefit from improving estimates of process-shift behavior and quality deviation than from devoting equivalent effort to refining relatively less influential cost coefficients.

The findings also support the growing use of condition-based and information-driven maintenance approaches. Rasay et al. demonstrated that Bayesian control charts can be used to support condition-based maintenance by connecting process information with maintenance decisions [19]. Although the present model is based on preventive maintenance intervals rather than a purely condition-based maintenance architecture, its integration with quality-control parameters reflects a similar conceptual foundation. Both approaches use information about process behavior to determine when intervention is economically justified. This suggests that the proposed model could potentially be extended in future applications by incorporating real-time condition-monitoring variables, control-chart signals, or predictive indicators of deterioration.

The regression-approximation component of the study further contributes to this operational framework. The number of failures, N_f , was modeled as a function of the preventive maintenance interval t_{PM} , and the estimated parameters indicated a preventive-maintenance interval of approximately 17 days. Modeling failure occurrence as a function of the maintenance interval provides an operationally useful approximation when exact analytical determination of short-term failures is infeasible. Such an approach is particularly relevant in practical systems where detailed lifetime distributions or degradation processes may not be fully observable. In this respect, the model reflects a

pragmatic balance between mathematical tractability and operational applicability.

The broader implications of the findings are also consistent with developments in digitalized quality and maintenance systems. Advances in artificial intelligence, explainable artificial intelligence, and digital process monitoring increasingly enable organizations to detect abnormalities earlier and coordinate interventions more effectively [21]. Digital Lean Six Sigma similarly emphasizes data-driven integration of quality improvement and process efficiency [22]. Supply-chain digitalization has also been associated with improved coordination, information visibility, and operational responsiveness [20]. The proposed model fits within this broader movement toward integrated, data-based operational management, as it relies on organizational maintenance, cost, and quality data to derive optimal decisions rather than treating such information streams independently.

The findings are also relevant beyond manufacturing. Quality assurance in healthcare laboratories and public facilities has demonstrated that reliable performance requires coordinated monitoring, equipment management, documentation, and process control [24, 26]. Performance evaluation using sigma metrics likewise shows how quality deficiencies can be identified and prioritized across the total testing process rather than at a single stage [16]. Similarly, sustainable diagnostic programs depend on integrated systems of proficiency testing, quality assurance, and operational coordination [27]. These parallels reinforce the general principle that quality and reliability outcomes improve when the system is managed holistically.

The managerial significance of the study is further strengthened by evidence that technological systems often fail to achieve their expected benefits when implementation barriers are not considered. Research on technology deployment has shown that institutional, financial, technical, and operational constraints can substantially affect implementation outcomes [23]. Integrated health programs similarly demonstrate that effective implementation depends on coordinated organizational processes rather than on the availability of technical solutions alone [28]. Therefore, although the proposed mathematical model produced substantial cost reductions, successful implementation requires adequate maintenance records, reliable quality data, organizational commitment, and technical capacity to update model parameters as operating conditions change.

The present findings also align with research emphasizing long-term reliability and lifecycle performance in

technologically intensive systems. Future-proof engineering systems require continued attention to degradation, maintenance, and technical innovation if they are to remain reliable and economically viable over time [18]. Likewise, quality deficiencies in critical products and technologies can impose substantial economic and societal costs [15]. The implication for the present study is that reducing maintenance and quality costs should not be interpreted merely as short-term expenditure reduction. Rather, optimized maintenance and quality-control policies can contribute to long-term asset performance, process stability, service reliability, and protection against the broader consequences of equipment and quality failures.

Taken together, the findings demonstrate that maintenance and quality control are economically and operationally interdependent. The substantial reduction in the total cost function, the significant difference between pre- and post-implementation costs, the superiority of the integrated model over the independent quality-control formulation, and the sensitivity of the solution to process-shift parameters all support the use of an integrated decision framework. The results are consistent with contemporary research advocating joint optimization of maintenance, quality, production, reliability, and process conditions [7, 10, 11]. They also extend the literature by illustrating how such integration can be implemented using actual organizational data in a wastewater-treatment operational context. Overall, the evidence suggests that preventive maintenance and quality-control decisions should be coordinated at the system level to minimize total cost while maintaining process stability and acceptable output quality.

The present study has several limitations that should be considered when interpreting its findings. First, the proposed model was tested using data from a single operational setting, namely a wastewater treatment plant, and the structure of costs, failure behavior, maintenance practices, and quality characteristics may differ across industries and technologies. Second, several model parameters were estimated from historical organizational records, which may contain measurement errors, incomplete documentation, or variations in data-recording practices. Third, the model considered a single-component device within a single-machine system and therefore did not fully represent complex multi-component systems with dependent failures, shared maintenance resources, or dynamic interactions among machines. Fourth, the failure function was approximated using regression rather than a detailed stochastic degradation or reliability model. Finally, the

sensitivity analysis was restricted to selected parameters and to increases of 10% and 20%, and therefore does not capture all possible combinations or nonlinear changes in operating conditions.

Future studies could extend the proposed framework to multi-component, multi-machine, or networked production systems and explicitly incorporate dependencies among equipment units. Additional research could integrate stochastic deterioration, imperfect maintenance, random repair times, multiple quality characteristics, production scheduling, inventory, energy consumption, and workforce constraints into the optimization model. Researchers may also examine condition-based or predictive maintenance versions of the model using real-time sensor data, machine-learning predictions, and dynamic control-chart signals. Future studies could apply robust optimization, Bayesian methods, simulation-based optimization, or metaheuristic algorithms to examine the behavior of the model under parameter uncertainty and larger decision spaces. Comparative applications across manufacturing, healthcare, utilities, energy, and process industries would also be useful for assessing the external validity and generalizability of the proposed approach.

Managers should consider preventive maintenance and quality control as interdependent functions and should avoid optimizing their associated costs in isolation. Organizations can improve decision quality by integrating maintenance records, failure data, quality-control information, rejection costs, repair times, and inspection costs within a unified analytical system. Particular attention should be given to parameters associated with process shifts and quality-characteristic deviations because the present findings indicate that these factors can materially alter optimal maintenance and inspection policies. Organizations should also periodically recalibrate the model as operating conditions, equipment age, production volume, and cost structures change. Establishing reliable data-collection procedures, ensuring accurate recording of maintenance and quality events, and linking operational databases to analytical decision-support tools can further increase the practical usefulness of the model and support sustained reductions in total operating cost.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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