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New Integrated Model for Maintenance Planning and Quality Control Policy for Multi-Component System Using an EWMA Chart

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ABSTRACT The performance of any production system is highly dependent on processing equipment that is free of faults and breakdowns. This can be achieved through maintenance planning and statistical quality control. The aim of this research is to develop a model for statistical quality control with an integrated optimization-based maintenance model for multicomponent series systems using an exponentially weighted moving average chart. The optimization model is based on both the preventive and corrective maintenance policies. The developed model is used to find the optimal values of sample size, sample frequency, width of control chart limit in units corresponding to the standard deviation, and interval of preventive maintenance while minimizing the total expected cost of the system per unit time. The study included a case study example to demonstrate its applicability and to analyze the influence of cost parameters on the developed integrated model. Finally, sensitivity analysis was conducted to demonstrate the effectiveness of the proposed model.

INDEX TERMS preventive maintenance, optimization, mathematical model, quality control, multi-component system, EWMA chart.

NOTATIONS

$(R_\delta)_E$	Probability of nonconforming items produced due to external reasons
$(R_\delta)_{M/C}$	Probability of nonconforming items produced due to machine failure
$[ETCPUT]_{(M*Q)_{EWMA}}$	Expected total cost per unit time of integrated maintenance and quality policy
ARL_{2_E}	Average run length due to external reasons when the system is in an out-of-control state
$ARL_{2_{M/C}}$	Average run length due to machine failure when the system is in an out-of-control state
ARL_1	Average run length when the system is in an in-control state
ARL_2	Average run length when the system is in an out-of-control state
C_F	Fixed cost per sample
C_{false}	Investigating a false alarm cost per unit time
C_{FCPCM}	Fixed cost per corrective maintenance
C_{Frej}	Cost of rejection when the process moves to out-of-control
C_{lP}	Cost of lost production
$C_{reseting}$	Cost of resetting
C_V	Variable cost per sample
$E\,[C_{CM}]_{FM_2}$	Expected cost of CM due to FM2
FC_{cm_i}	Fixed cost of corrective maintenance of i^{th} component
$MTTR_{CM}$	Mean time to repair for required corrective action

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$MTTR_{CM}$	Mean time to replacement for required corrective maintenance of FM2
N_{pm_i}	Number of preventive maintenances for i^{th} component
NF_i	Number of failures of i^{th} component
R'	Proportion of non-conforming units
T_{pm_i}	Preventive maintenance interval of i^{th}component
T_1	Expected time to determine the occurrence of an assignable cause
$T_{evalution}$	Evaluation time period available to carry out maintenance work
T_{false}	Expected time spent searching for a false alarm
$T_{resetting}$	Time to reset the process due to external reason
T_S	Time to take and chart a sample
TTR_{cm_i}	Time to replacement for corrective maintenance of i^{th} component
TTR_{pm_i}	Time to repair for preventive maintenance of i^{th} component
β_i	Shape parameter of i^{th} component
η_i	Scale and parameter of i^{th} component
θ_1	Failure due to external causes
θ_2	Failure due to machine degradation
μ_0	Process mean
σ_0	Process standard deviation
$E\left[C_{rejection}\right]_{M/C}$	Expected cost of rejection due to machine failure
$E\left[C_{false}\right]$	Expected cost for a false alarm
$E\left[C_{non-conforming}\right]$	Expected cost of non-conforming units when the process is in an in-control state
$E\left[C_{process}\right]$	Expected cost of process failure
$E\left[C_{reseting}\right]$	Expected cost of resetting
$E\left[C_{Sampling}\right]$	Expected cost of sampling
$E\left[TCQ\right]_{processfailure}$	Expected total cost of quality loss due to process failure
$E\left[T_{Cycle}\right]$	Expected process cycle time
$E\left[T_{false}\right]$	Expected time to investigate false alarms
$E\left[T_{in-control}\right]$	Expected in-control time
$E\left[T_{out-of-control}\right]$	Expected out-of-control time
$E\left[CMC\right]$	Expected cost of corrective maintenance
$E\left[PMC\right]$	Expected cost of preventive maintenance
$E\left[TMC\right]$	Expected total maintenance cost
FM1	Failure mode 1
FM2	Failure mode 2
$FN(\cdot)$	Cumulative distribution function of the standard normal distribution
Hs	Sample frequency
L	Optimal value of the control limit or decision boundary
LC	Labor cost
Ns	Sample size
PFM1	Probability of occurrence of failure due to FM1
PFM2	Probability of occurrence of failure due to FM2
PR	Production rate
δ	Magnitude of shift
θ	Process failure rate
λ	Control limit chart coefficient or smoothing parameter of the chart
τ	Mean elapsed time from the last sample prior to the assignable cause to the occurrence of the assignable cause when integrating maintenance and quality policy together

I. INTRODUCTION

The performance of a production system is significantly affected by the breakdown-free operations of equipment and processes. Performance can be improved if these breakdowns are minimized in a cost-effective manner. Maintenance actions and quality control policies play important roles in fulfilling this objective. A suitable preventive maintenance (PM) policy minimizes machine failure probability and improves machine performance in terms of product quality and production costs. Similarly, an appropriately designed quality control chart may assist in distinguishing any abnormal behaviors in processes and thereby aid in initiating a restoration action. However, both PM and quality control add costs, such as those related to down time, repair/replacement, sampling, and inspection. Traditionally, it is possible to optimize both of these activities independently. However, studies indicate the existence of a relationship between the maintenance of a component and process quality because maintenance tasks increase with component life and enhance the process quality [1]. Thus, joint consideration of PM and quality control policies may be more significant in terms of the cost of improving a production system's performance. Recent studies indicate that increasing research attention is focused on this joint consideration.

Several techniques and approaches have been performed on maintenance strategies and mathematical modeling [2]. Wang [3] suggested that most optimal maintenance models in the literature use the optimization criterion of minimizing total maintenance cost. Laggoune *et al.* [4] proposed a PM plan method to reduce the cost rate of a multicomponent series system subjected to random failures. The works in [2], [5], [6] used common planning approaches for multicomponent manufacturing systems involving group/block replacement models based on time, cost, or both. Samrout *et al.* [7] presented an approach to reduce preventive maintenance cost of series-parallel systems using ant colony optimization. Duarte *et al.* [8] introduced an optimization algorithm for maintenance management of a series system based on PM. In addition, Cassady and Kutanoglu [9] suggested an integrated model incorporating production scheduling and preventive maintenance planning for a single production machine to minimize the total expected weighted completion time of jobs. Kuo [10] presented a maintenance strategy for a joint machine and product quality control issue of a finite horizon discrete time state unobservable Markovian deteriorating batch production system, using dynamic programming. Kouki *et al.* [11] developed an approach joining quality control and maintenance aspects by considering a PM strategy with minimal repair to minimize the total cost (including costs of non-conforming units and maintenance) per unit time. Ho and Quinino [12] presented an integrated model for process control and on-line corrective maintenance using a variable sampling interval (VSI) and Markov chain approach. Mehrafrooz and Noorossana [13] improved the study of Linderman *et al.* [14] and suggested an integrated model jointly considering PM and complete failure. Yeung *et al.* [15] presented a model for optimization of an X-bar control chart in conjunction with an age-dependent preventive replacement policy. Zhou and Zhu [16] developed an integrated mathematical model for maintenance and process quality control using a grid-search approach.

Panagiotidou and Tagaras [17] proposed a model with an age-based PM policy for maintenance procedure optimization for a production process with two states of quality, namely process quality failure and shift.

Liu *et al.* [18] proposed a Markov chain method for the joint optimization of an X-bar chart and condition-based maintenance policy for a two-unit series system. Zhong and Ma [19] proposed an integrated model of SPC and maintenance for a two-stage dependent process through modeling of eight different production scenarios. Rasay *et al.* [20] developed an integrated model for maintenance planning and statistical process control for a single component of a machine system. The process has two operational states, including an in-control state and an out-of-control state, where the process failure mechanism is supposed as a general continuous distribution with non-decreasing failure rate. Bahria *et al.* [21] developed an integrated approach for the joint control of production, maintenance, and quality for batch manufacturing systems. They considered systems subject to degradation, which is the origin of the production of defective units. The quality control of lots produced was performed using an X-bar control chart.

Based on the abovementioned studies, the following observations are made:

1) Integrated models often ignore the possibility of component failure in which downtime of the machine or improper performance could lead to poor product quality. Therefore, effective methods for maintenance must be developed.
2) Most studies mainly focus on comprehensive PM or a preventive replacement policy that restores the equipment to a good-as-new state.
3) There is a lack of studies that show how to determine the optimal values of decision variable parameters of the process quality control model, i.e., sample size (Ns), frequency of sample frequency (Hs), width of control chart limit in units corresponding to the standard deviation (L), and chart parameter (λ)). There is also no clear strategy to determine the optimal average observation number for use in both in-control and out-of-control states.
4) As mentioned earlier, when a machine has a failure, it could create poor quality products, leading to product rejection. Corrective maintenance costs consist of time and costs involved in repair/replacement as well as the cost of damaged products.
5) In any production system, the corrective maintenance cost significantly exceeds the preventive maintenance cost. The cost of rejection is very high, thereby reducing the PM period. This aspect is largely neglected in most maintenance optimization models.

Thus, it is observed that most of the integrated models developed for integrating maintenance and process quality control do not employ an exponentially weighted moving average (EWMA) control chart. Also, previously developed integrated approaches do not consider maintenance of multi-component systems. Therefore, this study presents an integrated model to determine the optimal expected total cost of corrective maintenance (CM), PM, process failures, sampling, and inspection by jointly optimizing maintenance procedures and quality control chart parameters. In several preventive maintenance models, the system can be assumed to be in one of two states after each PM action: good-as-new or bad-as-old. There is an important case in which the failure pattern changes in a preventively maintained system. One method to model this considers incomplete maintenance in which the failure rate of the system after each PM action is between the two states of good-as-new and bad-as-old. It is assumed that each specific PM action reduces the rate of component failure and evolves with the component life. If the PM for a system is designed using incomplete maintenance, the component failure behavior is supposed to be changed after each PM action and affects the quality control chart policies. Thus, an EWMA chart is used for quality control [22].

This involves performing PM action when the deviation from the product feature used to measure quality is no longer at its target value. It is our goal to develop joint models that incorporate maintenance policy and quality control to take advantage of both methodologies. Therefore, the main contribution of this study is the implementation of a new integrated approach to optimize maintenance actions and process control policies to classify machine failures. When a potential failure occurs, CM actions for restoring the machine are performed. Simultaneously, the process is monitored using a control chart to identify the actual state of operation. When a quality shift is detected due to machine degradation (partial failure), the CM tasks necessary to restore the machine to an in-control state are performed. Whenever a quality shift is detected due to external reasons, a resetting of the process is initiated to return the operation to an in-control state. Hence, this type of maintenance action has double the benefits: eliminating costs related to out-of-control operations and machine degradation and improving machine reliability by protecting it against failures.

In the next section, the problem description, model building, and assumptions are presented. Section III presents the integrated cost model, followed by a solution procedure in Section IV. In Section V, the sensitivity analysis results are reported. Finally, Section VI concludes the paper.

II. PROBLEM DESCRIPTION

In this study, we considered two failure consequences associated with component failures: (1) failure leading to immediate breakdown of the machine (failure mode 1 (FM1)) and (2) failure leading to reduction in process quality due to shifting of the process mean (failure mode 2 (FM2)).

A failure is defined as any event whereby the machine either shuts down or produces more rejections than expected. For example, if a work head belt of a grinding machine is broken, the machine to stop working completely, while if a ball screw of a chuck nut is loosened, the grinding machine may continue to run but may also produce components with poor quality. Therefore, it is necessary to consider these types of failures and failure costs, which may be defined in maintenance planning decisions. The latter example above can be considered as FM2, i.e., deterioration of machine performance without complete failure [23], [24].

A. PROPOSED METHODOLOGY

Consider a production machine consisting of N serially related components, where each component can be exposed to degradation due to continuous operation over a period of time and produces matching and non-matching products. For each component, the time to failure can be represented by two Weibull distribution parameters: scale (η) and shape (β). The machine operates 6 days weekly through 12 working hours in two shifts. If a failure occurs in any components, minimal repair is conducted to return the machine to working order. The maintenance decision requires consideration of system availability, the available time for maintenance, and production requirements. For every component, either *replace* or *repair* is selected. The service age of a component is improved by maintenance; however, component failure may occur randomly. The proposed methodology is as follow:

Stage 1: Select a multi-component single machine production system, i.e., one for monitoring. The monitored production system must be in an ‘‘in-control’’ state prior to the monitoring process.

Stage 2: Monitor for quality loss of the product or any machine failure causing the process mean to shift. In this step, an EWMA control chart is used for monitoring a single critical to quality (CTQ) characteristic.

Stage 3: Build the integrated model of CM, PM, and SPC.

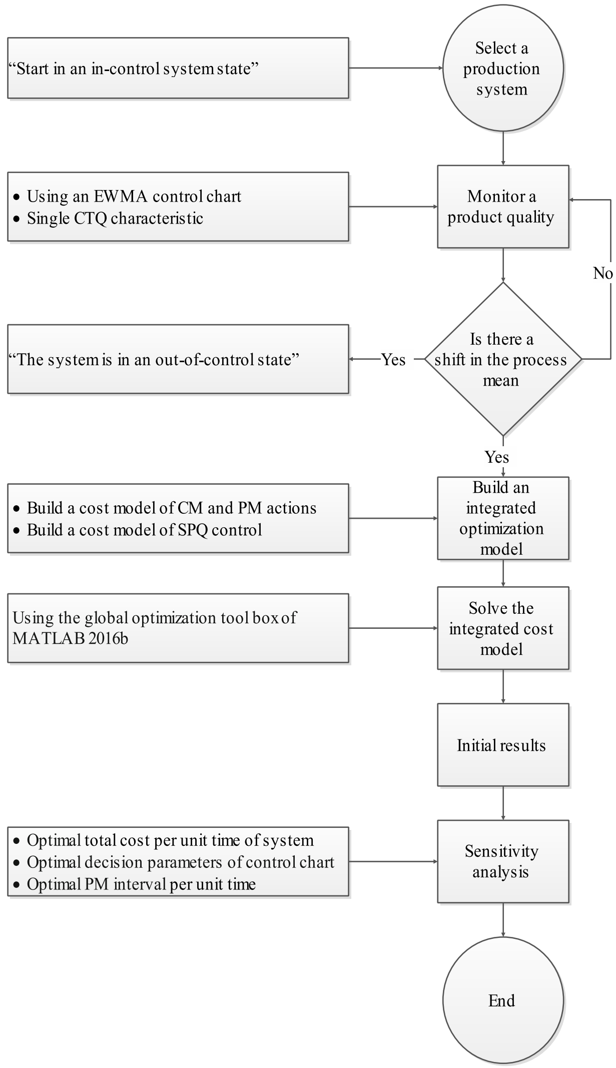

FIGURE 1. Flow chart of the proposed methodology.

Stage 4: Apply the global optimization tool box from the MATLAB software to solve the integrated model.

Stage 5: Conduct sensitivity analysis to determine the range of decision parameters of the control chart and the PM interval. These are used to show the impact of controlled parameters on the system as a whole. Figure 1 shows a flow chart of the proposed methodology and its implementation stages.

B. MODEL FORMULATION

The corrective maintenance actions are implemented to repair and restore the machine to active status when FM1 occurs. However, FM2 causes rejection of components; therefore, if FM2 is observed, the process is immediately stopped and corrective maintenance tasks are implemented to repair and restore the process to its normal state. Detection of the FM2 may always be possible, which leads to the machine continuing to produce more defective items than expected. In the case of FM2, the cause could be external (E), such

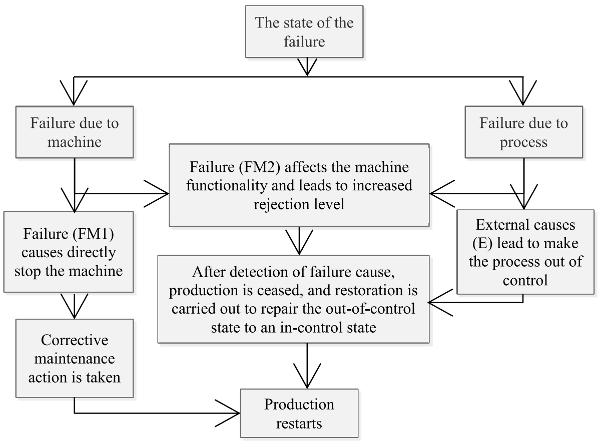

FIGURE 2. States of failure mode in machine and processing.

as environmental factors, operator errors, or incorrect tools. In this study, an EWMA control chart is used to monitor the production process to detect FM2 or any external causes. PM actions are used to minimize the probability of both FM1 and FM2 events. By reducing the causes of FM2, a reduction in costs due to an out-of-control status is achieved. As a result, PM consumes some of the machine production time and some production resources. Figure 2 illustrates the modes of machine and process failures.

C. ASSUMPTIONS

Our assumptions are as follows:

1) A multi-component series system produces a single part with a single (CTQ) characteristic.
2) The production process is in an in-control state with process mean μ_0 and standard deviation σ_0.
3) The time until the assignable cause occurs is a random exponentially distributed variable.
4) The process mean shift is $(\mu_0 + \delta)$, and the standard deviation (σ_0) remains constant. Additionally, δ denotes the magnitude of the shift.
5) The process is monitored using an EWMA control chart.
6) FM1 and FM2 are independent and based on a time to failure distribution. The probabilities of FM1 and FM2 are PFM1 and PFM2, respectively, and PFM1+PFM2 = 1. These probabilities can be acquired from quality and failure reports provided by maintenance and production line personnel. The reports includes component ID, time of repair, time to failure, action taken, failure mode, and failure cost.
7) Corrective maintenance should be minimized while preventive maintenance actions could be imperfect.
8) The required resources and services are always available.
9) The system stops during detection and restoration periods. After restoration by corrective maintenance, the system returns to the normal status process.

D. EXPONENTIALLY WEIGHTED MOVING AVERAGE CONTROL CHART

In the late 1950s, Roberts [25] introduced the first EWMA control chart, which was further studied by Crowder [26]–[28] and Lucas and Saccucci [29]. It is considered as a good alternative to the CUSUM and other control charts proposed by other researchers [25]. Gomes *et al.* [30], Aslam *et al.* [31], and Riaz and Ahmad [32] highlighted that EWMA charts are used for detecting small shifts in the process mean. EWMA can detect shifts of $0.5\sigma_0$ to $2\sigma_0$ much faster than Shewhart charts (i.e., X-bar charts and individual-X charts) with the same sample size. Montgomery [33] explained that although EWMA is presented as a statistical process monitoring tool, it really has a much wider interpretation. From the viewpoint of statistical process control, an EWMA control chart is comparable to a CUSUM control chart in its capacity of monitoring a process and detecting the presence of assignable causes that result in changes. However, EWMA forecasts where the average will be in the next period, which makes it easily applicable in industry. In addition, EWMA control charts may be used for autocorrelated processes with a slowly drifting mean. Therefore, EWMA is adapted for autocorrelated data for identifying similarities between sample observations and time lag between them; other control charts (i.e., CUSUM and Shewhart) assume independence between samples [30]. This makes EWMA a more powerful tool.

The EWMA statistic is defined as follows:

$$\mathrm{Z_i} = \lambda \mathrm{X_i} + (1-\lambda)\,\mathrm{Z_{i-1}}, \quad 0 < \lambda \leq 1 \tag{1}$$

In (1), λ is the chart parameter, which is pre-estimated. The initial value is the process mean, i.e., $\mathrm{Z}_0 = \mu_0$, where $\mathrm{Z_i}$ denotes the real value of X obtained from sample i. The upper and lower control limits UCL and LCL, respectively, and centerline CL for the proposed EWMA control chart are as defined as follows:

$$\mathrm{UCL} = \mu_0 + \mathrm{L}\sigma_0\sqrt{\frac{\lambda}{(2-\lambda)}\left[1-(1-\lambda)^{2i}\right]} \tag{2a}$$

$$\mathrm{CL} = \mu_0, \quad \text{and} \tag{2b}$$

$$\mathrm{LCL} = \mu_0 - \mathrm{L}\sigma_0\sqrt{\frac{\lambda}{(2-\lambda)}\left[1-(1-\lambda)^{2i}\right]} \tag{2c}$$

where L denotes the decision boundary of the control chart; it is a predefined constant depending on the false alarm rate. An out-of-control state is defined using the proposed EWMA control chart when $\mathrm{Z_i}$ is plotted without specific control limits. For large samples, $\left[1-(1-\lambda)^{2i}\right]$ tends to 1, and the upper and lower control limits are simplified as follows:

$$\mathrm{UCL} = \mu_0 + \mathrm{L}\sigma_0\sqrt{\frac{\lambda}{(2-\lambda)}} \quad \text{and } \mathrm{LCL} = \mu_0 - \mathrm{L}\sigma_0\sqrt{\frac{\lambda}{(2-\lambda)}}$$

In this study, parameters λ and L were used to determine the‘out-of-control average run length ARL_2, which is defined as the average number of observation units taken when the process mean has been shifted from μ_0 to $(\mu_0 + \delta)$, for the magnitude shift of δ, which occurs due to any external causes or degradation of the production machine. The average run length when the process mean is in an in-control state is denoted by ARL_1 and is computed using (3) [34].

$$ARL_1\,(a, b) = \frac{1}{1 - FN\left(\frac{(K-a)\sqrt{n}}{b}\right) + FN\left(\frac{(-K-a)\sqrt{n}}{b}\right)} \quad (3)$$

In this model, it assumed that the observed subgroups $\{X_{i,1}, X_{i,2}, \ldots, X_{i,n}\}$ at period time $i = 1, 2, \ldots n$, where n is the subgroup size, are independent and distributed as $X_{i,j} \sim N\,(\mu_0 + a\sigma_0, b\sigma_0)$, $i = 1, 2, \ldots, 1 \leq j \leq n$. The process is statistically in an in-control state when $a = 0$ or $b = 1$, while the process is considered in an out-of-control state when the process mean μ_0 has changed $(a \neq 0)$, the process standard deviation σ_0 has changed $(b \neq 1)$, or both.

In (3), $FN(\cdot)$ is the cumulative distribution function of the standard normal distribution, and $K = 3/\sqrt{n}$, which corresponds to the false alarm rate $\alpha = 0.0027$ or an in-control $ARL_1 = 370$. Several studies have computed ARL_2 depending on the pre-specified optimum value of ARL_1 of 370 [22]. Srivastava and Wu [35] proposed an optimum value of λ, which minimizes ARL_2 for given ARL_1. This is a very good approximate to out-of-control ARL_2, which is produced through a Markov-chain approach [29]. For sufficiently large ARL_1, the optimum λ is given by

$$\lambda \approx \frac{2c^*\delta^2}{b - \log(b)}, \quad (4)$$

where

$$b = 2\log\left[2\left(\frac{2}{\pi}\right)^{0.5} c^*\delta^2 T\right] \quad (4a)$$

where c^* is an optimal constant value that minimizes ARL_2. Srivastava and Wu [35] found that the optimal value of c^* is 0.5117.

The width of control limit L is approximated as

$$L \approx \left[b - \log(b)^{0.5} - \lambda\right] \quad (5)$$

The corresponding minimum ARL_2 is then expressed as

$$ARL_2 \approx \frac{1}{\delta^2}\left(1.2277L^2 - 2.835 + 9.740L^{-2}\right) + \frac{1}{2}(1 - \lambda) \quad (6)$$

III. COST MODEL METHODOLOGY AND OPTIMIZATION

To demonstrate the benefits of integrated PM and SPC with the EWMA control chart, the next section presents the cost model development to capture the costs correlated with process manufacturing that are affected by maintenance planning and quality control policies. These total costs include the preventive and corrective maintenance costs and the process failure costs through the evaluation period.

A. COST MODEL FOR CORRECTIVE AND PREVENTIVE MAINTENANCE POLICIES

The following data are required to determine the corrective and preventive maintenance costs:

1) Time to implement the maintenance actions and any logistical delays of materials,
2) costs of materials, labor, and downtime,
3) equipment restoration degree (i.e., good-as-new, bad-as-old, or imperfect) and restoration factor determined by expert judgement [36], and
4) probability of equipment failure captured from historical data.

The expected total maintenance cost is the sum of the expected cost of preventive and corrective maintenances and is expressed as

$$E[TMC] = E[CMC] + E[PMC] \quad (7)$$

E[CMC] and E [PMC] are corrective and preventive maintenance, respectively. These are described and calculated in the following sections.

1) CORRECTIVE MAINTENANCE POLICY COST MODEL

The corrective maintenance cost is the combination of costs due to failure mode detection (down time costs for repairing and restoring the machine during a given time period and costs of labor and materials required) and is expressed as

$$E[CMC] = \sum\nolimits_{i=1}^{N} \{[TTR_{cm_i} \times (PR \times C_{lP} + LC) + FC_{cm_i}] \times NF_i\} \quad (8)$$

TTR_{cm_i} is the replacement time for corrective maintenance of the i^{th} component, PR is the production rate, C_{lp} is the cost due to lost production, and LC is the labor cost. FC_{cm_i} is a fixed cost of corrective maintenance for the i^{th} component or the cost of the i^{th} component. NF_i is number of failures of the i^{th} component. In this study, the expected number of corrective maintenances (NF_i) was obtained using the hazard function for given values of η and β, which are the characteristic life and shape parameters, respectively, during a given PM interval for the machine (T_{PM}) [9].

$$NF_i = \int_0^{T_{pm_i}} z(t)\,dt = \int_0^{T_{pm_i}} \frac{\beta_i}{\eta_i^{\beta_i}} t^{\beta_i - 1} dt \quad (9)$$

where z (t) corresponds to the hazard function of the underlying Weibull probability distribution, and η_i and β_i are the scale and shape parameters of the i^{th} component, respectively.

2) PREVENTIVE MAINTENANCE POLICY COST MODEL

The preventive maintenance costs include the down time costs due to repairs and restoration of the components in addition to the costs of required labor and materials. The preventive maintenance cost is expressed as

$$E[PMC] = \sum\nolimits_{i=1}^{N} \{([TTR_{pm_i} \times (PR \times C_{lP} + LC)] + FC_{pm_i}) \times N_{pm_i}\} \quad (10)$$

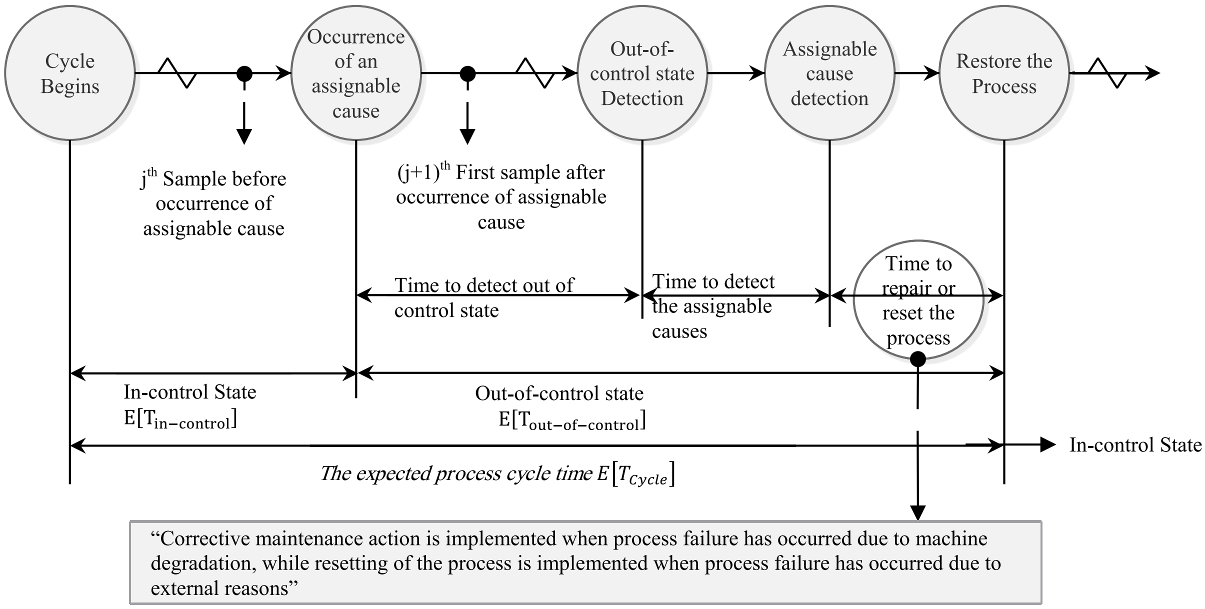

FIGURE 3. **An expected process control cycle length.**

TTR_{pm_i} is the preventive maintenance repair time of the ith component. FC_{pm_i} is the fixed cost of preventive maintenance of the ith component or the cost of consumables during the repair of the ith component. N_{pm_i} is the number of preventive maintenances of the ith component, which is calculated as [37]

$$N_{pm_i} = \frac{T_{evalution}}{T_{pm_i}} \tag{11}$$

T_{pm_i} is the preventive maintenance interval of the ith component and is calculated as [9]

$$T_{pm_i} = \eta_i \left[\frac{TTR_{pm_i}}{TTR_{cm_i}(\beta_i - 1)}\right]^{\frac{1}{\beta_i}} \tag{12}$$

B. COST MODEL OF PROCESS QUALITY POLICY $\left(E\,[TCQ]_{process\ failure}\right)$

The expected process control cycle length equation is derived and used to develop the expression for the expected process failure cost.

1) EXPECTED PROCESS CYCLE LENGTH $E\left[T_{Cycle}\right]$

The expected process cycle length is defined as the expected time between sequential in-control periods. This includes in-control time, out-of-control time, and time of process resetting or machine restoration. The expected cycle length is shown in Figure 3.

a: EXPECTED IN-CONTROL TIME $E\left[T_{in-control}\right]$:

The in-control time is assumed to follow a negative exponential distribution with mean $1/\theta$ and includes a mean time to failure and expected time to investigate false alarms $E\,[T_{false}]$ [38]. It is expressed as follows:

$$E\,[T_{in-control}] = 1/\theta + E\,[T_{false}] \tag{13}$$

where

$$E\,[T_{false}] = T_{false} \times \frac{S}{ARL_1} \tag{14}$$

T_{false} denotes the expected search time for a false alarm, ARL1 denotes the average number of samples taken before the process becomes out-of-control case or a false alarm occurs, and S denotes the expected number of samples while the process is in-control. With a process failure rate of θ, it is calculated as [39]

$$S = \left(e^{-\theta\times Hs}\right) \Big/ \left(1 - e^{-\theta\times Hs}\right) \tag{15}$$

This study assumes that the failure rate due to external reasons 'E' is θ_1, and the failure rate due to machine degradation (FM2) is θ_2. Thus, the overall process failure rate θ due to FM2 and 'E' is $\theta = \theta_1 + \theta_2$, where

$$\theta_1 = \frac{1}{MTBF_{Process}} \tag{16}$$

$$\theta_2 = \frac{N_f \times P_{FM_2}}{\text{evalution period}(T_{evalution})} \tag{17}$$

b: EXPECTED OUT-OF-CONTROL TIME $E\left[T_{out-of-control}\right]$:

The out-of-control time includes the following events:

(1) The time between occurrence of an assignable cause and the next sample [37]:

$$\left\{Hs \times \left(ARL_{2_{M/C}} \times \frac{\theta_2}{\theta} + ARL_{2_E} \times \frac{\theta_1}{\theta}\right)\right\} \tag{18}$$

(2) The expected time to an out-of-control state (τ), as calculated by Duncan [39], $\tau = Hs/2$

(3) The expected time to collect and plot the samples:

$$(\mathrm{Ns} \times \mathrm{T_S}) \tag{19}$$

(4) The expected time to validate an assignable cause, expressed as $\mathrm{T_1}$.

(5) The expected time to reset the process or restore the machine due to FM2:

$$\left(\mathrm{T_{resetting}} \times \frac{\theta_1}{\theta} + \mathrm{MTTR_{CM}} \times \frac{\theta_2}{\theta}\right) \tag{20}$$

$\mathrm{ARL2_{M/C}}$ and $\mathrm{ARL2_E}$ denote the average run length during an out-of-control period due to machine failure and due to external reasons, respectively, Ns denotes the sample size, $\mathrm{T_S}$ denotes the time to collect and plot the sample, and $\mathrm{T_{resetting}}$ denotes the time to reset the process if the failure is due to external reasons. Therefore, the out-of-control time can be expressed as [37]

$$\begin{aligned}\mathrm{E}\left[\mathrm{T_{out-of-control}}\right] &= \left\{\mathrm{Hs} \times \left(\mathrm{ARL2_{M/C}} \times \frac{\theta_2}{\theta} + \mathrm{ARL2_E} \times \frac{\theta_1}{\theta}\right)\right\} \\ &\quad - \tau + (\mathrm{Ns} \times \mathrm{T_S}) + \mathrm{T_1} \\ &\quad + \left(\mathrm{T_{resetting}} \times \frac{\theta_1}{\theta} + \mathrm{MTTR_{CM}} \times \frac{\theta_2}{\theta}\right)\end{aligned} \tag{21}$$

Hence, the expected process cycle time is the sum of both the expected in-control and expected out-of-control times. It is expressed as [37]

$$\begin{aligned}\mathrm{E}\left[\mathrm{T_{Cycle}}\right] &= \left\{\frac{1}{\theta} + \mathrm{T_{false}} \times \frac{\mathrm{S}}{\mathrm{ARL_1}}\right\} \\ &\quad + \left\{\mathrm{Hs} \times \left(\mathrm{ARL2_{M/C}} \times \frac{\theta_2}{\theta} + \mathrm{ARL2_E} \times \frac{\theta_1}{\theta}\right)\right\} - \tau \\ &\quad + (\mathrm{Ns} \times \mathrm{T_S}) + \mathrm{T_1} \\ &\quad + \left(\mathrm{T_{resetting}} \times \frac{\theta_1}{\theta} + \mathrm{MTTR_{CM}} \times \frac{\theta_2}{\theta}\right)\end{aligned} \tag{22}$$

2) EXPECTED COST OF PROCESS FAILURE $E\left[C_{process}\right]$

The expected process costs are considered when the operating process is in the in-control and out-of-control states. These costs include costs due to the defective products, sampling, downtime, cause analysis, and restoring the system.

a: EXPECTED COSTS WHILE THE OPERATING PROCESS CORRESPONDS TO THE IN-CONTROL STATE

$\mathrm{C_{false}}$ is the cost associated with false alarms. It consists of the cost of analysis for the source of the false alarm. Thus, the expected cost for a false alarm is expressed as follows:

$$\mathrm{E}\left[\mathrm{C_{false}}\right] = \mathrm{C_{false}} \times \mathrm{T_{false}} \times \frac{\mathrm{S}}{\mathrm{ARL_1}} \tag{23}$$

Let $\mathrm{C_F}$ be the fixed cost per sample and $\mathrm{C_V}$ be the variable cost per job. Thus, the expected cost per cycle for sampling is the sum of the fixed cost per sample and variable cost per job [37] as shown in (24) at the bottom of this page.

The expected cost of non-conforming units when the process is in-control is

$$\begin{aligned}\mathrm{E}\left[\mathrm{C_{non-conforming}}\right] &= \left(\mathrm{R'} \times \mathrm{PR} \times \mathrm{C_{Frej}}\right) \\ &\quad \times \left(\frac{1}{\theta} + \mathrm{T_{false}} \times \frac{\mathrm{S}}{\mathrm{ARL_1}}\right)\end{aligned} \tag{25}$$

The expected cost of identifying and repairing a valid alarm for an assignable cause due to external failure is further expressed as

$$\mathrm{E}\left[\mathrm{C_{reseting}}\right] = \left(\mathrm{C_{reseting}} \times \mathrm{T_{reseting}}\right) \times \left(\frac{\theta_1}{\theta}\right) \tag{26}$$

b: EXPECTED COSTS WHILE THE OPERATING PROCESS CORRESPONDS TO THE OUT-OF-CONTROL STATE

The cost of rejections when the process is in the out-of-control state due to machine failure is

$$\begin{aligned}\mathrm{E}\left[\mathrm{C_{rejection}}\right]_{\mathrm{M/C}} &= \left((\mathrm{R}_\delta)_{\mathrm{M/C}} \times \mathrm{PR} \times \mathrm{C_{Frej}}\right) \\ &\quad \times \left(\mathrm{Hs} \times \left(\mathrm{ARL2_{M/C}} \times \frac{\theta_2}{\theta} + \mathrm{ARL2_E} \times \frac{\theta_1}{\theta}\right) - \tau + \mathrm{Ns} \times \mathrm{T_S}\right) \\ &\quad \times \frac{\theta_2}{\theta}\end{aligned} \tag{27}$$

where $(\mathrm{R}_\delta)_{\mathrm{M/C}}$ denotes the probability of nonconforming items produced due to FM2. In addition, the cost of rejection when the process is in the out-of- control state due to external reasons is given as follows:

$$\begin{aligned}\mathrm{E}\left[\mathrm{C_{rejection}}\right]_{\mathrm{E}} &= \left((\mathrm{R}_\delta)_{\mathrm{E}} \times \mathrm{PR} \times \mathrm{C_{Frej}}\right) \\ &\quad \times \left(\mathrm{Hs} \times \left(\mathrm{ARL2_{M/C}} \times \frac{\theta_2}{\theta} + \mathrm{ARL2_E} \times \frac{\theta_1}{\theta}\right) - \tau + \mathrm{Ns} \times \mathrm{T_S}\right) \\ &\quad \times \frac{\theta_1}{\theta}\end{aligned} \tag{28}$$

$(\mathrm{R}_\delta)_{\mathrm{E}}$ denotes the type 2 error probability due to external reasons. Additionally, the proportion of non-conforming units R_δ due to the shift δ is as defined by Montgomery [33], i.e., $\mathrm{R}_\delta = 1 - \mathrm{F}(3-\delta) - \mathrm{F}(-3-\delta)$, where F denotes the standard normal cumulative distribution function, and δ denotes the magnitude of the shift due to FM2. The expected cost of finding and adopting a corrective action for a valid

$$\mathrm{E}\left[\mathrm{C_{Sampling}}\right] = \frac{(\mathrm{C_F} + \mathrm{C_V} \times \mathrm{Ns}) \times \left(\frac{1}{\theta} + \mathrm{T_{false}} \times \frac{\mathrm{S}}{\mathrm{ARL_1}} + \mathrm{Hs} \times \left(\mathrm{ARL2_{M/C}} \times \frac{\theta_2}{\theta} + \mathrm{ARL2_E} \times \frac{\theta_1}{\theta}\right) - \tau + (\mathrm{Ns} \times \mathrm{T_S})\right)}{\mathrm{Hs}} \tag{24}$$

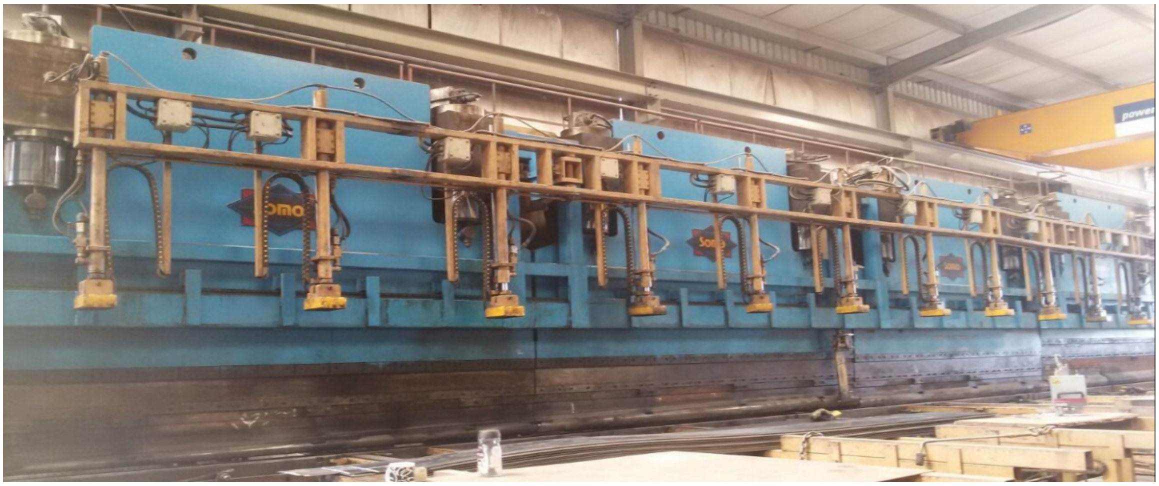

FIGURE 4. Sheet metal working machine.

alarm due to FM2 is given as

$$E\left[C_{CM}\right]_{FM_2} = \left\{\left[(MTTR_{CM})_{FM_2} \times \left(PR \times C_{lp} + LC\right)\right] + C_{FCPCM}\right\} \times \left(\frac{\theta_2}{\theta}\right) \tag{29}$$

The expected cost of process failure corresponds to the sum of expected costs while operating the process corresponding to in-control and the expected costs while operating the process corresponding to out-of-control. The sum of (23)–(29) is the expected cost of process failure per cycle and is expressed as

$$E\left[C_{process}\right] = \left\{E\left[C_{false}\right] + E\left[C_{Sampling}\right] + E\left[C_{non-conforming}\right] + E\left[C_{reseting}\right] + E\left[C_{rejection}\right]_{M/C} + E\left[C_{rejection}\right]_{E} + E\left[C_{CM}\right]_{FM_2}\right\} \tag{30}$$

In addition, the expected cost of the process failure quality for the evaluation period is given as

$$E\left[TCQ\right]_{process\ failure} = E\left[C_{process}\right] \times M \tag{31}$$

where

$$M = \frac{T_{evalution}}{E\left[T_{Cycle}\right]} \tag{32}$$

3) OPTIMIZATION COST MODE PER UNIT TIME OF SYSTEM $[ETCPUT]_{(M*Q)_{EWMA}}$

The expected total cost per unit time of the system is expressed as $[ETCPUT]_{(M*Q)_{EWMA}}$; it is assumed that production is in the in-control state:

$$[ETCPUT]_{(M*Q)_{EWMA}} = \frac{E\left[TQC\right]_{process\ failure} + E\left[TMC\right]}{T_{evalution}} \tag{33}$$

The economic objective involves minimizing $[ETCPUT]_{(M*Q)_{EWMA}}$. The model is solved to determine the optimal values of decision variables Ns, Hs, L, λ, and T_{PM}.

We minimize

$$[ETCPUT]_{(M*Q)_{EWMA}} = \frac{E\left[TQC\right]_{process\ failure} + E\left[TMC\right]}{T_{evalution}}$$

$$\begin{aligned} \text{subject to } Ns_{min} &\leq Ns_m \leq Ns_{max} \\ Hs_{min} &\leq Hs_m \leq Hs_{max} \\ L_{min} &\leq L_m \leq L_{max} \\ \lambda_{min} &\leq \lambda_m \leq \lambda_{max} \\ T_{PM_{min}} &\leq T_{PM_m} \leq T_{PM_{max}} \\ Ns;\, Hs;\, L;\, T_{PM} &\geq 0 \\ 0 &< \lambda \leq 1 \end{aligned}$$

IV. CASE STUDY

A manufacturing system for conical lighting poles (CLPs) is used in this case study. This system exists at the Power & Telecommunication Company. The manufacturing system is a sheet metal working machine, which combines eight hydraulic cylinders, four tanks of oil, four pumps, four hydraulic pipes, an electric panel, electric wires, four punches, and dies or bases, as shown in Figure 4.

In this section, a real-life case study is presented to prove the applicability of the developed integrated model. The case is a sheet metal working machine that operates 6 days a week through 12 working hours in two shifts daily and produces a single product: a 10-meter high CLP with a process mean of $\mu_0 = 5$ mm and a process standard deviation of $\sigma = 0.01$. The magnitude of the shift owing to external reasons is $\delta_E = 1$ and owing to machine failure is $\delta_{M/C} = 0.6$, which occurs at random and results in a shift of process mean from μ_0 to $(\mu_0 + \delta)$. In the present case, corrective and preventive actions are considered for maintenance. Table 1 lists the parameters of maintenance for components in the selected machine. A sampling procedure is used for process quality monitoring based on an EWMA control chart. The CTQ characteristic considered is the absence of die marks, such

TABLE 1. Parameters of maintenance for components in selected machine.

Index	Component	Number	β_i	η_i (h)	Component cost during replacement (SR)	Sub-component/ consumables cost through repair (SR)	TTR_{cm_i} (h)	TTR_{pm_i} (h)
1	Hydraulic Cylinder	8	2.5	2,500	28,000	800	8	2
2	Tank of oil	4	3.8	1,800	10,000	500	0.5	2.6
3	Pump	4	3.5	2,100	24,000	6,00	2.5	4.8
4	Hydraulic pipes	4	4.4	2,670	6,000	na	0.5	na
5	Electric panel	1	1.5	2,400	700,000	na	12	na
6	Electric wires	1	1.06	2,877	5,000	na	3	na
7	Punch	4	2.2	2,180	10,000	100	4	1.5
8	Die (base)	4	2.1	2,250	8,000	100	4	1

FIGURE 5. Die marks before and after correction.

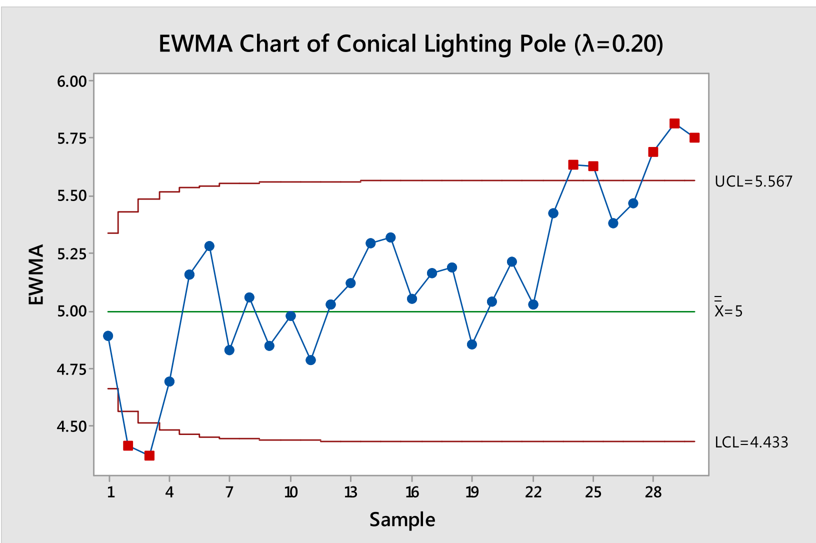

FIGURE 6. EWMA control chart of conical lighting pole samples.

as blows and scratches, as shown in Figures 5(a) and 5(b), respectively. These marks are observed by the naked eye and are then measured by a Vernier caliper device. Moreover, they show obviously when the CLP has a thickness of 5 mm or more. The normal defect value due to die marks is ±0.5 mm. Based on the quality control policy, the samples

TABLE 2. Initial parameters for case study.

Symbol	Value	Symbol	Value
PR (job/h)	19	C_F SR	50
T_S (h)	0.33	C_V SR/job	5
T_{false} (h)	0.5	C_{false} SR/h	5
T_1 (h)	0.5	C_{Frej} SR/job	400
$T_{resetting}$ (h)	1	$C_{resetting}$ SR/h	5.5
LC of preventing m/c SR/h	12.5	C_{lp} SR/h	8.33

TABLE 3. Optimal values of the proposed model decision parameters.

Symbol	Optimal value
$[ETCPUT]_{(M*Q)_{EWMA}}$	47.26
Ns^*	1
Hs^*	2.9
L^*	1.7
λ^*	0.2
$T_{PM}{}^*$	430

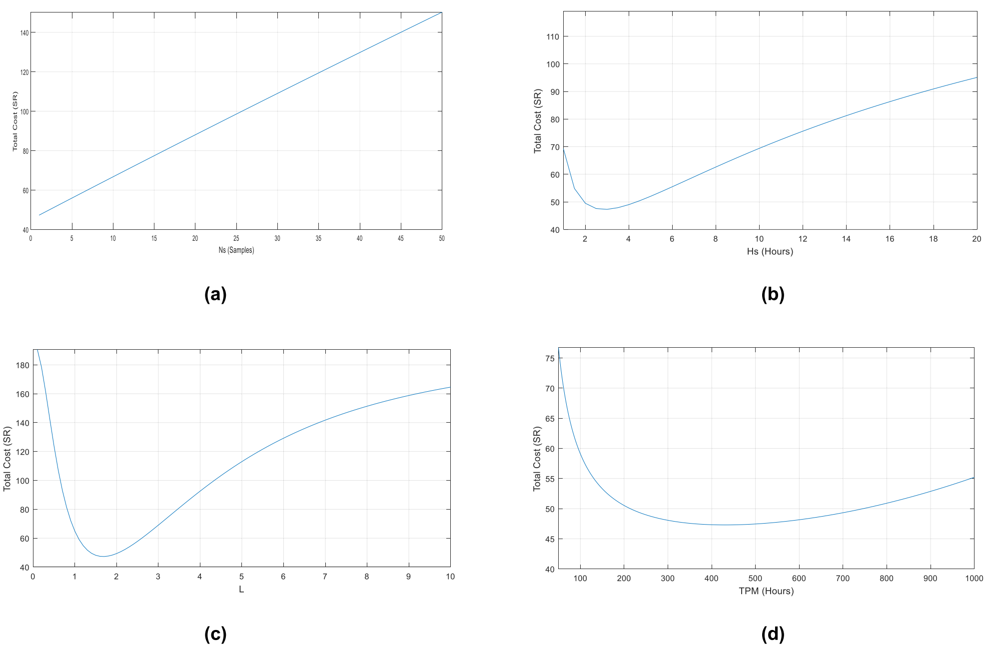

FIGURE 7. Influence of parameters on the proposed model's expected total cost: influence of (a) Ns, (b) Hs, (c) L, and (d) T_{PM}.

are taken from the production line at uniform intervals and inspected by the naked eye and Vernier caliper.

In this study, the EWMA chart is implemented with parameters $L = 1.7$ and different values of λ between 0 and 1. By using pilot runs, it was observed that the chart was effective at detecting small shifts in the process mean at $L = 1.7$ and $\lambda = 0.2$, as shown in Figure 6. The quality records observed that there are quality defects, such as blow and scratch marks, that were caused when three machine components failed: hydraulic cylinder, punch, and die, as shown in Table 1. To correct these marks, workers are forced to use grinding machines and a heating process, as shown in Figure 5(c), leading to additional manufacturing costs for the product. The details of the cost, time, and initial values of the parameters desired for the process quality control policy are listed in Table 2. The optimum results of the proposed integrated model are summarized in Table 3.

Figure 7(a) shows the effect of increasing the number of samples taken (Ns) on the expected total cost. It is observed that the optimum value of the number of samples taken is one

TABLE 4. Sensitivity of the basic variables and influence range of $[ETCPUT]_{((M*Q)\_EWMA)}$.

Symbol	Basic Level	Level A (+10%)	Level B (+20%)	$[ETCPUT]_{(M*Q)EWMA}$ Basic Level	Level A	Level B	Range
δ_E	1.0	1.10	1.20	47.26	44.00	41.06	41.06-47.26
$\delta_{M/C}$	0.60	0.66	0.72	47.26	47.47	47.45	47.26-47.47
T_{false}	0.50	0.55	0.60	47.26	47.26	47.26	47.26
T_1	0.50	0.55	0.60	47.26	47.26	47.26	47.26
$T_{restting}$	1.0	1.10	1.20	47.26	47.26	47.26	47.26
T_S	0.333	0.344	0.355	47.26	47.52	47.54	47.26-47.54
C_{Frej}	400	440	480	47.26	49.70	51.82	47.26-51.82
C_{false}	5	5.50	6.0	47.26	47.26	47.26	47.26
$C_{restting}$	5.5	6.05	6.60	47.26	47.26	47.51	47.26-47.51
C_V	5	5.5	6	47.26	47.67	47.84	47.26-47.84
C_F	50	55	60	47.26	49.18	50.78	47.26-50.78
C_{lp}	8.33	9.163	9.996	47.26	47.67	47.84	47.26-45.65
LC	12.5	13.75	15	47.26	47.51	47.53	47.26-47.53

TABLE 5. optimal value Ranges of the five decision parameters.

Decision variable	Ns*	Hs*	L*	λ*	$T_{PM}{}^*$
Range	1	[2.5- 3.5]	[1.5-2]	0.20	[425-435]

every three hours. This is also the optimum value of sample frequency (Hs), as shown in Figure 7(b). It is important to find the optimum values of the decision parameters of the control chart to find the optimum upper and lower control limits. Thus, Figure 7(c) displays the impact of changing the control limit width (L) on the expected total cost. It is observed that the optimum values of L are in the range of 1.5 to 2. Figure 7(d) illustrates the effect of the preventive maintenance interval (T_{PM}) on the proposed expected total cost; the optimum range of T_{PM} is 400 to 500 h.

V. SENSITIVITY ANALYSIS FOR DEVELOPED OPTIMIZATION MODE

An important issue is the sensitivity of the process and cost parameters used for estimating the effects of range on the quality of the developed integrated model for joint maintenance actions and process quality control policy. Table 4 shows the ranges of the effects on total cost per unit time when increasing basic variables based on company allowance policies of 10% (Level A) and 20% (Level B). The total cost is determined as 51.82 SR if the basic variables are increased by 20%, as in Level B, or it can stable at 47.26 SR in the basic level. In addition, Table 5 summarizes the ranges of optimal values for the four decision variables obtained from sensitivity analysis.

VI. CONCLUSION

In this study, an EWMA chart was used for monitoring process quality control. We also formulated an integrated model for joint maintenance actions and process quality control policy. The proposed methodology gives the optimal values of the decision parameters of process quality control and the preventive maintenance interval for optimizing the expected total hourly system cost. An analysis of sensitivity of the proposed integrated model was used to analyze the effect of the model parameters and the basic variables on the total system cost. The key conclusions from this research can be summarized as follows:

- The proposed methodology allows managers to monitor the different states of the production line and control the quality of production units.
- It also assists in planning and implementing the preventive maintenance interval required to improve the production yield and performance while minimizing downtime.
- The proposed methodology could be applied to a wide range of production manufacturing systems.
- The proposed methodology gives the expected total hourly system cost by determining the optimal values of the decision parameters of process quality control (Ns, Hs, L, and λ) and the preventive maintenance interval (TPM).

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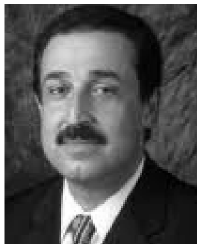

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