machines

MDPI

Article

Integrated Optimization Model for Maintenance Policies and Quality Control Parameters for Multi-Component System

Mustafa M. Nasr [1], Fadia Naji [2,*], Mokhtar Amrani [2,3], Mageed Ghaleb [2], Khaled N. Alqahtani [1], Asem Majed Othman [4] and Emad Hashiem Abualsauod [1]

1 Industrial Engineering Department, College of Engineering, Taibah University, Medina 41411, Saudi Arabia
2 Department of Industrial and Manufacturing System Engineering, College of Engineering, Taiz University, Taiz 00967, Yemen
3 Department of Renewable Energy Engineering, Faculty of Engineering and Technology, Philadelphia University, Amman 23218, Jordan
4 Department of Industrial and Systems Engineering, College of Engineering, University of Jeddah, Jeddah 19104, Saudi Arabia
* Correspondence: eng.fado@gmail.com

Abstract: The practical applications of integrated maintenance policies and quality for a multi-component system are more complicated, still rare, and incomplete to meet the requirements of Industry 4.0. Therefore, this work aims to extend the integration economic model for optimizing maintenance policies and quality control parameters by incorporating the Taguchi loss function for a multi-component system. An optimization model is developed based on preventive maintenance, corrective maintenance policies, and quality control parameters with the CUSUM (Cumulative Sum) chart, which is widely used for detecting small shifts in the process mean. The model was developed to minimize the expected total cost per unit of time and to obtain the optimal values of decision variables: the size of samples, sample frequency, decision interval, coefficient of the CUSUM chart, and preventive and corrective maintenance intervals. The solution steps were employed by selecting a case study in the Alahlia Mineral Water Company (AMWC). Then, the design of experiments based on one-factor-at-a-time was used to evaluate the effect of selected decision variables on the expected total cost. Finally, sensitivity analysis was performed on the selected decision variables to demonstrate the robustness of the developed model. A predictive maintenance plan was developed based on the optimal value of preventive maintenance interval, and the results showed that the performance of the maintenance plan realizes the full potential of the integrated mode. In addition, the case study results indicate that the extended integrated model for multicomponent is the new standard for the quality production of multi-component systems in future works.

Keywords: maintenance policies; statistical quality control; multi-component system; CUSUM chart; Taguchi loss function; mathematical model

Citation: Nasr, M.M.; Naji, F.; Amrani, M.; Ghaleb, M.; Alqahtani, K.N.; Othman, A.M.; Abualsauod, E.H. Integrated Optimization Model for Maintenance Policies and Quality Control Parameters for Multi-Component System. *Machines* **2023**, *11*, 435. https://doi.org/10.3390/machines11040435

Academic Editor: Tieling Zhang

Received: 3 February 2023
Revised: 24 March 2023
Accepted: 25 March 2023
Published: 29 March 2023

1. Introduction

Manufacturers face rising obstacles in today's highly competitive business climate, as well as the need for high levels of consumer satisfaction. Therefore, they strive to increase production performance by reducing breakdowns and quality losses in order to maximize profit and preserve competitive advantages. Throughout manufacturing cycles, systems or equipment wear down or degrade due to use and age. Moreover, systems might malfunction at any time, which can impede production. Therefore, maintenance—including inspection, repair, and replacement—is essential for boosting systems' availability and ensuring continuous production. Based on how they intend to handle failures and maintenance, there are two types of maintenance policies: preventive and corrective [1]. In practical applications, corrective maintenance (CM) is used to return equipment to its operational state after failure; as a result, this kind frequently results in severe delays and substantial financial losses. To reduce the likelihood of equipment failure or degradation, preventive maintenance (PM) is carried out at predetermined intervals or in accordance with predetermined criteria. These plans come with expenses, including those for samples, downtime, repairs, and inspections, among others. After that, integrating these two maintenance policies will result in cost savings.

Moreover, a good PM policy will lower the breakdown rates and process variances and maintain the expected productivity of the machine [2,3], which improves the quality levels. Therefore, quality control and maintenance policies are linked to cost savings and improving production performance. Furthermore, this will be ineffective when PM is performed on a single component (or machine) in a complicated production system. Hence, PM tasks should be performed on multi-component systems. Performing group PM tasks can significantly reduce total downtime and associated costs, such as labor costs, lost productivity due to machine breakdowns, and other production losses [4].

Since systems have many interrelated components, modeling and optimizing maintenance plans must consider the interactions between these connected components. These interactions also offer the chance for collective maintenance, which might lead to cost savings. Several approaches and models have been studied for maintenance optimization in multi-component systems [2,5–10]. However, there are few approaches (or models) for maintenance optimization in real-world multi-component systems. In earlier work by Dekker and Roelvink [11], a heuristic replacement strategy was utilized, applicable only if a fixed component category had been replaced. In another study, Huang [12] presented a new method based on the cost boundary condition for replacement scheduling and inferred that their approach is more effective. Similarly, Samrout et al. [13] presented an ant colony optimization method to minimize the PM cost of the multi-component system with constant failure rates. Moreover, Laggoune et al. [14] proposed a PM plan method for a multi-component system with random failures. Recently, the literature has reported integration methodologies for the multi-component system [15]. Magnanini and Tolio [16] proposed a mathematical model for preventive maintenance to minimize maintenance, inventory, and backlog costs. Furthermore, Andreas et al. [17] developed a holistic approach based on reinforcement learning algorithms to optimize maintenance plans to improve resource utilization in manufacturing systems.

Integrating quality control and maintenance policy models has been gaining popularity recently among researchers and industrial companies for improving product quality and reducing maintenance costs [18]. Several studies have been performed on integrating quality control and maintenance policy, and it was suggested that process quality control and machine maintenance should be examined simultaneously for cost-effectiveness. Integrating quality control and maintenance choices has been proven to considerably lower total production costs for single-machine units and multi-stage production systems. The studies by [19–23] showed that combining SPC (Statistical Process Control), maintenance policy, and production planning in the industrial system can significantly reduce costs. From a historical viewpoint, researchers began constructing combined economic models of control charts and maintenance utilizing X-bar control charts because of the association between quality control and maintenance [24–27]. Other studies by Baker [28] and Montgomery and Heikes [29] were conducted on the non-exponential probability distribution function of the in-control period. Consequently, Lorenzen and Vance [30] developed a unified model that is flexible enough to apply to a situation where production continues or ceases during the search or repair time. In addition, a study by Tagaras [24] integrated an economic model for maintenance procedures, process control, and other design parameters. After that, Rahim [25] developed a model for designing the optimal parameters of an X-bar control chart and PM periods for a manufacturing system with an increasing failure rate that follows the Weibull distribution.

Over time, researchers have paid greater attention to exponentially weighted moving average (EWMA) control charts than X-bar charts [31–33]. For example, Sultana et al. [34]

developed an economic model using an EWMA control chart based on the VSIFT (variable-sampling interval with fixed time) sampling policy and preventive maintenance. However, many studies currently prefer CUSUM over X-bar and EWMA charts. Moreover, CUSUM responded quickly and accurately when identifying shifts within one or two standard deviations [35].

Shrivastava et al. [36] developed a new model to combine PM and SPC-based CUSUM charts and determined the decision variables optimization, which effectively minimizes the total cost per unit of time. In addition, Li et al. [37] introduced a new integrated model for joint CUSUM control chart parameters and an age-based PM policy. They used a recursive algorithm and multiphase system to model each phase. Saha [38] recently integrated a new economic model for maintenance policy and quality control. Using the CUSUM control chart, the researcher monitored the process's mean and variance. Taguchi's quadratic loss function and a modified linear loss function were utilized to calculate the in-control and out-of-control processes. Farahani et al. [39] integrated a model to optimize statistical quality control policy: sample size, sampling interval, control limit, and preventive maintenance policy. The proposed model was developed based on a continuous Markov chain and $\overline{X}$ Chart to minimize the cost per unit of time. Regarding the multi-component system, works based on integrated maintenance policy and quality control are limited. Only one study integrated the quality and PM policy for the multi-component system by Al-Shayea et al. [40]. They utilized an EWMA chart to present a new model for integrated PM and SPC for a multi-component system.

It is evident from the literature mentioned above that the practical applications of integrated maintenance policies and quality for a multi-component system are more complicated and still rare and incomplete. Although a multi-component system provides a precious and comprehensive analysis that readily minimizes the overall maintenance costs and sustains high-quality products, very limited studies were conducted regarding the integrated quality and PM models for the multi-component system. Furthermore, multi-component systems require a complicated procedure that demands additional data than conventional methods. Moreover, this recent work requires a deep understanding and analysis of the small shift process. It is an ideal system for investigating a wide range of failure rates. Therefore, there is a need to develop a new model for integrating the CUSUM chart and PM policy for multi-component systems, which considers the limits and gaps in the previous studies. This research aims to extend the developed model by Pandey et al. [41] for integrating maintenance policy and quality control chart for the multi-component system using the CUSUM chart incorporating the Taguchi loss function.

The structure of this paper is as follows. The problem description is provided in Section 2. Section 3 describes the research methodology and explains the formulation of a multi-component system cost model. The selected case study is described in Section 4 to show how the constructed model may be used. Section 5 presents the results of the design of experiments and the sensitivity analysis to study the effects of decision variables on the expected cost. Finally, Section 6 presents the conclusions inferred from the research and provides future research directions.

2. Problem Description

Maintenance of multi-component systems is essential to ensure optimal functioning and longevity. Multi-component systems comprise multiple interconnected and interdependent parts, and failure of any one part can have significant consequences for the entire system. According to a study by Kamal, Arumugam, and Yousuf [42], "neglecting the maintenance of multi-component systems can lead to catastrophic consequences, including system failure, loss of production, and environmental disasters." Therefore, the maintenance of multi-component systems is critical for ensuring their reliable and safe operation, minimizing downtime, and maximizing productivity and profitability. In this paper, to improve the efficiency of such systems as well as their production quality, we considered the integration of statistical process control and maintenance policies for a multi-component system.

To address the quality issue, we have assumed that, at any period, the production process can be generally divided into two states. The first one is an in-control state which indicates that the production is smoothly running w*i*th no problems during a specific period. The second stage is the out-of-control state which happens after a certain amount of time due to machine (components or parts) wear or worker error, and products w*i*th quality issues are produced during this state. In addition, to address the machine down-times issue, we assume that downtimes can be categorized into the following two classes, according to their consequence on the production process [36]:

- Type 1 (F_1) is related to the mechanical failure of the machines in the system.
- Type 2 (F_2) is quality-related and is observed when the production process goes into an out-of-control state. When such failures are observed, an immediate shutdown occurs, and all corrective actions are carried out to restore the process to its normal operation (i.e., the in-control state). However, the process may also worsen due to external causes, such as operator mistakes, bad quality parts, environmental effects, etc. In this case, the process is reset to the in-control state.

The process was monitored to observe any occurrence of e*i*ther type of failure (F_1 and F_2) or any external causes (E). Therefore, these types of maintenance and quality planning failures must be considered. An optimization model is developed to generate integrated maintenance plans and quality control parameters for a real production system consisting of N components (i.e., a multi-component system). The following assumptions are considered while developing the optimization model:

- Each automatic machine can process only one part at a time, which imposes a single characteristic to quality (CTQ).
- Failure modes (F_1 and F_2) are independent. Failure reports from the company's records were used to obtain these probabilities.
- The required resources to detect, maintain and restore the process are always available, so no waiting times are considered.

3. Proposed Integrated Optimization Model

Figure 1 illustrates the adopted methodology to develop the proposed integrated optimization model. The proposed model integrates maintenance plans and quality control parameters to help improve the quality of the production operation in a real multi-component production system. The following steps briefly summarize the adopted methodology:

- Step 1: Defining the problem. The performance of the manufacturing system is significantly impacted by the breakdown of machines w*i*th multi-component.
- Step 2: Select the quality control chart and maintenance policy to develop the model.
- Step 3: Select the production system.
- Step 4: Monitor the selected machine w*i*th multi-component using a CUSUM chart.
- Step 5: Monitor the failure and repair rate. In this step, the data related to the mean time between failure and the mean time to repair all selected components were gathered and fitted for suitable distributions.
- Step 6: Develop the integrated model based on CM, PM intervals, and CUSUM chart parameters.
- Step 7: Solve the developed integrated maintenance policy and quality control mathematical model.
- Step 8: Sensitivity analyses were conducted to illustrate the robustness of the developed model due to the stochastic nature of the problem under investigation.
- Step 9: Discuss the obtained results.

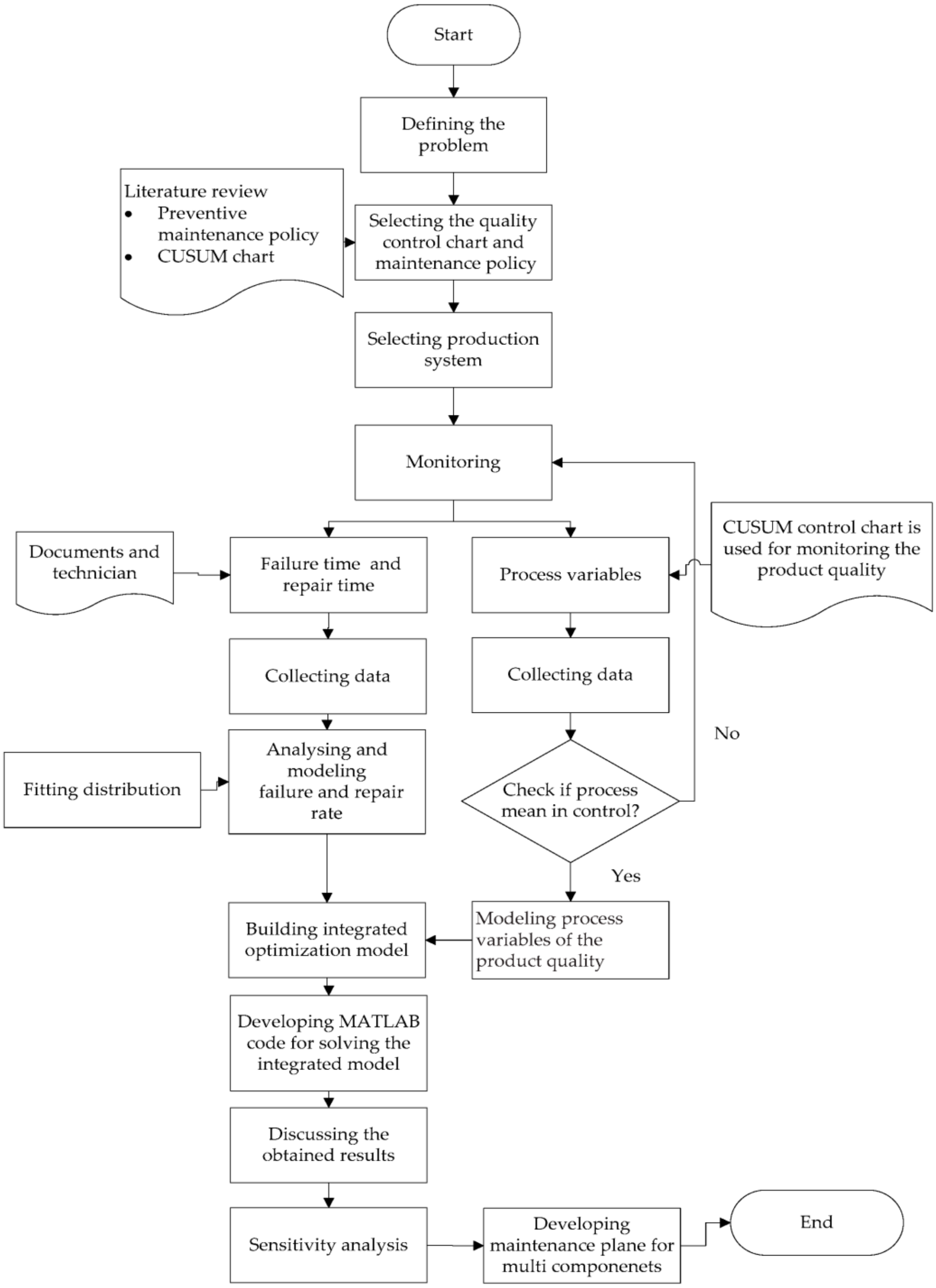

Figure 1. The workflow for the development of the integrated optimization model.

In the developed optimization model, we have suggested using the CUSUM control chart for detecting minor shifts in the process mean (i.e., normal state) during operation. The CUSUM control chart has been proven effective in such cases (i.e., analyzing quality characteristics of a product or monitoring failures that cause the process mean to shift during operation) [36–38], which motivates us to use it in our integrated model. For more details about the CUSUM control chart calculations, the reader is referred to [43]. The notations used in the developed model with their descriptions are listed in the appendix (under the List of Abbreviations section). However, we will define all the notations used in the text after the proposed model (i.e., objective function and constraints). The following stochastic and non-linear optimization model is proposed to solve the considered problem:

$$\text{Minimize } E[TC]_{(M*Q)CUSUM} \tag{1}$$

Subject to

$$n_{min} \le n_i \le n_{max} \ \ \forall i = 1, \ldots, N \tag{2}$$

$$h_{min} \le h_i \le h_{max} \ \ \forall i = 1, \ldots, N \tag{3}$$

$$d_{min} \le d_i \le d_{max} \ \ \forall i = 1, \ldots, N \tag{4}$$

$$k_{min} \le k_i \le k_{max} \ \ \forall i = 1, \ldots, N \tag{5}$$

$$t_{min}^{PM} \le T_i^{PM} \le t_{max}^{PM} \ \ \forall i = 1, \ldots, N \tag{6}$$

where $E[TC]_{(M*Q)CUSUM}$ is the expected total cost per unit of time function, which is a stochastic and non-linear function that includes maintenance (corrective and preventive) and quality (using CUSUM control charts) related costs. $E[TC]_{(M*Q)CUSUM}$ can be calculated using Equations (7)–(25). While n, h, d, k, and T_i^{PM} are the decision variables representing sample size, sampling frequency, control limit coefficient, decision interval, and preventive maintenance interval, respectively. The model will be solved to identify the optimal values for n, h, d, k, and T_i^{PM} while minimizing the total expected cost per unit of time ($E[TC]_{(M*Q)CUSUM}$). The model introduces the lower and upper bounds for each decision variable using constraints (2)–(6). The model will also predict the preventive maintenance interval, as shown in the case study section (Section 4).

As mentioned above, the expected total cost function per hour ($E[TC]_{(M*Q)CUSUM}$) consists of corrective maintenance cost (C_{CM}), preventive maintenance cost (C_{PM}), and cost of process quality loss ($[CQ]_{P-F}$). Thus, it is calculated as follows:

$$E[TC]_{(M*Q)CUSUM} = C_{CM} + C_{PM} + [CQ]_{P-F} \tag{7}$$

According to Pandey et al. [41], the corrective and preventive maintenance cost can be estimated as follows:

$$C_{CM} = \sum_{i=1}^{N} \left\{ \left[t_i^{CM} \times (P \times C_{PL} + C_L) + FC_i^{CM} \right] \times n_i^{CM} \right\} \tag{8}$$

$$C_{PM} = \sum_{i=1}^{N} \left\{ \left[t_i^{PM} \times (P \times C_{PL} + L) + FC_i^{PM} \right] \times n_i^{PM} \right\} \tag{9}$$

where t_i^{CM} and t_i^{PM} are the repair times required to perform a corrective and a preventive maintenance action on component i, FC_i^{CM} and FC_i^{PM} are the fixed cost of corrective and preventive maintenance actions conducted on component i, n_i^{CM} and n_i^{PM} are the expected number of corrective and preventive maintenance actions to be performed on component i, P is the production rate (Carton/h), C_{PL} is the cost of production lost (USD/h), and C_L is the cost of maintenance labor (USD/h). The expected number of corrective and preventive maintenance actions (n_i^{CM} and n_i^{PM}) are estimated, based on the assumption that the component i failures follow a Weibull distribution, as follows [44,45]:

$$n_i^{CM} = \int_0^{t_i^{PM}} \frac{\alpha_i}{{\gamma_i}^{\alpha_i}} t^{\alpha_i - 1} dt \tag{10}$$

$$n_i^{PM} = \frac{t_e}{T_i^{PM}} \tag{11}$$

where α_i and γ_i are the ith component's shape and scale parameters of the Weibull distribution, and t_e is the evaluation time. The preventive maintenance interval (T_i^{PM}) can also be estimated as follows [44]:

$$T_i^{PM} = \gamma_i \left[\frac{t_i^{PM}}{t_i^{CM}(\alpha_i - 1)} \right]^{1/\alpha_i} \tag{12}$$

Al-Shayea et al. [40] extended equations 10, 11 and 12 for multicomponents.

Finally, the expected costs associated with process quality loss during the evaluation period ($[CQ]_{P-F}$) are calculated using the following equation:

$$[CQ]_{P-F} = E\left[C_p\right] \times \frac{t_e}{t_c} \tag{13}$$

where $E\left[C_p\right]$ is the expected cost of process quality, and t_c is the length of time between sequential in-control periods of a process cycle. On the one hand, $E\left[C_p\right]$ includes the operating cost during the in-control and out-of-control states, which consists of the following cost functions:

- $E\left[C_f\right]$: the expected cost of false alarms, which includes the cost of both investigating and analyzing the false alarms, and it is given as

$$E\left[C_f\right] = C_f \times t_f \times \frac{S}{ARL_0} \tag{14}$$

where C_f is the cost associated with false alarms, t_f is the time required to investigate false alarms, and S is the expected number of samples. At the same time, the process is in the in-control state, and ARL_0 is the average run length when the process is in the in-control state. Both S and ARL_0 can be obtained as follows [41]:

$$S = \frac{e^{-\lambda h}}{1 - e^{-\lambda h}} \tag{15}$$

where h is the sampling frequency (the decision variable from Equation (3)) and λ is the total process failure rate due to external (λ_1) and machine degradation (λ_2), where $\lambda = \lambda_1 + \lambda_2$.

$$ARL_0 = \frac{e^{(2kb)} - 2kb - 1}{2k^2} \tag{16}$$

where k is the control limit coefficient of the CUSUM chart, and $b = d + 1.661$, where d is the critical threshold associated with the CUSUM chart.

- $E[C_s]$: the expected sampling cost per cycle, which can be calculated as follows [45]:

$$E[C_s] = \frac{(F + V \times n) \times \left\{ \frac{1}{\lambda} + t_f \times \frac{S}{ARL_0} + \left[h \times \left(ARL_1^{MC} \times \frac{\lambda_2}{\lambda} + ARL_1^{E} + \frac{\lambda_1}{\lambda} \right) \right] - \tau + (n \times t_s) \right\}}{h} \tag{17}$$

where F is the fixed cost, V is the variable cost, n is the sample size (the decision variable from Equation (2)), ARL_1^{MC} represents the average run length during a period of out-of-control operation due to machine failure, ARL_1^{E} is the average run length during an out-of-control period caused by external reasons, τ represents the average elapsed time between the last sample before an assignable cause and its occurrence when the maintenance and quality policies are linked, τ is also estimated as $h/2$, and t_s is the time required for sampling and chart plotting. Similar to ARL_0 obtained in Equation (16), ARL_1^{MC} and ARL_1^E are calculated using the following equation:

$$ARL_1 = \frac{e^{-2b(\delta-k)} + 2b(\delta-k) - 1}{2(\delta-k)^2} \tag{18}$$

where δ is the process magnitude, which has the value δ_{MC} for ARL_1^{MC} and δ_E for ARL_1^E.

- $E[L_{in}]$: the quality loss per unit of time in the control state, which is calculated using the Taguchi loss function (TLF), and is given as [45]

$$E[L_{in}] = P \times \frac{A\sigma^2}{n\Delta^2} \times \left[1 - \frac{2k}{\sqrt{2\pi}} e^{\frac{-k^2}{2}} - \beta\right] + \left(R' \times P \times C_r\right) \tag{19}$$

where A is the scrap or rework cost, R' is the percentage of non-conforming units in an in-control state, and Δ is a tolerance factor.

- $E[L_{out}]_{MC}$: the quality loss per unit time when the process is in an out-of-control state due to machine degradation, which is also calculated using the Taguchi loss function (TLF) and is given as [45]

$$E[L_{out}]_{MC} = P \times \frac{A\sigma^2}{n\Delta^2} \times \left[\begin{array}{c} \left(1+\delta_{MC}^2 \times n\right) \times \left\{\begin{array}{c} 1 - f\left(k - \delta_{MC} \times \sqrt{n}\right) + \\ f\left(-k - \delta_{MC} \times \sqrt{n}\right) \end{array}\right\} + \\ \frac{k+\delta_{MC}\times\sqrt{n}}{\sqrt{2\pi}} e^{\frac{-(k-\delta_{MC}\times\sqrt{n})^2}{2}} + \frac{k-\delta_{MC}\times\sqrt{n}}{\sqrt{2\pi}} e^{\frac{-(k+\delta_{MC}\times\sqrt{n})^2}{2}} \end{array}\right] + \left(R'_{\delta_{MC}} \times P \times C_r\right) \tag{20}$$

where $f(■)$ is the normal density function of a quality characteristic in an out-of-control state, and $R'_{\delta_{MC}}$ probability of non-conforming items being produced as a result of machine failure.

- $E[L_{out}]_E$: the quality loss per unit of time when the process is in an out-of-control state due to external factors (E), which is also calculated using the Taguchi loss function (TLF) and is given as [45]

$$E[L_{out}]_{MC} = P \times \frac{A\sigma^2}{n\Delta^2} \times \left[\begin{array}{c} \left(1+\delta_{E}^2 \times n\right) \times \left\{\begin{array}{c} 1 - f\left(k - \delta_{E} \times \sqrt{n}\right) + \\ f\left(-k - \delta_{E} \times \sqrt{n}\right) \end{array}\right\} + \\ \frac{k+\delta_{E}\times\sqrt{n}}{\sqrt{2\pi}} e^{\frac{-(k-\delta_{E}\times\sqrt{n})^2}{2}} + \frac{k-\delta_{E}\times\sqrt{n}}{\sqrt{2\pi}} e^{\frac{-(k+\delta_{E}\times\sqrt{n})^2}{2}} \end{array}\right] + \left(R'_{\delta_{E}} \times P \times C_r\right) \tag{21}$$

where R'_{δ_E} probability of non-conforming items being produced due to external factors.

- $E[C_r]$: the expected cost of detecting and repairing the process due to external causes (E).

$$E[C_r] = C_S \times t_r \times \frac{\lambda_1}{\lambda} \tag{22}$$

where C_S is the cost of resetting the process, and t_r is the expected time to reset the process.

- $E[C_{CM}]_{F_2}$: the expected cost of resetting and restoring the process (through CM) after a downtime of Type 2 (F_2), which is calculated as follows:

$$E[C_{CM}]_{F2} = \left\{MT_{CM}^{F_2} \times [P \times C_{PL} + L] + FC_p^{CM}\right\} \times \frac{\lambda_2}{\lambda} \tag{23}$$

where $MT_{CM}^{F_2}$ is the time required for corrective repairs, and FC_p^{CM} is the fixed cost for the conducted corrective repairs.

Thus, $E\left[C_p\right]$ is obtained as follows:

$$E\left[C_p\right] = E\left[C_f\right] + E[C_s] + E[L_{in}] + E[L_{out}]_{MC} + E[L_{out}]_E + E[C_r] + E[C_{CM}]_{F_2} \tag{24}$$

On the other hand, t_c includes time spent in control, time spent out of control, and time spent resetting processes or restoring machines. According to Pandey et al. study [45], the expected cycle length (t_c) can be calculated as follows:

$$t_c = \left[\frac{1}{\lambda} + t_f \times \frac{S}{ARL_0}\right] + \left[h \times \left(ARL_1^{MC} \times \frac{\lambda_2}{\lambda} + ARL_1^{E} \times \frac{\lambda_1}{\lambda}\right)\right] - \tau + (n \times t_s) + t_a + \left[t_r \times \frac{\lambda_1}{\lambda} + MT_{CM}^{F_2} \times \frac{\lambda_2}{\lambda}\right] \tag{25}$$

where t_a is the time required to determine the occurrence of assignable causes.

Based on the developed integrated optimization model introduced above in Equations (1)–(25), an optimal predictive maintenance plan will be developed to reduce defects and improve productivity. Figure 2 shows a flowchart for this process, which will result in developing a predictive maintenance policy based on the optimized maintenance interval for each machine (or component), i.e., T_i^{PM}.

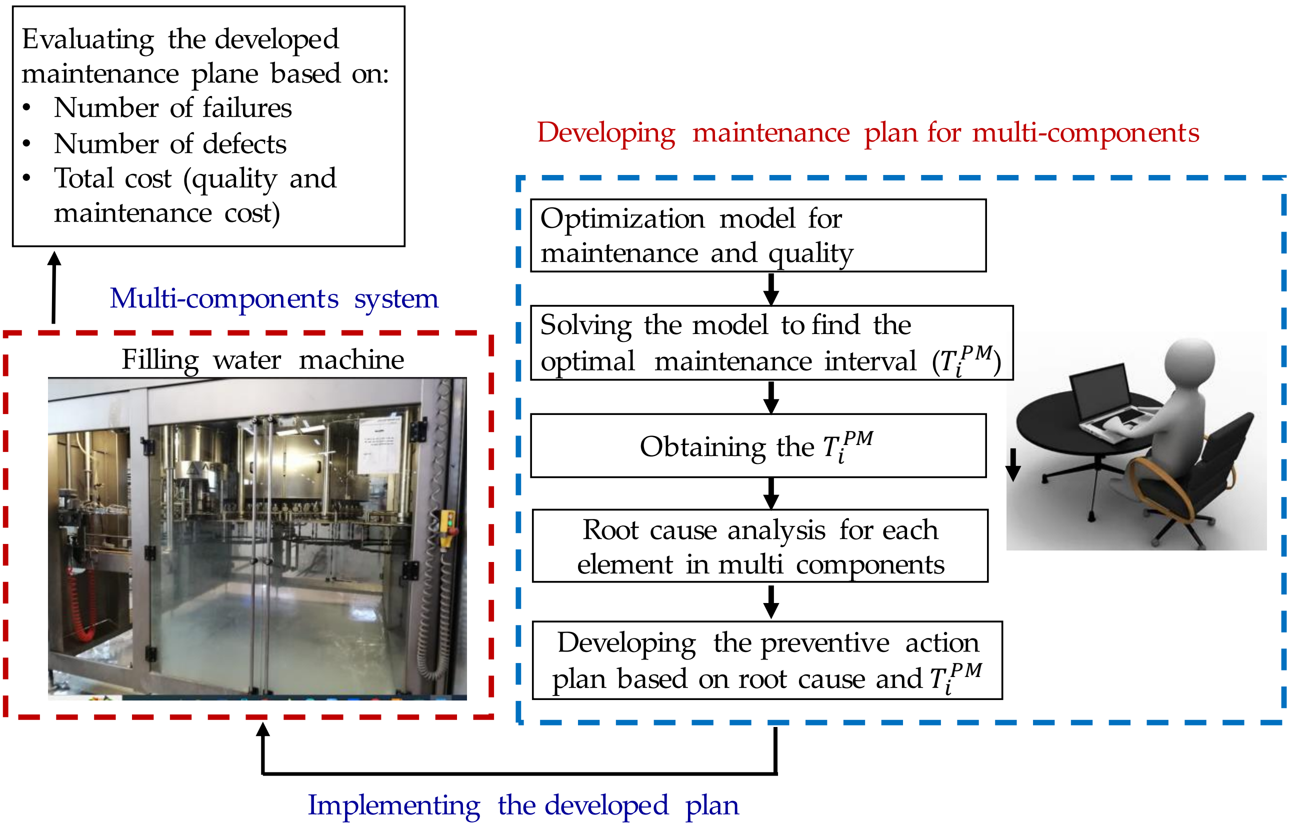

Figure 2. Flowchart for developing and implementing the predictive maintenance model.

4. Case Study

An automatic filling system is part of a fully automatic water bottling production line that is installed and operates in the National Mineral Water Company (AMWC). As shown in Figure 3, an automatic filling system is a filling machine consisting of the main components: Fill box flux, Flowmeter, Valve battery, Seals and O-rings for filling heads. Those components have been determined based on each component's importance and relation to this study. In this study, the filling machine represents a real-life application that demonstrates the suitability of the extended integration model. Maintenance and quality are two major issues in the company. The number of failures increased due to insufficient maintenance plans for detecting and preventing the failure of the main components. In addition, those failures influence product quality. However, the maintenance of this automated machine is very complex and needs a model for reducing the number of failures and enhancing product quality. This study aims to develop an integrated maintenance policy and quality model to overcome these issues.

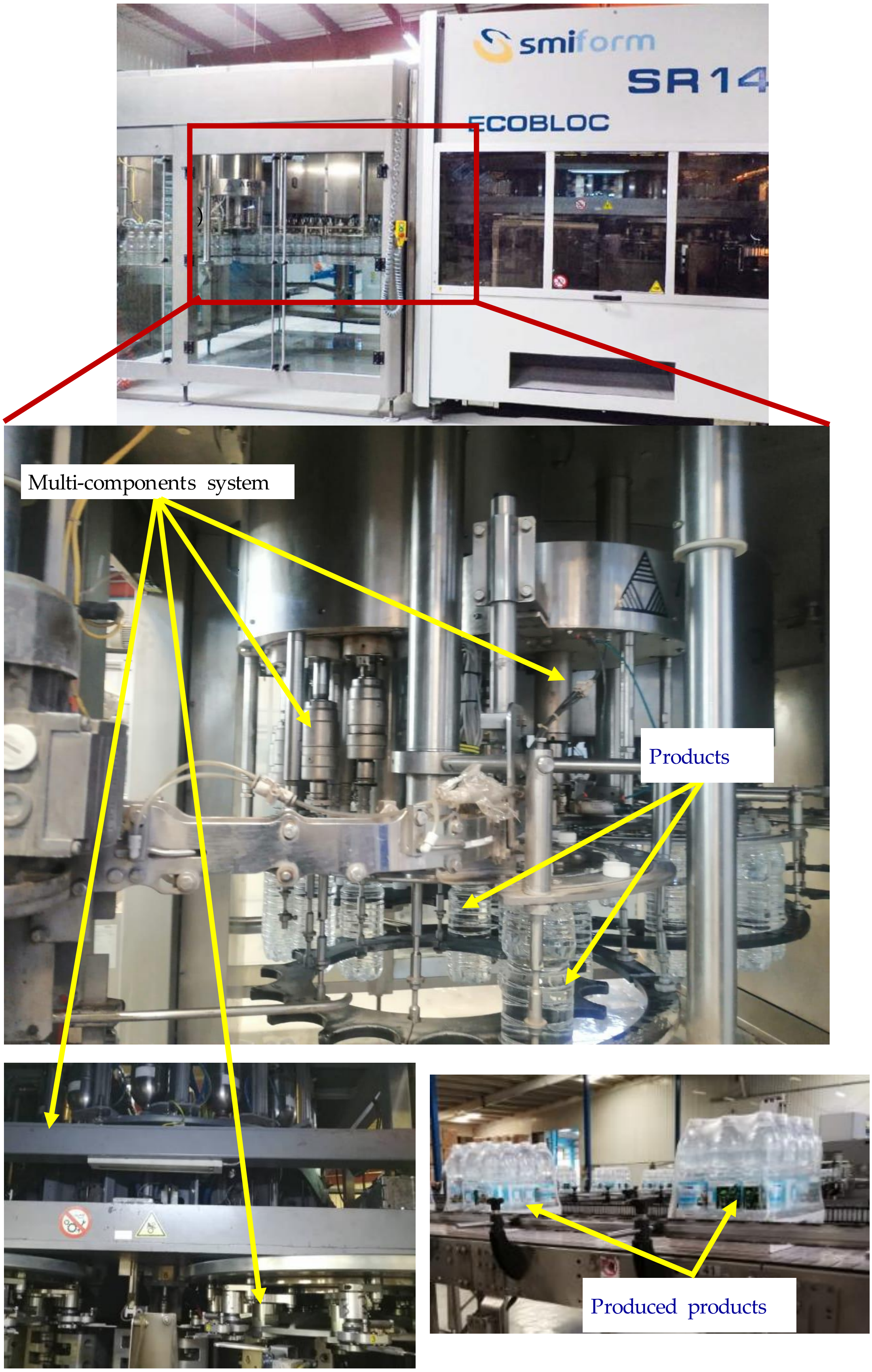

Figure 3. Filling process in the selected company.

5. Results

Failure data for machine components are collected and analyzed using the ReliaSoft Weibull++6 software to fit the distribution for each component. The analysis results show that each component failure can be modeled by a Weibull distribution. In addition, the Weibull distribution parameters (shape and scale parameter) for each component failure were used to calculate the number of failures and the preventive maintenance interval. Table 1 shows the Weibull parameters of the filling machine components.

Table 1. Parameters of maintenance for filling machine components.

(N_i)	Components	Number	Shape Parameter αi	Scale Parameter γi (hr)	Component Cost during Replacement (USD)	Sub-Component/ Consumable Cost through Repair (USD)	TR_{CMi} (h)	TR_{PMi} (h)
1	Filling Head	54			19,440 (USD 360/pc)	-	-	-
	Seals and O-rings for filling heads	108 set	3.7761	1294.3	8700 (USD 80.55/pc)	90	2	4
2	Flowmeter	54	1.4934	4426.8	162,000 (USD 3000/pc)	n/a	1.25	n/a
3	Valve Battery	14	1.7101	3745.1	14,000 (USD 1000/pc)	350	1	9
4	Fill box Flux	27	1.3329	4768.7	26,490 (USD 981/pc)	n/a	1.5	n/a

The filling machine runs in three shifts per day, 8 h per shift, for six days per week. The machine fills 330 mL water bottles w*i*th a process mean of 327 mL. and a process standard deviation of 1.5. The size of the shift that is due to external reasons is $\delta_E = 1$, and the shift due to machine failure is $\delta_{m/c} = 0.8$, which happens randomly and causes the process means to shift from μ_0 to ($\mu_0 + \delta$). The process quality monitoring is being monitored by using a CUSUM chart analysis. At this stage, the sought-after critical to quality characteristic (CTQ) is the shortage in filling the bottle's water volume. According to the adapted quality control policy, samples of filled water bottles were taken from the production line every hour (h), inspected by the naked eye, confirmed, and measured using a liquid measuring cup. The CUSUM chart is implemented as shown in Figure 4. It is evident that there is a shift in the process mean. This shift in the process is due to failure in the Seals and O-rings of the filling head (component number one) and valve battery (component number three). To solve this issue in the quality acceptance and to eliminate the process shifts, the PM must be scheduled and periodically replace the O-rings, change the O-rings of the valve battery, or change the card and check the inner springs of the valve battery.

The initial values of the necessary parameters of the process quality control chart to develop the integrated model are presented in Table 2.

The developed model is composed of mathematical equations to find the optimal values of sample frequency, sample size, the width of the control chart limit, and the preventive maintenance interval while minimizing the total expected cost of the maintenance and quality control. A computer programming code of the integrated model has been developed using MATLAB2020a. An optimal set of decision variables that minimizes the expected total cost per unit of time for the system ($E[TC]_{(M*Q)CUSUM}$) are presented in Table 3.

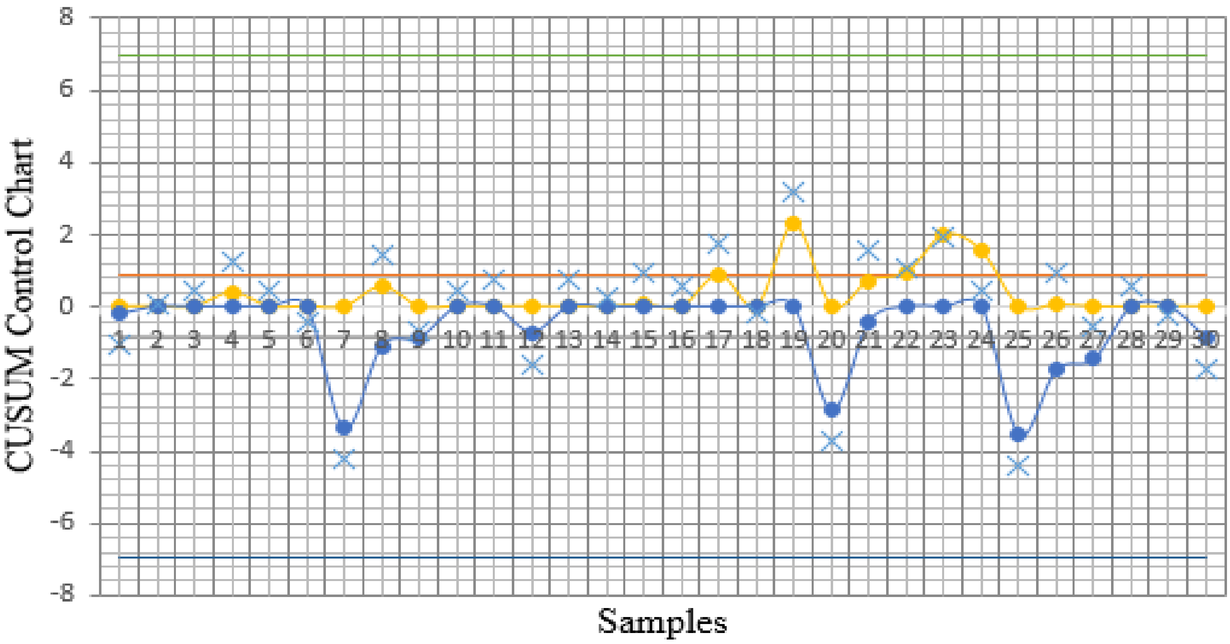

Figure 4. CUSUM chart in the water bottle production in AMWC.

Table 2. Initial parameters and their values in the case study.

Parameter	Value	Parameter	Value
P (cartons/h)	600	F (USD/bottle)	0.016
t_s (h)	0.33	V (USD/bottle)	0.036
t_f (h)	0.5	C_r	0.138
t_a (h)	0.5	C_f	9.2
t_r (h)	0.25	C_s	9
L(USD)/h	10	Δ	3
C_{PL} USD/h	8	A USD/bottle	0.069
δ_E	1	δ_{MC}	0.8

Table 3. An optimal set of decision variables for the proposed model.

Variables	Optimal Value
n	1
d	$\simeq$10
h	5
k	0.10166
T_i^{PM}	800
$E[TC]_{(M*Q)\ CUSUM}$	81.5479

5.1. Design of Experiments Based on One-Factor-at-a-Time

The one-factor-at-a-time approach was used to study the influence of the addressed decision variables on the expected total cost. Figure 5a illustrates the impact of sample frequency (h) on the anticipated total cost. Other parameters, decision interval, sample size, and preventive maintenance interval, were kept constant. It can be observed that the sampling frequency increases from 1 to 5, and the expected total cost slightly decreases and increases with the increase in h. Pandey et al. [45] found that the total cost decreases by reducing the sampling frequency from 2 samples per second to 3.5 samples per second and increases with increasing sample frequency. Figure 5b depicts the anticipated total cost decrease with the increase in decision interval (d). This can be explained by the fact that the increase in interval (d) will decrease the ARL, which will reduce the probabilities of repair, rejection, and out-of-control costs. Figure 5c shows the expected cost variations with the change in the control limit coefficient (k). It shows that the cost remains constant and started to rise with a value of 0.6 and higher for the control limit coefficient (k). Since the standard deviation value is fixed, increasing the control limit coefficient (k) value will increase the region between the control limits, which, in turn, increases the possibility of a poor product being accepted. Thus, rejection, repair, and out-of-control costs also decrease. Regarding the effect of preventive maintenance interval on the total cost, Figure 5d shows how the total cost decreases with the increase in PM interval until it reaches a certain point where the cost goes up again. That increase in cost is because longer PM intervals come with a higher probability of failure, which results in more costs (CM and replacement costs). The point with the minimum maintenance cost is the optimal PM interval.

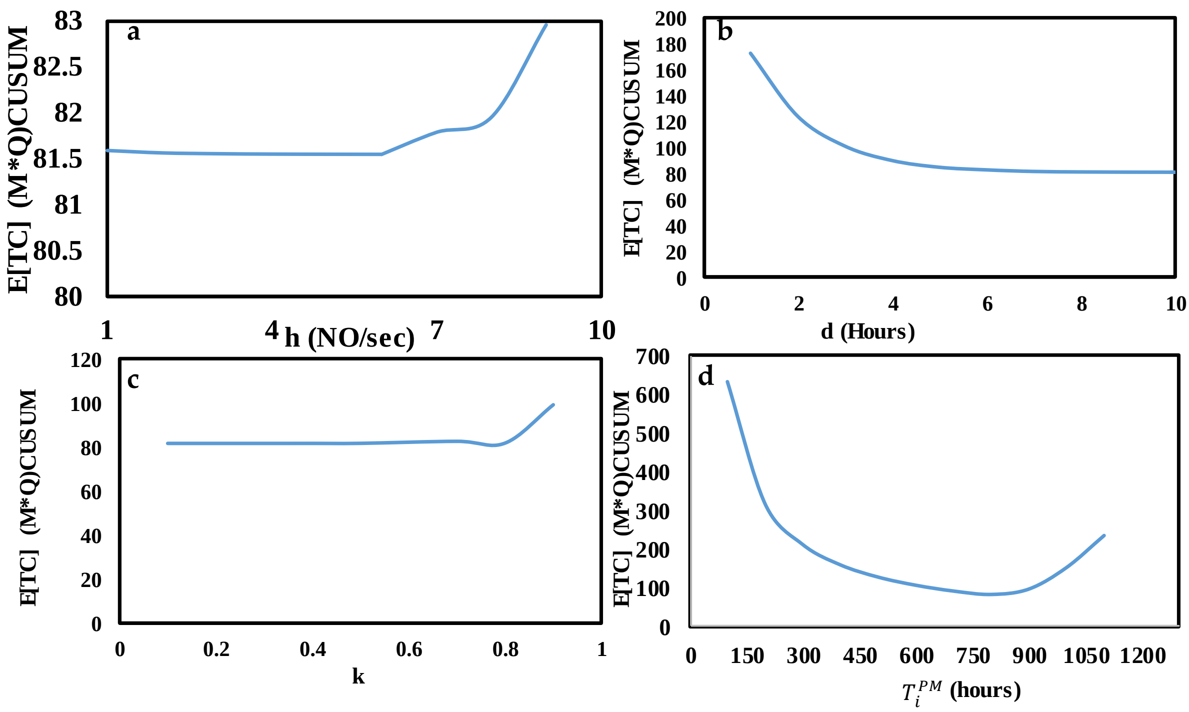

Figure 5. The impact of selected decision parameters on the expected total cost. (**a**) illustrates the impact of sample frequency (h) on the anticipated total cost, (**b**) the anticipated total cost decrease with the increase in decision interval (d), (**c**) the expected cost variations with the change in the control limit coefficient (k), (**d**) the total cost decreases with the increase in PM interval until.

Therefore, the obtained optimal ranges of the decision variables of the developed maintenance and quality control model are summarized in Table 4. In addition, the obtained optimal range of CUSUM chart parameters will be used to develop the CUSUM chart for monitoring product quality.

Table 4. Ranges of optimal values for the five decision variables.

Decision Variables	Ranges
n	1
d	8–≃10
h	4–5
k	0.10166
T_i^{PM}	750–850

5.2. Sensitivity Analysis

The sensitivity analysis issue is crucial and has been used for estimating the effects of the cost variables and process over the selected range on the integrated model of preventive policy and statistical quality control chart. In addition, this analysis further illustrates the relationship between CUSUM parameters and preventive maintenance, as well as the performance of the integrated model [39]. A sensitivity analysis was conducted on the importance of cost and process variables. Table 5 presents the selected variables and their range. Level 1 is the basic level employed to solve the integrated model for the secreted case study. Levels 2 and 3 were chosen based on the company allowance policies, representing the increase in the primary level by +10% (level 2) and +20% (level 3). After identifying the range, the developed model was solved according to the presented values of each variable to calculate the total cost per unit of time. The obtained results illustrate that the expected total cost per unit of time values are close to the optimal values found earlier in a similar setting. Consequently, the results show that the optimum design of the integrated maintenance policy and quality control chart model based on the CUSUM chart is generally robust to errors in variable estimation. The analysis shows that the proposed integrated model is robust to errors in variable estimations up to (+20%).

Table 5. Results of the sensitivity analysis and influence range of the basic variables on $E[TC]_{(M*Q)CUSUM}$.

Parameter	Basic Level 1	Level 2 (+10%)	Level 3 (+20%)	$E[CT]_{(M*Q)CUSUM}$ Basic Level	Level 2	Level 3	Range
ts	0.33	0.363	0.396	81.5479	81.5479	81.5479	81.5479
tf	0.5	0.55	0.6	81.5479	81.5479	81.5479	81.5479
ta	0.5	0.55	0.6	81.5479	81.5479	81.5479	81.5479
tr	0.25	0.275	0.3	81.5479	81.5479	81.5479	81.5479
A	0.069	0.0759	0.0828	81.5479	81.5479	81.5479	81.5479
F	0.016	0.176	0.0192	81.5479	81.5479	81.5479	81.5479
V	0.036	0.0396	0.0432	81.5479	81.5479	81.5479	81.5479
Cr	0.138	0.1518	0.1656	81.5479	81.5479	81.5479	81.5479
Cf	9.2	10.12	11.04	81.5479	81.5479	81.5479	81.5479
Cs	9	9.9	10.8	81.5479	81.5479	81.5479	81.5479
Lp	8	8.8	9.6	81.5479	89.6698	97.7117	81.5479–97.7117
L	10	10.10	12	81.5479	81.5496	81.5815	81.5479–81.5815

5.3. Preventive Actions to Reduce the Defects

More frequent defects are analyzed and evaluated periodically, and proper preventive actions are taken to keep these defects at a minimum. A policy is set to monitor the components in the filling stage and implement a preventive maintenance interval (T_i^{PM}) to predict future failures. The policy calls for each component to be checked against all possible failures in a very cost and time-effective way so that the filling process runs smoothly and the system is more available for production. Therefore, machine breakdown is much less, and the cost is reduced.

Based on this study, the developed predictive maintenance introduces preventive maintenance intervals (T_i^{PM}) with a timely schedule for preventive maintenance jobs for the N-components in the filling machine to spot any possible failure or defect. These preventive maintenance intervals should take place every 800 h. Figure 6 shows the improvement in total cost per hour. The total cost per hour is only USD 81.5479, which is much less than USD 163.12 by approximately 50% of lost production per hour due to product defects and the waste of production time during the repair of these defects. Therefore, the results indicate that the performance of the developed integrated model realizes the full potential of the maintenance model.

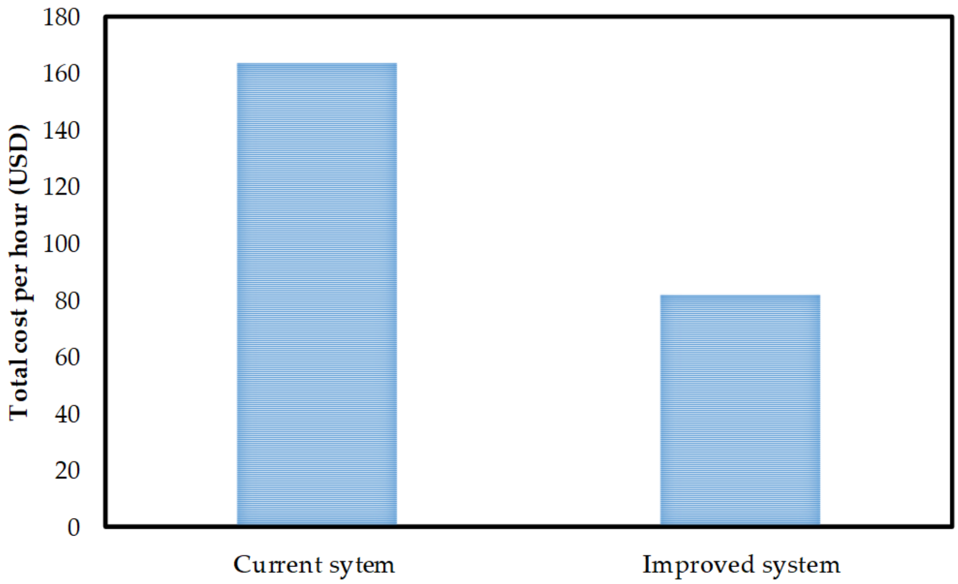

Figure 6. Comparison between the current system and the improved system.

The results obtained from the CUSUM chart were used to optimize the preventive maintenance interval (T_i^{PM}). Table 6 lists the developed solutions based on the optimized T_i^{PM} values for the main causes that should be implemented to reduce defects.

Table 6. The developed maintenance plan for multi-components based on optimal T_i^{PM}.

No.		Components
1		Seals and O-rings for filling heads
	Problem	Leakage in water
	Root causes	Replace the Seals and O-rings
	Solution	Periodically replace the O-rings
2		Flowmeter
	Problem	Water not flowing or continually flows
	Root causes	Malfunction with the internal electronic card
	Solution	Replace the flowmeter
3		Valve Battery
	Problem	Water not flowing according to the set level
	Root causes	The presence of an air leak from the O-rings An issue with the electronic card of the valve battery An issue in the inner Spring of the valve
	Solution	Change the O-rings of the valve battery or change the card. Change the inner springs of the valve battery
4		Fillbox Flux
	Problem	The filling cycle is not initiated, or filling heads are not working
	Root causes	An issue with the motherboard. The problem with the data cable The problem with the control system
	Solution	Check the electronic card for repair or replacement if available otherwise, replace it with a new Fillbox Repair the cable data or replace Reinstall the program for the Fill box to reset the system

6. Conclusions

This study proposed an extended integrated economic model for maintenance policies (maintenance interval) and CUSUM chart parameters for the multi-component system. This integration model is used to predict and optimize the preventive maintenance interval, sampling interval, sample frequency, sample size, and control limit chart to minimize the total cost per unit of time. The case study illustrates the problem, and sensitivity analysis demonstrates the dependence between quality control parameters and maintenance. The model has the following potential utilizations:

- Managers can control the quality of produced units and monitor the production line and its different states using the proposed solution steps.
- The proposed methodology helps to identify the optimal preventive maintenance interval needed to improve production output and minimize downtime w*i*th enhanced product quality.
- A maintenance plan for a multi-component system was developed based on the optimal value of preventive maintenance interval. The result showed that the total cost was reduced by approximately 50% compared w*i*th the current system.

This study shows that maintenance and process quality control based on the CUSUM chart is a more effective and powerful integrated model for improving product quality and process performance. This study could be expanded to include the integrated quality control and reliability-centered maintenance policy using the mixed EWMA and CUSUM control charts to detect a shift in the process mean.

Author Contributions: Conceptualization, F.N.; methodology, F.N., M.M.N. and M.G.; software, M.M.N. and M.G.; investigation, F.N.; resources, M.M.N. and M.G.; data curation, F.N., M.M.N. and M.G.; writing—original draft preparation, F.N.; writing—review and editing, M.M.N., M.G., K.N.A., E.H.A. and A.M.O.; visualization, F.N. and M.M.N.; supervision, M.A., M.M.N. and K.N.A.; Funding acquisition, K.N.A., E.H.A. and A.M.O. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data are available on request from corresponding author.

Acknowledgments: The authors would like to acknowledge the support provided by Taiz University.

Conflicts of Interest: The authors declare no conflict of interest.

List of Abbreviations

Notation	Descriptions
Decision variables	
h	Sample frequency (average number of samples obtained in one second (NO/second)
d	Decision Interval (hours)
k	Coefficient of control limit
n	Sample size
T_i^{PM}	Preventive maintenance interval (hours)
Parameters	
CTQ	Critical to quality characteristic
$f(\blacksquare)$	The normal density function of quality characteristic ($\blacksquare$)
n_i^{CM}	Number of corrective maintenance actions
n_i^{PM}	Number of preventive maintenance actions
$E[L_{in}]$	Quality loss per unit time in the control state (USD)
$E[L_{out}]_{MC}$	Quality loss per unit of time due to machine degradation (USD)
$E[L_{out}]_E$	Quality loss per unit of time due to external factors (E) (USD)
N	Number of components
n_i^{PM}	Number of preventive maintenance for ith component
P	Production rate (Carton/hour)
S	Expected number of samples while the process is in-control
R'	The proportion of non-conforming units when the process is in-control state
$R'_{\delta_{MC}}$	Probability of non-conforming items produced due to machine failure
R'_{δ_E}	Probability of non-conforming items produced due to external factors

δ	Magnitude of shift
μ_0	Target value (mm)
σ_0	Standard deviation
λ	Process failure rate
λ_1	Failure rate due to an external factor
λ_2	Failure rate due to machine degradation
αi	The shape parameter of Weibull distribution for *i*th component
γi	Scale parameter of Weibull distribution for *i*th component
Δ	Tolerance factor
Cost parameters	
A	Scrap or rework cost (USD)
C_{CM}	Corrective maintenance cost (USD)
C_{pM}	Preventive maintenance cost (USD)
$[CQ]_{P-F}$	Cost of process quality loss ($[CQ]_{P-F}$) (USD)
$E\left[C_p\right]$	The expected cost of process quality (USD)
$E\left[C_f\right]$	The expected cost of false alarms (USD)
$E[C_s]$	Expected sampling cost per cycle (USD)
$E[C_r]$	The expected cost of detecting and repairing the process due to external factors (E) (USD)
$E[C_{CM}]_{F_2}$	The expected cost of resetting and restoring the process (through CM) after a downtime of Type 2 (USD)
C_f	Cost of investigating a false alarm per unit of time (USD)
C_S	Cost of resetting (USD)
C_{PM}	The expected cost of preventive maintenance (PM) (USD)
$[CQ]_{P-F}$	The expected total cost of quality loss due to process failure
$E[TC]_{(M*Q)CUSUM}$	Expected total cost per unit of time (USD/hour)
F	Fixed cost of the sample (USD)
FC_i^{CM}	Fixed cost for corrective maintenance (USD)
FC_p^{CM}	Fixed cost of corrective maintenance of *i*th component (USD)
FC_i^{PM}	Fixed cost of preventing maintenance of *i*th component(USD)
C_L	The labor cost (USD/hour)
C_{PL}	Cost of production lost (USD/hour)
V	The variable cost of the sample
Statistical properties parameters	
ARL_0	Average run length in-control state (average number of samples taken before a false alarm occurs)
ARL_1	Average run length in an out-of-control state
ARL_1^E	Average run length due to external factors
ARL_1^{MC}	Average run length due to machine failure
Time parameters	
t_i^{CM}	Repair times required to perform corrective maintenance (hours)
t_i^{PM}	Repair times required to perform preventive maintenance (hours)
MTF	Mean time between process failure (hours)
t_a	An estimate of the time it takes to determine if assignable causes have occurred (hours)
t_c	Cycle time (hours)
t_e	Time evaluation period (hours)
t_f	False alarm search time (hours)
t_r	Expected time to reset the process (hours)
t_i^{CM}	Time required for corrective maintenance of *i*th component (hours)
t_i^{PM}	Time required for preventive maintenance of *i*th component (hours)
t_s	Time for the sample and plot a chart (hours)

References

1. He, Y.; Gu, C.; Chen, Z.; Han, X. Integrated Predictive Maintenance Strategy for Manufacturing Systems by Combining Quality Control and Mission Reliability Analysis. *Int. J. Prod. Res.* **2017**, *55*, 5841–5862. [CrossRef]
2. Esmaeili, E.; Karimian, H.; Najjartabar, M. Analyzing the Productivity of Maintenance Systems Using System Dynamics Modeling Method. *Int. J. Syst. Assur. Eng. Manag.* **2018**, *10*, 201–211. [CrossRef]
3. Pei, Y.; Liu, Z.; Xu, J.; Qi, B.; Cheng, Q. Grouping Preventive Maintenance Strategy of Flexible Manufacturing Systems and Its Optimization Based on Reliability and Cost. *Machines* **2023**, *11*, 74. [CrossRef]
4. Mishra, A.K.; Shrivastava, D.; Vrat, P. An Opportunistic Group Maintenance Model for the Multi-Unit Series System Employing Jaya Algorithm. *Opsearch* **2020**, *57*, 603–628. [CrossRef]
5. Azadeh, A.; Abdolhossein Zadeh, S. An Integrated Fuzzy Analytic Hierarchy Process and Fuzzy Multiple-Criteria Decision-Making Simulation Approach for Maintenance Policy Selection. *Simulation* **2016**, *92*, 3–18. [CrossRef]
6. Dao, C.D.; Zuo, M.J. Selective Maintenance of Multi-State Systems with Structural Dependence. *Reliab. Eng. Syst. Saf.* **2017**, *159*, 184–195. [CrossRef]
7. Laggoune, R.; Chateauneuf, A.; Aissani, D. Preventive Maintenance Scheduling for a Multi-Component System with Non-Negligible Replacement Time. *Int. J. Syst. Sci.* **2010**, *41*, 747–761. [CrossRef]
8. Shi, H.; Zeng, J. Real-Time Prediction of Remaining Useful Life and Preventive Opportunistic Maintenance Strategy for Multi-Component Systems Considering Stochastic Dependence. *Comput. Ind. Eng.* **2016**, *93*, 192–204. [CrossRef]
9. Shaheen, B.W.; Németh, I. Integration of Maintenance Management System Functions with Industry 4.0 Technologies and Features—A Review. *Processes* **2022**, *10*, 2173. [CrossRef]
10. Wang, K.; Deng, C.; Ding, L. Optimal Condition-Based Maintenance Strategy for Multi-Component Systems under Degradation Failures. *Energies* **2020**, *13*, 4346. [CrossRef]
11. Dekker, R.; Roelvink, I.F.K. Marginal Cost Criteria for Preventive Replacement of a Group of Components. *Eur. J. Oper. Res.* **1995**, *84*, 467–480. [CrossRef]
12. Huang, J. A Heuristic Replacement Scheduling Approach for Multi-Unit Systems with Economic Dependency. *Int. J. Reliab. Qual. Saf. Eng.* **1996**, *3*, 1–10. [CrossRef]
13. Samrout, M.; Yalaoui, F.; Châtelet, E.; Chebbo, N. New Methods to Minimize the Preventive Maintenance Cost of Series-Parallel Systems Using Ant Colony Optimization. *Reliab. Eng. Syst. Saf.* **2005**, *89*, 346–354. [CrossRef]
14. Laggoune, R.; Chateauneuf, A.; Aissani, D. Opportunistic Policy for Optimal Preventive Maintenance of a Multi-Component System in Continuous Operating Units. *Comput. Chem. Eng.* **2009**, *33*, 1499–1510. [CrossRef]
15. Rivera-Gómez, H.; Gharbi, A.; Kenné, J.P.; Montaño-Arango, O.; Corona-Armenta, J.R. Joint Optimization of Production and Maintenance Strategies Considering a Dynamic Sampling Strategy for a Deteriorating System. *Comput. Ind. Eng.* **2020**, *140*, 106273. [CrossRef]
16. Magnanini, M.C.; Tolio, T. Switching- and Hedging- Point Policy for Preventive Maintenance with Degrading Machines: Application to a Two-Machine Line. *Flex. Serv. Manuf. J.* **2020**, *32*, 241–271. [CrossRef]
17. Kuhnle, A.; Jakubik, J.; Lanza, G. Reinforcement Learning for Opportunistic Maintenance Optimization. *Prod. Eng.* **2019**, *13*, 33–41. [CrossRef]
18. Zhou, W.H.; Zhu, G.L. Economic Design of Integrated Model of Control Chart and Maintenance Management. *Math. Comput. Model.* **2008**, *47*, 1389–1395. [CrossRef]
19. Cheng, G.; Li, L. Joint Optimization of Production, Quality Control and Maintenance for Serial- Parallel Multistage Production Systems. *Reliab. Eng. Syst. Saf.* **2020**, *204*, 107146. [CrossRef]
20. Duffuaa, S.; Kolus, A.; Al-Turki, U.; El-Khalifa, A. An Integrated Model of Production Scheduling, Maintenance and Quality for a Single Machine. *Comput. Ind. Eng.* **2020**, *142*, 106239. [CrossRef]
21. Salmasnia, A.; Abdzadeh, B.; Namdar, M. A Joint Design of Production Run Length, Maintenance Policy and Control Chart with Multiple Assignable Causes. *J. Manuf. Syst.* **2017**, *42*, 44–56. [CrossRef]
22. Salmasnia, A.; Soltani, F.; Heydari, E.; Googoonani, S. An Integrated Model for Joint Determination of Production Run Length, Adaptive Control Chart Parameters and Maintenance Policy. *J. Ind. Prod. Eng.* **2019**, *36*, 401–417. [CrossRef]
23. Fath, B.D.; Bizon, N.; Yang, L.; Liu, Q.; Xia, T.; Ye, C.; Li, J. Preventive Maintenance Strategy Optimization in Manufacturing System Considering Energy Efficiency and Quality Cost. *Energies* **2022**, *15*, 8237. [CrossRef]
24. Ben-Daya, M. Integrated Production Maintenance and Quality Model for Imperfect Processes. *IIE Trans. (Institute Ind. Eng.)* **1999**, *31*, 491–501. [CrossRef]
25. Rahim, M.A. Economic Design of X Control Charts Assuming Weibull In-Control Times. *J. Qual. Technol.* **1993**, *25*, 296–305. [CrossRef]
26. Lee, B.H.; Rahim, M.A. An Integrated Economic Design Model for Quality Control, Replacement, and Maintenance. *Qual. Eng.* **2001**, *13*, 581–593. [CrossRef]
27. Hajej, Z.; Nyoungue, A.C.; Abubakar, A.S.; Mohamed Ali, K. An Integrated Model of Production, Maintenance, and Quality Control with Statistical Process Control Chart of a Supply Chain. *Appl. Sci.* **2021**, *11*, 4192. [CrossRef]
28. Baker, K.R. Two Process Models in the Economic Design of an x Chart. *AIIE Trans.* **1971**, *3*, 257–263. [CrossRef]
29. Montgomery, D.C.; Heikes, R.G. Process Failure Mechanisms and Optimal Design of Fraction Defective Control Charts. *AIIE Trans.* **1976**, *8*, 449–455. [CrossRef]

30. Lorenzen, T.J.; Vance, L.C. The Economic Design of Control Charts: A Unified Approach. *Technometrics* **1986**, *28*, 3. [CrossRef]
31. Haq, A.; Awais, M. New Shewhart-EWMA and Shewhart-CUSUM Control Charts for Monitoring Process Mean. *Sci. Iran.* **2018**, *26*, 3796–3818. [CrossRef]
32. Moskowitz, H.; Plante, R.; Chun, Y.H. Effect of Process Failure Mechanisms on Economic X Control Charts. *IIE Trans. (Inst. Ind. Eng.)* **1994**, *26*, 12–21. [CrossRef]
33. Liew, J.Y.; Khoo, M.B.C.; Neoh, S.G. A Study on the Effects of a Skewed Distribution on the EWMA and MA Charts. *AIP Conf. Proc.* **2014**, *1605*, 1034–1039. [CrossRef]
34. Sultana, I.; Ahmed, I.; Azeem, A.; Sarker, N.R. Economic Design of Exponentially Weighted Moving Average Chart with Variable Sampling Interval at Fixed Times Scheme Incorporating Taguchi Loss Function. *Int. J. Ind. Syst. Eng.* **2018**, *29*, 428–452. [CrossRef]
35. De Vargas, V.D.C.C.; Lopes, L.F.D.; Souza, A.M. Comparative Study of the Performance of the CuSum and EWMA Control Charts. *Comput. Ind. Eng.* **2004**, *46*, 707–724. [CrossRef]
36. Shrivastava, D.; Kulkarni, M.S.; Vrat, P. Integrated Design of Preventive Maintenance and Quality Control Policy Parameters with CUSUM Chart. *Int. J. Adv. Manuf. Technol.* **2016**, *82*, 2101–2112. [CrossRef]
37. Li, Y.; Chen, Z.; Pan, E. Joint Economic Design of CUSUM Control Chart and Age-Based Imperfect Preventive Maintenance Policy. *Math. Probl. Eng.* **2018**, *2018*, 9246372. [CrossRef]
38. Saha, R. Integrated Economic Design of Quality Control and Maintenance Management Using CUSUM Chart with VSIFT Sampling Policy. Master's Thesis, Bangladesh University of Engineering and Technology, Dhaka, Bangladesh, 2017.
39. Farahani, A.; Tohidi, H.; Shoja, A. An Integrated Optimization of Quality Control Chart Parameters and Preventive Maintenance Using Markov Chain. *Adv. Prod. Eng. Manag.* **2019**, *14*, 5–14. [CrossRef]
40. Al-Shayea, A.; Noman, M.A.; Nasr, E.A.; Kaid, H.; Kamrani, A.K.; El-Tamimi, A.M. New Integrated Model for Maintenance Planning and Quality Control Policy for Multi-Component System Using an EWMA Chart. *IEEE Access* **2019**, *7*, 160623–160636. [CrossRef]
41. Pandey, D.; Kulkarni, M.S.; Vrat, P. A Methodology for Simultaneous Optimisation of Design Parameters for the Preventive Maintenance and Quality Policy Incorporating Taguchi Loss Function. *Int. J. Prod. Res.* **2012**, *50*, 2030–2045. [CrossRef]
42. Kamal, M.M.; Arumugam, S.; Yousuf, M. Importance of Maintenance in the Context of Multicomponent Systems. *J. Qual. Maint. Eng.* **2015**, *4*, 433–448.
43. Page, E.S. Control Charts for the Mean of a Normal Population. *J. R. Stat. Soc. Ser. B* **1954**, *16*, 131–135. [CrossRef]
44. Cassady, C.R.; Kutanoglu, E. Integrating Preventive Maintenance Planning and Production Scheduling for a Single Machine. *IEEE Trans. Reliab.* **2005**, *54*, 304–309. [CrossRef]
45. Pandey, D.; Kulkarni, M.S.; Vrat, P. A Methodology for Joint Optimization for Maintenance Planning, Process Quality and Production Scheduling. *Comput. Ind. Eng.* **2011**, *61*, 1098–1106. [CrossRef]