

Mohammed A. Noman ✉
Adel AL-Shayea
Emad Abouel Nasr
Husam Kaid
Abdulrahman Al-Ahmari
Ali K. Kamrani
Haitham A. Mahmoud

<https://doi.org/10.21278/TOF.451021920>
ISSN 1333-1124
eISSN 1849-1391

A MODEL FOR MAINTENANCE PLANNING AND PROCESS QUALITY CONTROL OPTIMIZATION BASED ON EWMA AND CUSUM CONTROL CHARTS

Summary

The performance of a production system is highly dependent on the smooth operation of various equipment and processes. Thus, reducing failures of the equipment and processes in a cost-effective manner improves overall performance; this is often achieved by carrying out maintenance and quality control policies. In this study, an integrated optimization method that addresses both maintenance strategies and quality control practices is proposed using an exponentially weighted moving average (EWMA) chart, in which both corrective and preventive maintenance policies are considered. The integrated model has been proposed to find optimal decision variables of both the process quality decision parameters and the optimal interval of preventive maintenance (i.e., N_s , H_s , L , λ , and t_{PM}) to result in overall optimal expected hourly total system costs. A case study is then utilized to investigate the impact of cost criteria on the proposed integrated model and to compare the proposed model with a model using the cumulative sum (CUSUM) control chart. The improved model outputs indicate that there is a reduction of 34.6% in the total expected costs compared with those of the other model using the CUSUM chart. Finally, an analysis of sensitivity to present the effectiveness of the model parameters and the main variables in the overall costs of the system is provided.

Key words: optimization model, maintenance planning, process quality control, EWMA chart, CUSUM chart

1. Introduction

The output of any given production system heavily depends on the failure-free equipment producing products with no defects. Thus, decreasing equipment failures improves the overall performance; this goal can be achieved by carrying out maintenance and quality control policies. Reducing the machine breakdowns or failures leads to enhanced product quality and reduces production costs; this can be achieved by employing appropriate preventive maintenance (PM) strategies. Similarly, quality control programs have been designed to identify process abnormalities; however, both PM and quality control methods increase costs, including the costs of downtime, maintenance, replacement, sampling, and inspection. Traditionally, researchers have independently focused on improving these

activities. However, they showed a correlation between equipment maintenance and equipment performance or process quality. Maintenance procedures increase the life of equipment, thus improving process quality [1]. Therefore, both maintenance and process quality strategies are taken into consideration in order to improve throughput of a production system. Recent studies have shown that research interest focused on common considerations.

This study provides an integrated approach to determine the expected optimal total costs, corrective and preventive maintenance, PM process, process failure, sampling, and inspection pass as well as jointly optimize the maintenance procedure and parametric quality control charts. In many PM models, the system assumes a match between the two situations, i.e., the new and the old state, during each PM action. When the failure mode in the system changes, the system is maintained in a preventive way. One method of designing a model is to consider incomplete maintenance. After each action of the new PM, the system is as bad as the old one. Each specific PM program should reduce the failure rate and improve the service life of the equipment. When the PM system model is designed with incomplete maintainability, it is assumed that every PM process will change the failure behaviour of the equipment. Therefore, this will affect the control strategy. In addition to incomplete maintenance, exponentially weighted moving average (EWMA) chart has been recently used [2].

PM procedures are implemented to measure the change of a quality control variable with product characteristic deviation. Therefore, implementing PM procedures can improve the product quality by reducing the deviation of a target value. The purpose of this study is to develop a common model that would involve maintenance strategy, quality control, and common optimization simultaneously. This study primarily provides a generalized model for improving maintenance procedures and process control strategies as well as the classification methods of equipment and process faults. In the proposed chart, the direct execution of a corrective maintenance (CM) action indicates a complete failure of a component. Furthermore, to determine the actual operational status, the control chart is used in the control and evaluation process. A CM action is then executed to restore the control state when a part of the machine fault with degraded quality is detected. The proposed method should thus present two main advantages: i) elimination of the quality costs related to an out-of-control operation due to either machine degradation or external reasons, and ii) improved reliability of a machine by protecting it against failures.

2. Literature Review

2.1 Analysis of published papers

In this section, prior studies related to the incorporation of maintenance and quality control systems and related observations are summarized. Researchers interested in maintenance-related literature and design of quality control charts should refer to studies [3-10]. Ben-Daya and Duffuaa [11] stressed the importance of the incorporation of the process quality control in PM. Rahim [12] incorporated PM time and X control chart to monitor a system's increase in failure rate with produced units to determine optimal design parameters. Rahim [13], Ben-Daya [14], and Ben-Daya and Rahim [15] aimed to decrease the increasing hazard rate because of process deterioration during the in-control period by integrating a PM action and X control chart. Cassady [16] studied the incorporation of an X-chart and a PM action based on age of equipment. Yeung [17] and Cassady [16] developed a model for maintenance and quality simultaneously using an X-chart for process monitoring in a production system and they determined optimal decision variables of the control chart and the optimal maintenance interval for corrective and condition-based maintenance. Readers interested in more details on these integrated models should refer to Ben-Daya and Rahim's [18] overview of integrated models combining production processes, quality control methods, and maintenance procedures.

Common maintenance of mechanical equipment and product quality control in different times and under limited visibility and degraded production systems have been studied in the Markovian group [19]. Lindermand [20] provided a general analysis model to determine how to coordinate SPC and planned maintenance procedures to reduce the total costs. To make the best use of PM procedures, two quality-related economic models were then introduced by Panagiotidou and Tagaras [21]; moreover, Panagiotidou and Tagaras [22] developed an economic model to maximize ideal and incomplete maintenance procedures, e.g., two operating conditions of equipment such as in-control and out-of-control states and in SPC. Chiu and Huang [23] proposed a model to design an optimal PM control chart using a fixed sampling interval and risk increase rate. In addition, they believe that after PM, the production system will become a good new state. By combining the economic design and maintenance management of the control chart, Zhou and Zhu [24] established a comprehensive cost optimization model using a network search method. Here, the comprehensive cost optimization model was analyzed to identify the optimal value of variables, including sample size (N_s) and sample frequency (H_s), and they displayed the corresponding standard deviation of the control chart (L) and control coefficient (λ) to reduce the total costs per unit time. Recently, the studies of Panagiotidou and Nenes [25] proposed a controller design chart that adopts Shewhart's development model, which combines the maintenance procedure and quality control strategy. Pandey et al. [26] provided an integrated approach to improve operational policy maintenance, shop scheduling, quality control, production scheduling, and production system control.

This integrated maintenance and quality control model uses a PM parametric control chart to provide an optimal time interval and reduce the total costs of the system, as well as to carry out an optimal PM interval and identify an optimal payment order in the production process, which reduces penalty costs because of the schedule delay [27]. Pandey et al. [26] also proposed a compact model to optimize PM intervals and a parameterized control chart using a compact Taguchi loss function to reduce the total costs per unit time. Liu et al. [28] studied identical series systems of two units and developed economical designs suitable for the system's X control chart and used five continuous phases of the Markov chain approach to describe the identical series systems, thus determining improved control plan parameters using an economic design to reduce maintenance costs. Manafizadeh and Javan [29] advanced a model to optimize maintenance planning, monitor the quality of the operation and schedule production. The model uses a cumulative sum (CUSUM) chart to control and improve the quality of the process and to reduce production defects. Yen et al. [30] developed an integrated mathematical approach to control the statistical process and maintenance decisions, reduce the expected costs and improve the decision variable selection using a genetic algorithm. Divya et al. [31] provided an incorporated approach to shared PM procedures and process quality control strategy using CUSUM control chart parameters. Their model was then used to identify an optimal value of five resolution variables, (N_s , H_s , λ , tPM , and resolution break (L)), thus reducing the projected total costs of the system. Lu et al. [32] proposed a reliability model integrating quality improvement policy into PM using a decision-making approach that merged the quality loss into the total costs to determine an optimal schedule of PM actions.

2.2 Open problems in related studies

The following open problems have been observed in the studies on this subject:

1. Integrated models have not been able to account for the downtime due to a failure or improper performance of equipment which required maintenance action. They have instead only focused on practical quality problems.
2. Most of the maintenance models from the literature interested in comprehensive PM or preventive replacement policies deal with restoring the equipment to a good-as-new state.

3. There currently exists no clear way to determine an optimal number of observations in internal and external control systems in a process quality control model.
4. As regards the loss of product quality caused by the failure of equipment, which leads to the scrapping of products, any costs should include manufacturing costs, time loss, repair costs, replacement and product rejection costs; this has not yet been incorporated in any model.
5. In any production system, when the production rejection costs are high, CM costs exceed PM costs, thus reducing the PM period. This aspect has largely been ignored in prior models to improve maintenance.

Therefore, this study aims to develop an integrated optimization method that addresses both maintenance strategies and quality control practices. For this purpose, CM and PM processes, process failures, sampling rates, and inspection passes are determined while optimizing the expected total costs. Thus, the developed model will offer improved maintenance procedures, process control strategies, and classification methods for equipment and process faults. Furthermore, the proposed method should present two main advantages: i) the operation quality costs of external equipment is out of control due to external reasons, and ii) an improved reliability of the machine, resulting in fewer breakdowns.

3. Proposed methodology

The proposed integrated model addresses both PM and process quality using the process quality method proposed by Divya et al. [31] and an EWMA control chart. The proposed integrated model is then used to identify optimal values of five decision variables (i.e., N_s , H_s , L , λ , and t_{PM}) that yield optimal expected hourly total system's costs. Single machine component is considered and monitored to study the effectiveness of the EWMA chart. It is assumed that the mechanical system failures follow a two-parameter Weibull distribution with a characteristic life and shape parameter η and β , respectively. The machine was also assumed to operate six days a week for 7 working hours in three shifts daily.

The proposed methodology for maintenance planning and quality control policies is summarized in the following five steps that are also presented in the flow chart, Fig. 1.

1. First, a production system of single product (i.e., a single component in a single machine) is selected for monitoring. The monitored production system must be in an in-control state before the monitoring process can begin.
2. The selected product is then monitored for quality loss or any machine failure that causes a shift in the process mean. The EWMA control chart is used to monitor one property critical to quality (CTQ).
3. An integrated model is then built to include CM, PM, and SPC models.
4. The integrated model is then solved using the Global Optimization Toolbox in MATLAB. The results provided by using the CUSUM method and the developed EWMA control chart are then compared.
5. Finally, a sensitivity analysis of each of the five decision variables is performed to determine their acceptable ranges and to demonstrate how they affect the total expected system costs.

3.1 Model description

Two machine failure types were considered, as summarized in Fig. 2: a direct machine breakdown, or failure mode 1 (FM_1), and a shift in the process mean, resulting in a reduction in the process quality, or failure mode 2 (FM_2). Here *failure* is defined as any event that occurs because of machine downtime or during machine runtime when higher rejections are produced. FM_2 represents a partial failure that causes poor machine performance without total failure (i.e., FM_1) [33, 34].

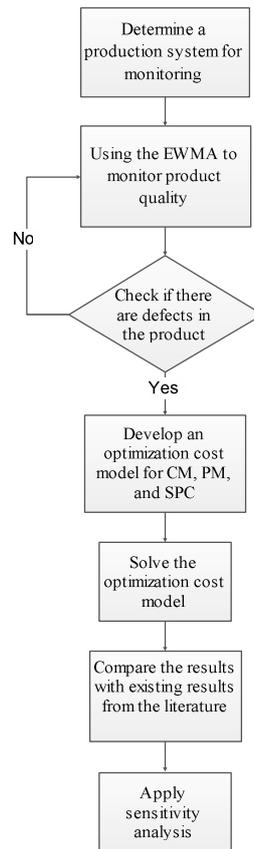


Fig. 1 Flowchart of the proposed methodology

When either FM_1 or FM_2 is detected, CM is assumed to be carried out immediately to repair and restore the machine to the normal, active status. However, as FM_2 may not be detected immediately, the process continues producing defective items until discovered to be defective. In addition to the failure caused by undetected FM_2 , external causes (E) may also cause process deterioration, such as environmental factors, operator errors, or use of incorrect tools. An EWMA control chart is thus used to monitor the process and detect any instances of E or FM_2 .

Applying PM actions to the machine reduces breakdowns and minimizes losses because of unplanned downtime. PM actions are assumed to reduce the occurrence probability of both FM_1 and FM_2 . Decreasing FM_2 leads to a reduction in the quality costs incurred during an out-of-control status. The implementation of PM consumes some of the productive machine time and production resources.

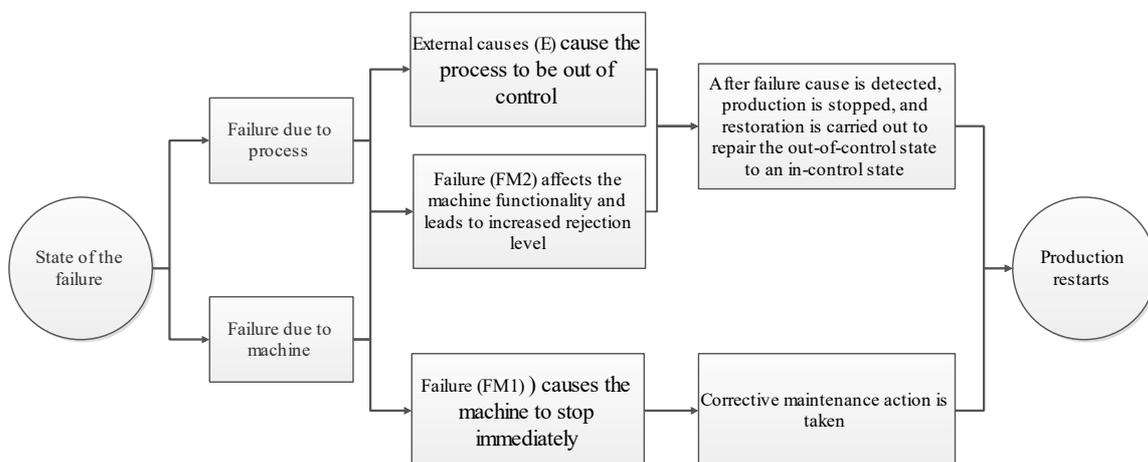


Fig. 2 Failure mode states

3.2 Assumptions

The following assumptions were made in the development of this model:

1. A single property CTQ is monitored using a EWMA control chart of a single product produced by a single production machine system.
2. The production system has been monitored when it has been in an in-control state, and its process mean is μ_0 with standard deviation σ_0 . And when the process mean has a shift, it is changed to $(\mu_0 + \delta)$, where δ denotes the magnitude of the shift.
3. Suppose that the two types of failure FM1 and FM2 are independent and the total probability of their occurrence as shown by $PFM1+PFM2 = 1$, where this probability is obtained from quality reports of the production line which include the following information: type of failure, time of failure, time of repair or replacement and cost of failure.
4. CM actions are minimized and PM actions can be imperfect.
5. The system stops during detection and restoration periods; then, the system returns to normal operating conditions after the CM action has been finished.

3.3 Average run lengths of EWMA and CUSUM control charts

3.3.1 EWMA chart

The EWMA control chart was first introduced in the late 1950s by Roberts [35]. After that, it was improved by Crowder [36-38] and Lucas and Saccucci [39] to become a good alternative to the traditional control charts (i.e., Shewhart and CUSUM). The EWMA control chart is designed to detect small shifts in the process mean. Namely, frequent small shifts in the process mean cannot be detected by using the traditional control charts. Thus, these shifts affect the optimal value of the out-of-control ARL, which the study aims to make as little as possible and to reduce the number of out-of-control periods of the process. Many researchers, such as Gomes et al. [40], Aslam et al. [41] and Riaz et al. [42], highlighted that the EWMA chart is better than Shewhart's and CUSUM charts at achieving this goal, including shifts in a standard deviation. The EWMA chart adapts to automatic relevant data, while Shewhart's and CUSUM charts assume independence between sample observations. In addition, Vera do Carmo C et al. [43] have proved that the EWMA control chart was more efficient than the CUSUM chart in detecting small changes in the process average. Moreover, it is less sensitive to the lack of natural assumptions [40]. The EWMA statistic has been defined as follows:

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

where λ is a pre-estimated control chart parameter. Suppose that the initial value of the process mean can be shown, i.e., $Z_0 = \mu_0$, and suppose that Z_i is the real value of X obtained from sample i . Thus, the EWMA statistic, as calculated by A. S. Adel, M. et al. [44] is defined as follows:

$$UCL = \mu_0 + L\sigma_0 \sqrt{\frac{\lambda}{(2-\lambda)} [1 - (1 - \lambda)^{2i}]}, \quad (2a)$$

$$CL = \mu_0, \quad (2b)$$

$$LCL = \mu_0 - L\sigma_0 \sqrt{\frac{\lambda}{(2-\lambda)} [1 - (1 - \lambda)^{2i}]}. \quad (2c)$$

where UCL and LCL are the upper and the lower control limits of the EWMA chart, respectively, CL is the centreline and L is the control chart decision boundary, a pre-defined constant based on the false alarm rate. The process is defined as out-of-control by the EWMA

control chart when Z_i plots without specific control limits. For large samples, $[1 - (1 - \lambda)^{2i}]$ tends to 1; therefore, the upper and the lower control limits can be simplified as follows:

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

The parameters λ and L are then used to identify the average out-of-control run length, ARL_2 , which is the average number of observation units taken when the process mean has shifted from μ_0 to $(\mu_0 + \delta)$; the magnitude shift δ occurs because of any external cause or machine degradation. The average in-control run length, ARL_1 , is then computed as follows [45]:

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

Here, subgroup size n is independent and has been obtained from subgroups $\{X_{i,1}, X_{i,2}, \dots, X_{i,n}\}$ at period $i = 1, 2, \dots, n$, and has a distribution of $X_{i,j} \sim N(\mu_0 + a\sigma_0, b\sigma_0)$, where $i = 1, 2, \dots$, and $1 \leq j \leq n$. When $a = 0$ or $b = 1$, the process is in an in-control state. When the process is in an out-of-control state, the mean μ_0 will be changed, $a \neq 0$, the standard deviation σ_0 will be changed and $b \neq 1$.

Where $y = 3/\sqrt{n}$, corresponding to a false alarm rate $\alpha = 0.002$, $FN(\cdot)$ is the cumulative distribution function of the standard normal distribution. Zhang et al. [45] suggested that the optimal $ARL_1 = 370$. Several computed ARL_2 depend on the pre-specified optimal value of ARL_1 as 370 [2]. Srivastava and Wu [46] proposed an optimal value of λ which minimizes ARL_2 for given ARL_1 . The optimum λ is given by [44] as follows:

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

where $c^* = 0.5117$ and

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

The width of control limit L is estimated as follows:

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

Thus, the optimal value of ARL_2 can be obtained approximated as follows:

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

3.3.2 CUSUM chart

The CUSUM chart is another control chart used for monitoring a process mean based on samples taken from the process at certain times (e.g., hours, shifts, days, weeks, or months). The conventional CUSUM chart was designed by Bagshaw and Johnson [47] and Moustakides [48] to minimize the out-of-control ARL_2 for a mean shift while maintaining a given in-control ARL_1 . The CUSUM performance can be measured using the average run length (i.e., ARL_2), which is the average number of samples required to signal an out-of-control case or produce a false alarm. ARL_2 is commonly used as an index of the effectiveness of the control chart, whereas the in-control ARL_1 is used as an index of the false alarm rate. Therefore, the economic design of CUSUM charts depends on the value the of average run lengths. For the given CUSUM chart, samples of the size n are taken from a normal distribution $N(\mu, \sigma^2)$, using a reference value of k and a decision interval of h . When the

decision interval is exceeded, the production should be stopped and an assignable cause should be found. Thus, the CUSUM statistic, as calculated by Divya et al. [31], is defined as follows:

$$M_i^+ = \max[0, x_i - (\mu_0 + k) + M_{i-1}^+], \quad (7a)$$

$$M_i^- = \max[0, (\mu_0 - k) - x_i + M_{i-1}^-], \quad (7b)$$

where M_i^+ and M_i^- are the upper and lower control limits of the CUSUM chart, respectively. *ARLs* for the CUSUM chart are calculated here using Alwan's [49] modification of Woodall and Adams' [50] method, as by Divya et al. [31], as:

$$ARL = \frac{e^{(-2\Delta k) + 2\Delta b - 1}}{2\Delta^2}, \quad (8)$$

where $\Delta = \delta - k$, and $b = h_1 + 1.1661$, where h_1 is the critical threshold associated with the CUSUM. Therefore, when the process is in an in-control state, $\delta = 0$, as in Divya et al. [31]. The in-control *ARL* can thus be calculated as:

$$ARL_1 = \frac{e^{(2k^2) - 2bk - 1}}{2k^2}. \quad (9)$$

If the process moves to an out-of-control state, $\Delta = \delta - k$, and the optimal value of the out-of-control *ARL* can be calculated as:

$$ARL_2 = \frac{e^{(-2\delta k + k^2) + 2(\delta - k)b - 1}}{2(\delta - k)^2}. \quad (10)$$

4. Cost model

To illustrate the impacts and benefits of the proposed method using the EWMA control chart to integrate PM and SPC, a set of cost models was developed to capture the cost plan and quality control policies related to and affected by the production process. These costs include corrective and PM costs and process failure costs during the evaluation period.

4.1 Expected cost model: corrective and preventive maintenance

Information required to model the costs associated with CM and PM include: 1) time for implementing the maintenance procedures and any possible logistical delays due to required materials or labour; 2) costs of materials, labour, downtime, and other maintenance-related activities; 3) required degree of equipment restoration (i.e., as good as new, as bad as old, or imperfect), expressed using a restoration factor and determined by an expert planner [51]; and 4) probability of equipment failure based on historical data.

4.1.1 CM policy

All costs attributed to the failure mode detection during the given time period, including downtime costs incurred during machine reparation and restoration, have been calculated. Costs of labour and materials are required for proper formulation of this model. Thus, the CM costs are expressed as follows:

$$E[C_{CM}]_{FM_1} = \{[(MTTR_{CM})_{FM_1} \times (PR \times C_{lp} + LC)] + C_{FCPCM}\} \times P_{FM_1} \times N_f, \quad (11)$$

where $MTTR_{CM}$ is the mean CM time incurred following FM_1 (h), PR denotes the production rate, C_{lp} denotes the lost production cost, LC denotes the labour costs, and C_{FCPCM} denotes the fixed costs of the CM action. This model includes costs such as costs for material, lubricant oil, and maintenance equipment. When the maintenance includes only the replacement of a

component, the CM costs are considered equal to the component replacement cost number of CM actions, N_f . Here, N_f is a function of the PM interval (t_{PM}) and restoration factors and is determined using a regression model of η and β values during the evaluation period, as proposed by Divya et al. [31] and shown in (12).

$$N_f = 0.0437 * t_{PM}^{0.8703}. \quad (12)$$

4.1.2 PM policy

Incomplete PM costs include the cost of downtime because of the repair and restoration of a part in a single machine, as well as the costs of labour and required materials. PM costs are thus expressed as follows:

$$E[C_{PM}] = \{[(MTTR_{PM}) \times (PR \times C_{lp} + LC)] + C_{FCPPM}\} \times \frac{T_{evaluation}}{t_{PM}}. \quad (13)$$

4.2 Expected cost model: process quality ($E[TCQ]_{process\ failure}$)

This section discusses mathematical equations that are intended to calculate both the production process cycle time and the expected process failure costs.

4.2.1 Production process cycle time $E[T_{Cycle}]$

The cycle time of the production process is determined by the expected run cycle length, which controls the time between the series periods. This cycle includes, as presented in detail in Fig. 3, the in-control and out-of-control time as well as the time required to re-adjust the process or restore the machine.

4.2.1.1 Expected in-control time $E[T_{in-control}]$

The in-control time is expressed using a negative exponential distribution with a mean of $1/Y$ and includes the mean time to failure and the expected time to inspect false alarms $E[T_{false}]$. It is expressed as in Lorenzen and Vance's [52] model as follows:

$$E[T_{in-control}] = 1/Y + E[T_{false}], \quad (14)$$

where

$$E[T_{false}] = T_{false} \times \frac{S}{ARL_1}, \quad (15)$$

where ARL_1 indicates the average number of samples before an out-of-control state or false alarm have appeared, T_{false} indicates the expected time of a false alarm search, and S refers to average samples taken when the process is in an in-control state with a process failure rate Y . These average samples are then calculated by Lorenzen and Vance [52] as follows:

$$S = (e^{-Y \times Hs}) / (1 - e^{-Y \times Hs}). \quad (16)$$

Two types of process failures were assumed: Y_1 because of an external cause, and Y_2 because of machine degradation. Thus, $Y = Y_1 + Y_2$, where

$$Y_1 = \frac{1}{MTBF_{Process}}, \quad (17)$$

$$Y_2 = \frac{N_f \times P_{FM2}}{evaluation\ period\ (T_{evaluation})}. \quad (18)$$

4.2.1.2 Expected out-of-control time $E[T_{in-control}]$

The expected out-of-control time can be derived from five events, as indicated by Duncan [3]:

1. The time between the appearance of a customizable cause and the next sample observation, calculated as follows:

$$\left\{ Hs \times \left(ARL_{2M/C} \times \frac{Y_2}{Y} + ARL_{2E} \times \frac{Y_1}{Y} \right) \right\}, \quad (19)$$

where $ARL_{2M/C}$ and ARL_{2E} indicate the average run length during an out-of-control state when caused by a machine failure and external cause, respectively;

2. The time observed through the out-of-control state of a process (t), calculated as by Duncan [3] as: $t = Hs/2$;
3. The time spent performing sample analysis, calculated as follows:

$$Ns \times T_s, \quad (20)$$

where Ns is the sample size and T_s indicates the time to take and plot a sample;

4. The time it takes to validate an assignable cause, denoted by T_1 ; and
5. The time required to reset the process or restore the machine if the failure is attributed to FM2, calculated as follows:

$$\left(T_{resetting} \times \frac{Y_1}{Y} + MTTR_{CM} \times \frac{Y_2}{Y} \right), \quad (21)$$

where $T_{resetting}$ is the time needed to reset the process when the failure occurred due to external reasons.

Thus, the following equation expresses the period that was needed to calculate the expected out-of-control time:

$$E[T_{out-of-control}] = \left\{ Hs \times \left(ARL_{2M/C} \times \frac{Y_2}{Y} + ARL_{2E} \times \frac{Y_1}{Y} \right) \right\} - t + (Ns \times T_s) + T_1 + \left(T_{resetting} \times \frac{Y_1}{Y} + MTTR_{CM} \times \frac{Y_2}{Y} \right). \quad (22)$$

The production process cycle time is then calculated as the sum of the expected in-control and out-of-control time in (14) and (22), respectively, as:

$$E[T_{cycle}] = \left\{ \frac{1}{Y} + T_{false} \times \frac{s}{ARL_1} \right\} + \left\{ Hs \times \left(ARL_{2M/C} \times \frac{Y_2}{Y} + ARL_{2E} \times \frac{Y_1}{Y} \right) \right\} - t + (Ns \times T_s) + T_1 + \left(T_{resetting} \times \frac{Y_1}{Y} + MTTR_{CM} \times \frac{Y_2}{Y} \right). \quad (23)$$

4.2.2 Expected cost model of process failure $E[C_{process}]$

The expected process costs include the costs incurred during the in-control and out-of-control states and involve the costs related to the number of produced defective items, to sampling, downtime, cause and effect analysis, and system restoration.

4.2.2.1 When operating in an in-control state

This part includes the following costs: 1) costs of a false alarm, C_{false} , 2) sampling expected costs per cycle, 3) costs of nonconforming units, and 4) costs of exploring and repairing cause(s) of failure.

Thus, the expected costs for false alarm are given as follows:

$$E[C_{false}] = C_{false} \times T_{false} \times \frac{S}{ARL_1}. \quad (24)$$

Hence, the sampling expected costs per cycle can be calculated as a sum of both sample fixed and variable costs, as:

$$E[C_{Sampling}] = (C_F + C_V \times Ns) \times \left(\frac{1}{Y} + T_{false} \times \frac{S}{ARL_1} + Hs \right) \times \left(\frac{(ARL_{2M/C} \times \frac{Y_2}{Y} + ARL_{2E} \times \frac{Y_1}{Y}) - t + (Ns \times T_S)}{Hs} \right), \quad (25)$$

where C_F refers to the sample fixed costs and C_V refers to the sample variable costs.

Due to nonconforming units produced when the process is an in-control state, this leads to more costs that can be expressed as follows:

$$E[C_{non-conforming}] = (R' \times PR \times C_{Frej}) \times \left(\frac{1}{Y} + T_{false} \times \frac{S}{ARL_1} \right). \quad (26)$$

The expected costs associated with exploring and repairing a true alarm due to a customizable reason because of external failure are as follows:

$$E[C_{reseting}] = (C_{reseting} \times T_{reseting}) \times \left(\frac{Y_1}{Y} \right). \quad (27)$$

4.2.2.2 Operation in an out-of-control state

When there is a malfunction in the machine that leads to the process being in the out-of-control state, the rejection costs can be calculated as follows:

$$E[C_{rejection}]_{M/C} = ((R_\delta)_{M/C} \times PR \times C_{Frej}) \times \left(Hs \times \left(ARL_{2M/C} \times \left(\frac{Y_2}{Y} + ARL_{2E} \times \frac{Y_1}{Y} \right) - t + Ns \times T_S \right) \times \frac{Y_2}{Y} \right), \quad (28)$$

where $(R_\delta)_{M/C}$ indicates the probability of production nonconforming items when machine failure has occurred. Also, if the process is in an out-of-control state due to an external cause the rejection costs can be calculated as follows:

$$E[C_{rejection}]_E = ((R_\delta)_E \times PR \times C_{Frej}) \times \left(Hs \times \left(ARL_{2M/C} \times \left(\frac{Y_2}{Y} + ARL_{2E} \times \frac{Y_1}{Y} \right) - t + Ns \times T_S \right) \times \frac{Y_1}{Y} \right), \quad (29)$$

where $(R_\delta)_E$ is the probability of producing nonconforming units when failure has occurred because of external reasons. The proportion of nonconforming units R_δ because of the shift δ was calculated by Montgomery [53] as $R_\delta = 1 - F(3 - \delta) - F(-3 - \delta)$, where F represents the standard normal cumulative distribution function.

The expected corrective costs associated with exploring and diagnosing a valid alarm due to failure mode are expressed as follows:

$$E[C_{CM}]_{FM_2} = \{[(MTTR_{CM})_{FM_2} \times (PR \times C_{lp} + LC)] + C_{FCPCM}\} \times \left(\frac{\theta_2}{\theta} \right). \quad (30)$$

Thus, by combining the mathematical equations from (24) to (30), the expected costs of process failure per cycle can be expressed as follows:

$$E[C_{process}] = \{E[C_{false}] + E[C_{sampling}] + E[C_{non-conforming}] + E[C_{reseting}] + E[C_{rejection}]_{M/C} + E[C_{rejection}]_E + E[C_{CM}]_{FM_2}\}. \quad (31)$$

Therefore, all costs related to process quality during the evaluation period are calculated as follows:

$$E[TCQ]_{process\ failure} = E[C_{process}] \times N, \quad (32)$$

where

$$N = \frac{T_{evaluation}}{E[T_{cycle}]}. \quad (33)$$

5. Optimal cost model per unit time $[ETCPUT]_{(M*Q)EWMA}$

Assuming that the production run begins in an in-control state, as presented in detail in Section 4, the model is optimized as follows:

$$Minimize[ETCPUT]_{(M*Q)EWMA} = \frac{E[TCQ]_{process\ failure} + E[C_{CM}]_{FM_1} + E[C_{PM}]}{T_{evaluation}}. \quad (34)$$

The economic objective function involves minimizing $[ETCPUT]_{(M*Q)EWMA}$ and can be determined by solving the optimal value of the five selected decision variables (Ns, Hs, L, λ , and t_{PM}). The model constraints are as follows:

Subject to:

$$Ns_{min} \leq Ns_m \leq Ns_{max}$$

$$Hs_{min} \leq Hs_m \leq Hs_{max}$$

$$L_{min} \leq L_m \leq L_{max}$$

$$\lambda_{min} \leq \lambda_m \leq \lambda_{max}$$

$$t_{PM_{min}} \leq t_{PM_m} \leq t_{PM_{max}}$$

$$Ns; Hs; L; t_{PM} \geq 0$$

$$0 < \lambda \leq 1$$

6. Cost model methodology of independent models

To examine effectiveness of the proposed model using an EWMA chart, two independent models were implemented and are discussed in the following subsections.

6.1 Independent maintenance model

Here, only planned maintenance actions are considered; the probability of quality degradation because of a machine failure is not considered. This CM model is expressed as follows:

$$E[C_{CM}] = \{[MTTR_{CM} \times (PR \times C_{lp} + LC)] + C_{FCPCM}\} \times N_f. \quad (35)$$

The PM model is expressed as follows:

$$E[C_{PM}] = \{[MTTR_{PM} \times (PR \times C_{lp} + LC)] + C_{FCPPM}\} \times \frac{T_{evaluation}}{t_{PM}}. \quad (36)$$

Therefore, the expected maintenance costs can be calculated as stand-alone for the planning period as follows:

$$[CPUT]_{Maint.} = \frac{E[C_{CM}] + E[C_{PM}]}{T_{evaluation}} \quad (37)$$

Thus, the optimal PM interval for the planning period is determined by minimizing the $[CPUT]_{Maint.}$ (i.e., (37)).

6.2 Independent SPC model with EWMA chart

The expected process cycle length and SPC model are calculated as follows:

$$E[T_{Cycle}]_{EWMA} = \frac{1}{Y_E} + T_{false} \times \frac{S}{ARL1} + \{Hs \times (ARL_{2E})\} - t + Ns \times T_S + T_1 + T_{restore} \quad (38)$$

$$E[C]_{EWMA} = C_{false} \times T_{false} \times \frac{S}{ARL1} + \frac{(C_F + C_V \times Ns) \times \left(\left(\frac{1}{Y_E} + T_{false} \times \frac{S}{ARL1} \right) + (Hs \times ARL_{2E}) - t + Ns T_S \right)}{Hs} + (R' \times PR \times C_{Frej}) \times \left(\frac{1}{Y_E} + T_{false} \times \frac{S}{ARL1} \right) + ((R_\delta)_E \times PR \times C_{Frej}) \times ((Hs \times ARL_{2E}) - t + Ns \times T_S) + (C_{resetting} \times T_{resetting}) \quad (39)$$

Therefore, the expected SPC total costs per cycle time for the EWMA control chart model are calculated as follows:

$$[CPUT]_{SPC} = \frac{E[C]_{EWMA}}{E[T_{Cycle}]_{EWMA}} \quad (40)$$

Thus, the optimal values of the decision variables of the EWMA chart (Ns , Hs , L , λ) are determined by minimizing $[CPUT]_{SPC}$ (i.e., (40)).

7. Case study

To verify the proposed integrated model, the numerical example solved by Divya et al. [31] is solved here as a case study. A single machine component is considered and assumed to have a failure distribution following a two-parameter Weibull distribution with a characteristic life and shape parameter of $\eta = 1000$ and $\beta = 2.5$, respectively. The machine was assumed to operate six days a week for 7 working hours in three shifts daily. The time required to perform a preventive maintenance action (TPM) is equal to seven hours with a PM restoration factor (RFPM) of 60% restoration of the component life. The time required to perform a corrective maintenance action is equal to 12 hours with a CM restoration factor (RFCM) of 0. A CTQ characteristic was assumed to be monitored by the EWMA control chart with a symmetrical bilateral tolerance $\Delta = \pm 0.05$. The process began in an in-control state with a process mean of $\mu_0 = 24$ mm and a process standard deviation of $\sigma_0 = 0.01$ mm. Furthermore, the shift magnitude caused by external reasons and the shift magnitude caused by an external failure were assumed as $\delta_E = 1$ and $\delta_{M/C} = 0.60$, respectively. The shift occurs at random and results in a shift of the process mean from μ_0 to $(\mu_0 + \delta_E \sigma_0)$ and $(\mu_0 + \delta_{M/C} \sigma_0)$. The initial values of all input parameters are summarized in Table 1. The Global Optimization Toolbox of MATLAB R2016b was used to solve the optimization problem in the proposed integrated model, and the optimal values of decision variables that minimize the expected total costs of the system per unit time using the developed integrated model $[ETCPUT]_{(M*Q)EWMA}$ and using the CUSUM chart proposed by Divya et al. [31] $[ETCPUT]_{(M*Q)CUSUM}$ are shown in Table 2. For further clarification, all total costs using the two EWMA and CUSUM control charts are compared in Fig. 4. In addition, the numerical

results of the EWMA and CUSUM charts are summarized in Fig. 5 and Fig. 6, respectively, which present the impact of each of the decision variables (H_s, L, λ, t_{PM}) on the expected total costs of the system per unit time $[ETCPUT]_{(M*Q)EWMA}$ and the decision variables (h_1, h, k, t_{PM}) on $[ETCPUT]_{(M*Q)CUSUM}$.

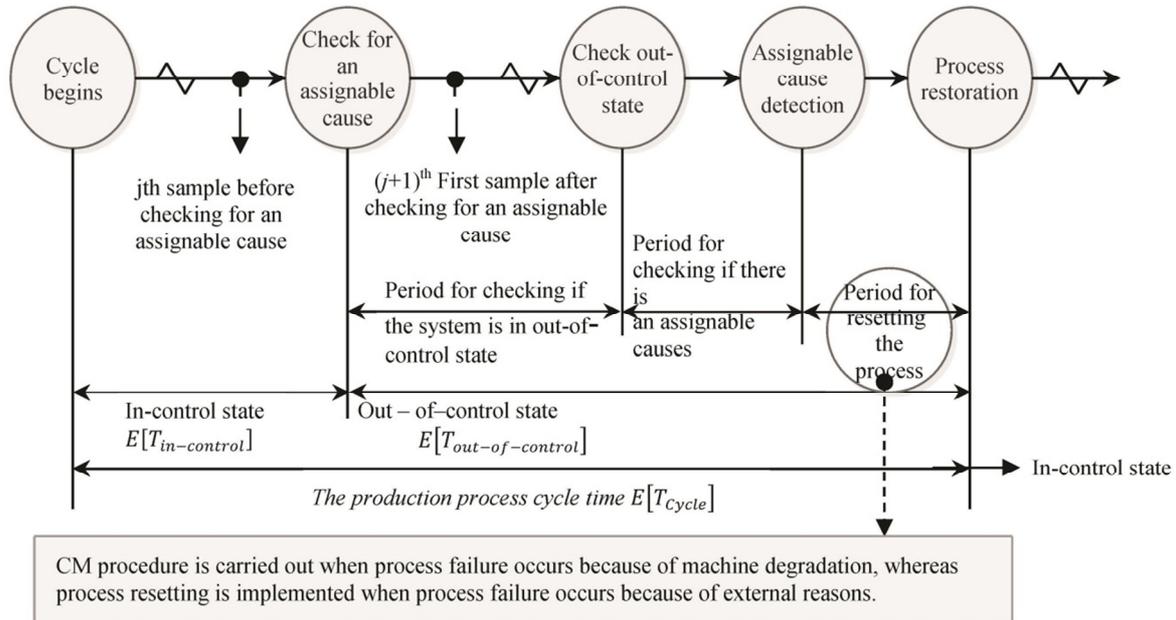


Fig. 3 The production process cycle time [44]

Table 1 Initial parameters for numerical illustration as in [31]

Symbol	Parameter value	Symbol	Parameter value
PR (job/hr)	10	C_F Rs	50
T_S (hr)	0.33	C_V Rs/job	5
T_{false} (hr)	1	C_{false} Rs/ hr	700
T_1 (hr)	1	C_{Frej} Rs/job	1200
$T_{resetting}$ (hr)	2	$C_{resetting}$ Rs/ hr	500
LC of preventing m/c Rs/ hr	200	C_{FCPCM} Rs/component	10,000
C_{lp} Rs/ hr	50	C_{FCPPM} Rs/component	800

Table 2 Comparison between the results of CUSUM chart and proposed EWMA chart

CUSUM Chart		EWMA Chart	
Symbol	Optimal value	Symbol	Optimal value
$[ETCPUT]_{(M*Q)CUSUM}$	534	$[ETCPUT]_{(M*Q)EWMA}$	349.44
$[CPUT]_{Maint.+SPC}$	634	$[CPUT]_{Maint.+SPC}$	357.07
n^*	1	Ns^*	1
h_1^*	5.03	Hs^*	4.5
K^*	0.414	λ^*	1
h^*	0.26	L^*	0.46
t_{PM}^*	199	t_{PM}^*	170

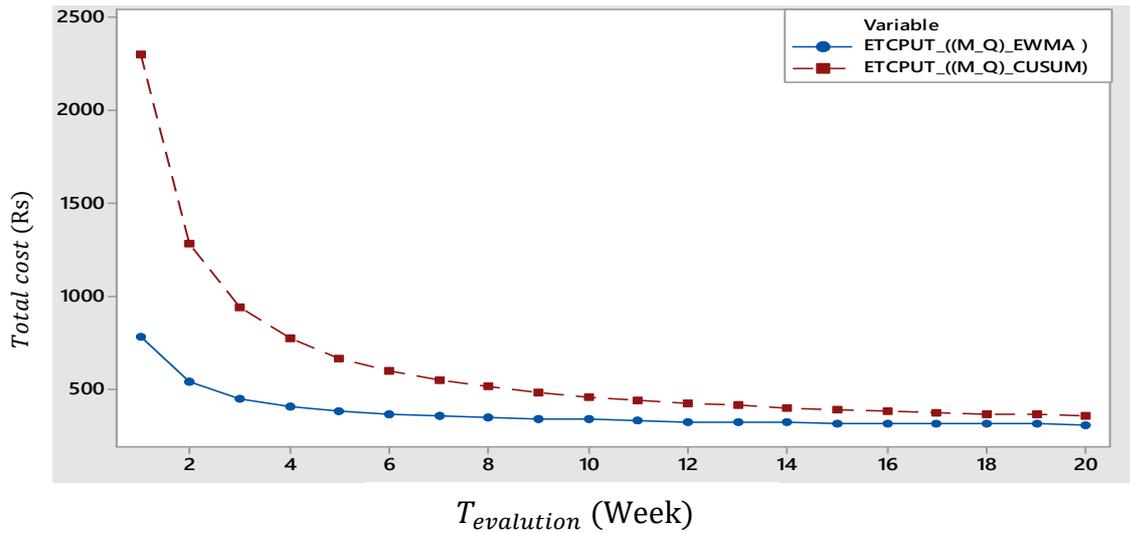


Fig. 4 Total costs in multi-evaluation period using EWMA and CUSUM charts

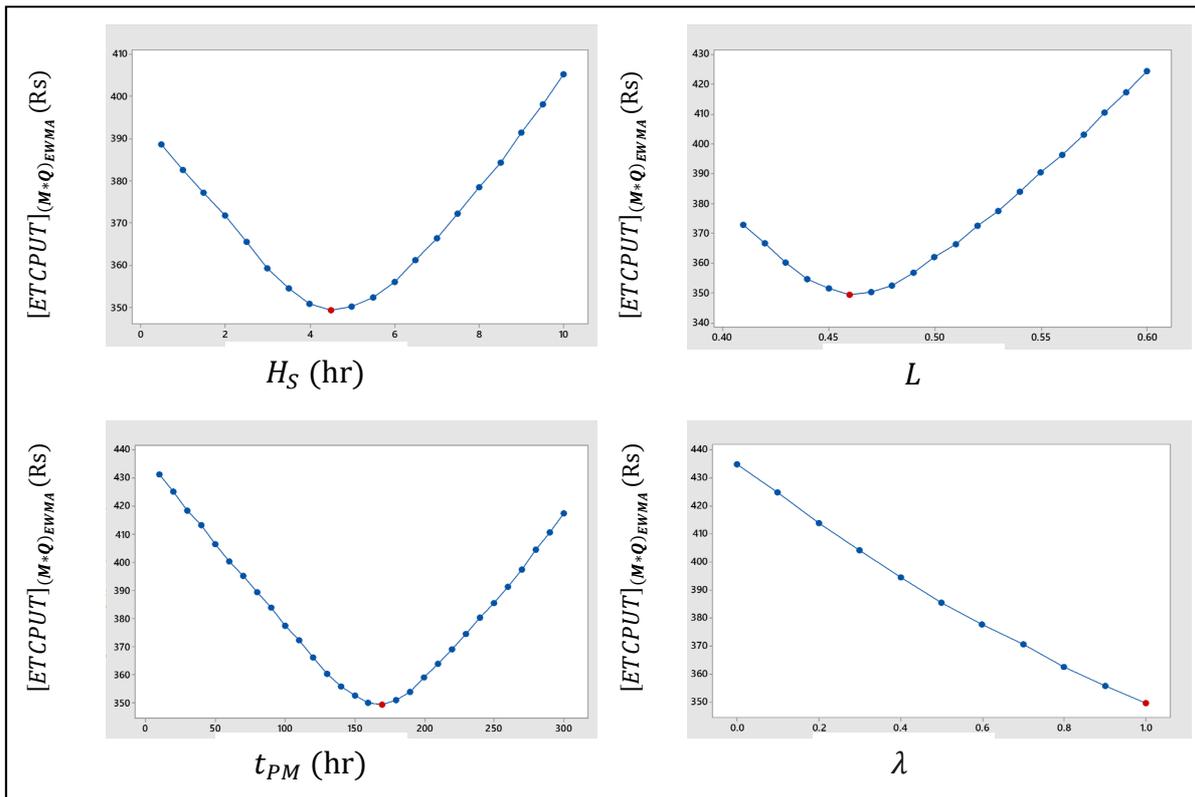


Fig. 5 Effect of decision variables on the expected total costs calculated by means of the proposed integrated model considering EWMA chart

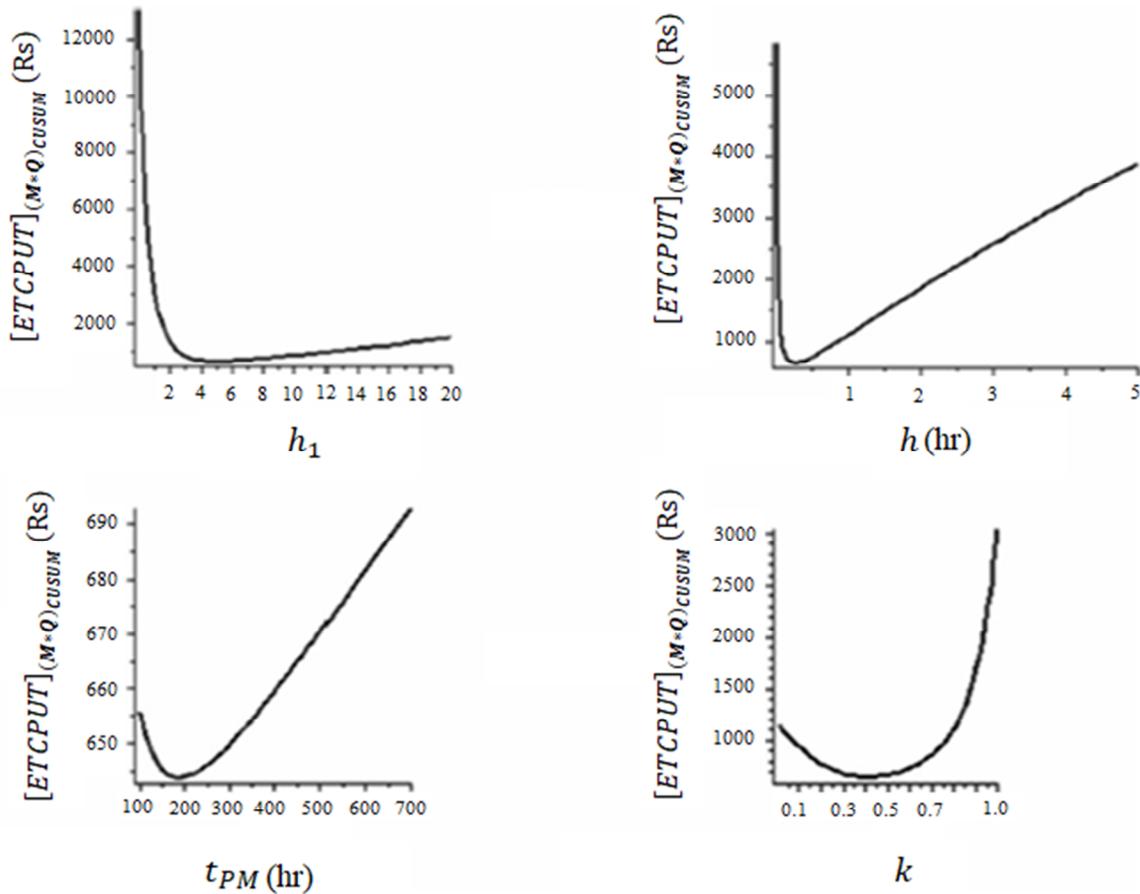


Fig. 6 Effect of decision variables on the integrated model expected total costs considering CUSUM chart [31]

8. Sensitivity analysis

A sensitivity analysis was then performed; the impact on the expected total system's costs by increasing each basic variable by 10% and 20%, as was done by Divya et al. [31], is summarized in Table 3. Moreover, from the sensitivity analysis, the optimal value range of the four decision variables and the corresponding values of the objective function at different levels of the model parameters are determined and summarized in Table 4. The optimal decision variables are obtained by minimizing Eq. 34. Therefore, a total of 30 instances are solved to investigate the sensitivity of the model parameters as indicated in Table 4 and to compare the impact of levels 2 and 3 to case 1, which is considered as a basic model value. The results determine how different values of the parameter variables affect the expected total system's costs. However, the optimal economic design is relatively more sensitive to errors in the estimation of the most of the parameters and the costs to a company for manufacturing a product out of specification.

Table 3 Sensitivity of basic variables and effect on $[ETCPUT]_{(M*Q)EWMA}$

Parameter	Basic level	Level 2 (+ 10 %)	Level 3 (+ 20 %)	$[ETCPUT]_{(M*Q)EWMA}$			
				Basic level	Level 2	Level 3	Range
δ_E	1	1.1	1.2	349.44	343.74	337.92	337.92–349.44
$\delta_{M/C}$	0.6	0.66	0.72	349.44	349.28	349.17	349.17–349.44
T_{false}	1	1.1	1.2	349.44	349.44	349.45	349.44–349.45
T_1	1	1.1	1.2	349.44	349.16	349.22	349.16–349.44

$T_{restting}$	2	2.2	2.4	349.44	349.55	349.83	349.44–349.83
T_S	0.333	0.344	0.355	349.44	349.44	349.44	349.44
C_{Frej}	1200	1320	1440	349.44	372.63	395.81	349.44–395.81
C_{false}	700	770	840	349.44	349.45	349.46	349.44–349.46
$C_{restting}$	500	550	600	349.44	349.87	350.31	349.44–350.31
C_{FCPCM}	10000	11000	12000	349.44	353.12	356.81	349.44–356.81
C_{FCPPM}	800	880	960	349.44	349.91	350.41	349.44–350.41
C_V	5	5.5	6	349.44	349.56	349.77	349.44–349.77
C_F	50	55	60	349.44	350.54	351.63	349.44–351.63
C_{lp}	50	55	60	349.44	353.70	357.96	349.44–357.96
LC	200	220	240	349.44	350.97	352.85	349.44–352.85

Table 4 Range of optimal values of four decision variables of the improved model using EWMA chart

Decision variable	Hs^*	L^*	λ^*	t_{PM}^*
Range	4 – 5	0.45 – 0.47	1	160 – 180

9. Conclusion

This paper proposes a model for maintenance planning and process quality control in a production system using two quality control charts, the EWMA chart and the CUSUM chart and compares the output results of the proposed model. It is found that the proposed model determines optimal values of process quality decision parameters (i.e., Ns , Hs , L , λ) and the optimal PM interval (t_{PM}) needed to minimize the total expected costs of all required maintenance procedures. Consequently, the proposed integrated model using the EWMA control chart demonstrates superior results when compared with the results obtained using the CUSUM chart. An analysis of the average run lengths determined by the EWMA control chart indicates its improved performance over the CUSUM control chart because the EWMA chart is very sensitive to shifts in the process mean. Furthermore, two independent models are proposed to examine the effectiveness of the integrated model. A case study is then employed; the results indicate that the proposed integrated model performance is superior to those of the independent models. A sensitivity analysis is then performed to clarify the effect of parameter variation on the overall costs of the system to help manufacturers distinguish between more sensitive parameters and less sensitive parameters. The presented results can lead to a number of potential future investigations as follows:

1. The study presented in this paper is restricted to a single machine, but the proposed approach is interesting to be used for joint maintenance, process quality control, and production scheduling for different shop floor environments such as open-shops, job-shops, flow shops, etc., with multiple machines, multi-component systems and various flow patterns and sequence dependent/independent setup times.
2. The objective function in this paper is to minimize expected costs per unit time. Other objective functions may also be investigated, such as machine availability, process capability, etc.
3. As part of future research, a more practical improvement can be attempted by developing analytical or simulation model.
4. The Taguchi quality loss function method could be used to calculate loss due to process shift.

Acknowledgments

This project was funded by the National Plan for Science, Technology and Innovation (MAARIFAH), King Abdulaziz City for Science and Technology, Kingdom of Saudi Arabia, award number (14-ELE69-02-R).

Notations

$T_{evaluation}$: evaluation period

C_{false} : costs occurring due to a false alarm inspection

PR : production rate

μ_0 : process mean in an in-control system

σ_0 : process standard deviation in an in-control system

R' : nonconforming units

C_{Frej} : rejection costs in an out-of-control system due to process failure

$(R_\delta)_E$: nonconforming item probability in an out-of-control system that occur because of an exterior effect

δ_E : shift magnitude that occurs because of an exterior effect

$(R_\delta)_{M/C}$: probability of production of nonconforming items when machine failure has occurred

$\delta_{M/C}$: shift magnitude that occurs because of machine failure

T_S : time obtained by taking one sample and charting it

T_1 : observed via time required for finding an assignable cause

T_{false} : time spent for searching a false alarm

C_F : fixed costs of a sample

C_V : variable costs of a sample

$C_{resetting}$: costs of resetting

$T_{resetting}$: time needed for resetting a process to a normal state

$(MTTR_{CM})_{FM_1}$: mean time required to repair a failure of FM1 type

$(MTTR_{CM})_{FM_2}$: mean time required to repair a failure of FM2 type

$MTTR_{CM}$: mean repair time required for a corrective action

$MTTR_{PM}$: mean repair time required for a preventive action

$MTBF_{Process}$: mean time between the failures of the process

C_{lp} : costs of lost production

LC : costs of maintenance personnel

C_{FCPCM} : CM fixed costs

C_{FCPPM} : PM fixed costs

P_{FM_1} : probability of a type 1 failure (FM1)

P_{FM_2} : probability of type 2 failure (FM2)

Y_1 : failure due to an external cause

Y_2 : failure that occurs because of machine degradation

t : average time elapsed from the last sample before the assignable cause has been found to the occurrence of the assignable cause when integrating maintenance and quality control

N_s : sample size

H_s : sample frequency

L : decision boundary of the control chart

λ : smoothing parameter of the control chart

t_{PM} : preventive maintenance interval

h : sample interval

h_1 : decision interval

k : control limit coefficient

ARL_1 : average run length in an in-control system

ARL_{2E} : average run length in an out-of-control system that occurs because of an exterior effect

$ARL_{2M/C}$: average run length in an out-of-control system that occurs because of a machine failure

Y : process failure rate

N_f : number of failures

N_{PM} : Number of PM actions

$E[C_{process}]$: process failure costs

$E[C_{false}]$: false alarm costs

$E[C_{sampling}]$: sampling costs

$E[C_{non-conforming}]$: expected costs of nonconforming units due to an in-control system

$E[C_{resetting}]$: resetting the expected costs

$E[C_{rejection}]_{M/C}$: expected costs of rejection when a machine failure has occurred

$E[C_{rejection}]_E$: expected costs of rejection when a failure due to an external reason has occurred

$E[C_{CM}]_{FM_1}$: CM costs incurred because of failure mode (FM1)

$E[TCQ]_{process\ failure}$: quality loss costs in an out-of-control system incurring because of the process failure

$[ETCPUT]_{(M*Q)EWMA}$: total costs incurred in an out-of-control system of both maintenance and quality strategies using EWMA control chart

$[ETCPUT]_{(M*Q)CUSUM}$: total costs incurred in an out-of-control system of both maintenance and quality strategies using CUSUM control chart

$[CPUT]_{Maint.}$: total maintenance costs

$[CPUT]_{SPC}$: total costs of statistical process control (SPC)

REFERENCES

- [1] D. Pandey, M. S. Kulkarni, and P. Vrat, "Joint consideration of production scheduling, maintenance and quality policies: a review and conceptual framework," *International Journal of Advanced Operations Management*, vol. 2, pp. 1-24, 2010. <https://doi.org/10.1504/ijaom.2010.034583>
- [2] P. S. Hariba and S. D. Tukaram, "Economic design of a nonparametric EWMA control chart for location," *Production*, vol. 26, pp. 698-706, 2016. <https://doi.org/10.1590/0103-6513.209916>
- [3] A. J. Duncan, "The economic design of X charts used to maintain current control of a process," *Journal of the American Statistical Association*, vol. 51, pp. 228-242, 1956. <https://doi.org/10.2307/2281343>
- [4] S. M. Alexander, M. A. Dillman, J. S. Usher, and B. Damodaran, "Economic design of control charts using the Taguchi loss function," *Computers & industrial engineering*, vol. 28, pp. 671-679, 1995. [https://doi.org/10.1016/0360-8352\(94\)00219-d](https://doi.org/10.1016/0360-8352(94)00219-d)
- [5] A. Hassan, M. Shariff Nabi Baksh, and A. M. Shaharoun, "Issues in quality engineering research," *International Journal of Quality & Reliability Management*, vol. 17, pp. 858-875, 2000. <https://doi.org/10.1108/02656710010325093>
- [6] D. Sherwin, "A review of overall models for maintenance management," *Journal of quality in maintenance engineering*, vol. 6, pp. 138-164, 2000. <https://doi.org/10.1108/13552510010341171>

- [7] H. Wang, "A survey of maintenance policies of deteriorating systems," *European journal of operational research*, vol. 139, pp. 469-489, 2002. [https://doi.org/10.1016/s0377-2217\(01\)00197-7](https://doi.org/10.1016/s0377-2217(01)00197-7)
- [8] A. Garg and S. Deshmukh, "Maintenance management: literature review and directions," *Journal of Quality in Maintenance Engineering*, vol. 12, pp. 205-238, 2006. <https://doi.org/10.1108/13552510610685075>
- [9] A. Schiffauerova and V. Thomson, "A review of research on cost of quality models and best practices," *International Journal of Quality & Reliability Management*, vol. 23, pp. 647-669, 2006. <https://doi.org/10.1108/02656710610672470>
- [10] G. Nenes and G. Tagaras, "The economically designed two-sided Bayesian control chart," *European Journal of Operational Research*, vol. 183, pp. 263-277, 2007. <https://doi.org/10.1016/j.ejor.2006.09.074>
- [11] M. Ben-Daya and S. Duffuaa, "Maintenance and quality: the missing link," *Journal of quality in maintenance engineering*, vol. 1, pp. 20-26, 1995. <https://doi.org/10.1108/13552519510083110>
- [12] M. Rahim, "Economic design of x control charts assuming Weibull in-control times," *Journal of Quality Technology*, vol. 25, pp. 296-299, 1993. <https://doi.org/10.1080/00224065.1993.11979475>
- [13] M. Rahim, "Joint determination of production quantity, inspection schedule, and control chart design," *IIE Transactions*, vol. 26, pp. 2-11, 1994. <https://doi.org/10.1080/07408179408966632>
- [14] M. Ben-Daya, "Integrated production maintenance and quality model for imperfect processes," *IIE Transactions*, vol. 31, pp. 491-501, 1999. <https://doi.org/10.1080/07408179908969852>
- [15] M. Ben-Daya and M. Rahim, "Effect of maintenance on the economic design of x-control chart," *European Journal of Operational Research*, vol. 120, pp. 131-143, 2000. [https://doi.org/10.1016/s0377-2217\(98\)00379-8](https://doi.org/10.1016/s0377-2217(98)00379-8)
- [16] C. R. Cassady, R. O. Bowden, L. Liew, and E. A. Pohl, "Combining preventive maintenance and statistical process control: a preliminary investigation," *IIE Transactions*, vol. 32, pp. 471-478, 2000. <https://doi.org/10.1080/07408170008963924>
- [17] T. G. Yeung, C. R. Cassady, and K. Schneider, "Simultaneous optimization of [Xbar] control chart and age-based preventive maintenance policies under an economic objective," *IIE transactions*, vol. 40, pp. 147-159, 2007. <https://doi.org/10.1080/07408170701592515>
- [18] M. Ben-Daya and M. Rahim, "Integrated production, quality & maintenance models: an overview," in *Integrated Models in Production Planning, Inventory, Quality, and Maintenance*, ed: Springer, 2001, pp. 3-28. https://doi.org/10.1007/978-1-4615-1635-4_1
- [19] Y. Kuo, "Optimal adaptive control policy for joint machine maintenance and product quality control," *European Journal of Operational Research*, vol. 171, pp. 586-597, 2006. <https://doi.org/10.1016/j.ejor.2004.09.022>
- [20] K. Linderman, K. E. McKone-Sweet, and J. C. Anderson, "An integrated systems approach to process control and maintenance," *European Journal of Operational Research*, vol. 164, pp. 324-340, 2005. <https://doi.org/10.1016/j.ejor.2003.11.026>
- [21] S. Panagiotidou and G. Tagaras, "Optimal preventive maintenance for equipment with two quality states and general failure time distributions," *European Journal of Operational Research*, vol. 180, pp. 329-353, 2007. <https://doi.org/10.1016/j.ejor.2006.04.014>
- [22] S. Panagiotidou and G. Tagaras, "Evaluation of maintenance policies for equipment subject to quality shifts and failures," *International Journal of Production Research*, vol. 46, pp. 5761-5779, 2008. <https://doi.org/10.1080/00207540601182260>
- [23] H.-N. Chiu and B.-S. Huang, "The economic design of x-control charts under a preventive maintenance policy," *International Journal of Quality & Reliability Management*, vol. 13, pp. 61-71, 1996. <https://doi.org/10.1108/02656719610108323>
- [24] W.-H. Zhou and G.-L. Zhu, "Economic design of integrated model of control chart and maintenance management," *Mathematical and computer Modelling*, vol. 47, pp. 1389-1395, 2008. <https://doi.org/10.1016/j.mcm.2007.09.008>
- [25] S. Panagiotidou and G. Nenes, "An economically designed, integrated quality and maintenance model using an adaptive Shewhart chart," *Reliability Engineering & System Safety*, vol. 94, pp. 732-741, 2009. <https://doi.org/10.1016/j.ress.2008.07.003>
- [26] D. Pandey, M. S. Kulkarni, and P. Vrat, "A methodology for joint optimization for maintenance planning, process quality and production scheduling," *Computers & Industrial Engineering*, vol. 61, pp. 1098-1106, 2011. <https://doi.org/10.1016/j.cie.2011.06.023>

- [27] D. Pandey, M. S. Kulkarni, and P. Vrat, "A methodology for simultaneous optimisation of design parameters for the preventive maintenance and quality policy incorporating Taguchi loss function," *International Journal of Production Research*, vol. 50, pp. 2030-2045, 2012. <https://doi.org/10.1080/00207543.2011.561882>
- [28] L. Liu, M. Yu, Y. Ma, and Y. Tu, "Economic and economic-statistical designs of an control chart for two-unit series systems with condition-based maintenance," *European Journal of Operational Research*, vol. 226, pp. 491-499, 2013. <https://doi.org/10.1016/j.ejor.2012.11.031>
- [29] N. Manavizadeh and E. A. Javan, "A New Approach in Joint Optimization of Maintenance Planning, Process Quality and Production Scheduling," *International Journal*, vol. 3, 2014.
- [30] H. Yin, G. Zhang, H. Zhu, Y. Deng, and F. He, "An integrated model of statistical process control and maintenance based on the delayed monitoring," *Reliability Engineering & System Safety*, vol. 133, pp. 323-333, 2015. <https://doi.org/10.1016/j.res.2014.09.020>
- [31] D. Shrivastava, M. S. Kulkarni, and P. Vrat, "Integrated design of preventive maintenance and quality control policy parameters with CUSUM chart," *International Journal of Advanced Manufacturing Technology*, vol. 82, pp. 2101-2112, 2016. <https://doi.org/10.1007/s00170-015-7502-7>
- [32] B. Lu, X. Zhou, and Y. Li, "Joint modeling of preventive maintenance and quality improvement for deteriorating single-machine manufacturing systems," *Computers and Industrial Engineering*, vol. 91, pp. 188-196, 2016. <https://doi.org/10.1016/j.cie.2015.11.019>
- [33] J. J. Black and O. Mejabi, "Simulation of complex manufacturing equipment reliability using object oriented methods," *Reliability Engineering & System Safety*, vol. 48, pp. 11-18, 1995. [https://doi.org/10.1016/0951-8320\(95\)00008-p](https://doi.org/10.1016/0951-8320(95)00008-p)
- [34] B. K. Lad and M. Kulkarni, "Integrated reliability and optimal maintenance schedule design: a life cycle cost based approach," *International Journal of Product Lifecycle Management*, vol. 3, pp. 78-90, 2008. <https://doi.org/10.1504/ijplm.2008.019971>
- [35] S. Roberts, "Control chart tests based on geometric moving averages," *Technometrics*, vol. 1, pp. 239-250, 1959. <https://doi.org/10.1080/00401706.1959.10489860>
- [36] S. V. Crowder, "A simple method for studying run-length distributions of exponentially weighted moving average charts," *Technometrics*, vol. 29, pp. 401-407, 1987. <https://doi.org/10.2307/1269450>
- [37] S. V. Crowder, "Average run lengths of exponentially weighted moving average control charts," *Journal of Quality Technology*, vol. 19, pp. 161-164, 1987. <https://doi.org/10.1080/00224065.1987.11979055>
- [38] S. V. Crowder, "Design of exponentially weighted moving average charts," *Journal of Quality Technology*, vol. 21, pp. 155-162, 1989. <https://doi.org/10.1080/00224065.1989.11979164>
- [39] J. M. Lucas and M. S. Saccucci, "Exponentially weighted moving average control charts: properties and enhancements," *Technometrics*, vol. 32, pp. 1-12, 1990. <https://doi.org/10.1080/00401706.1990.10484583>
- [40] I. C. Gomes, S. A. Mingoti, and C. D. L. Oliveira, "A novel experience in the use of control charts for the detection of nosocomial infection outbreaks," *Clinics*, vol. 66, pp. 1681-1689, 2011. <https://doi.org/10.1590/s1807-59322011001000004>
- [41] M. Aslam, M. Azam, and C.-H. Jun, "A new control chart for exponential distributed life using EWMA," *Transactions of the Institute of Measurement and Control*, vol. 37, pp. 205-210, 2015. <https://doi.org/10.1177/0142331214537293>
- [42] QUA Khaliq, M. Riaz and S. Ahmad, "On designing a new Tukey-EWMA control chart for process monitoring," *The International Journal of Advanced Manufacturing Technology*, vol. 82, pp. 1-23, 2016. <https://doi.org/10.1007/s00170-015-7289-6>
- [43] C. Vera do Carmo, L. F. D. Lopes, A. M. J. C. Souza, and I. Engineering, "Comparative study of the performance of the CuSum and EWMA control charts," vol. 46, pp. 707-724, 2004. <https://doi.org/10.1016/j.cie.2004.05.025>
- [44] A.-S. Adel, M. A. Noman, E. A. Nasr, H. Kaid, A. K. Kamrani, and A. M. El-Tamimi, "New Integrated Model for Maintenance Planning and Quality Control Policy for Multi-Component System using an EWMA Chart," *IEEE Access*, 2019. <https://doi.org/10.1109/access.2019.2950815>
- [45] L. Zhang, G. Chen, and P. Castagliola, "On t and EWMA t charts for monitoring changes in the process mean," *Quality and Reliability Engineering International*, vol. 25, pp. 933-945, 2009. <https://doi.org/10.1002/qre.1012>
- [46] M. Srivastava and Y. Wu, "Evaluatiok of optimum weights and average run lenghts in ewma control charts," *Communications in Statistics-Theory and Methods*, vol. 26, pp. 1253-1267, 1997. <https://doi.org/10.1080/03610929708831980>

- [47] M. Bagshaw and R. A. J. J. o. t. R. S. S. B. Johnson, "The influence of reference values and estimated variance on the ARL of CUSUM tests," vol. 37, pp. 413-420, 1975.
<https://doi.org/10.1111/j.2517-6161.1975.tb01555.x>
- [48] George V. Moustakides. "Optimal Stopping Times for Detecting Changes in Distributions." *Ann. Statist.* 14 (4) 1379 - 1387, December, 1986. <https://doi.org/10.1214/aos/1176350164>
- [49] L.C. Alwan, "Designing an effective exponential cusum chart without the use of nomographs," *Communications in Statistics - Theory and Methods*, 29:12, 2879-2893, 2000.
<https://doi.org/10.1080/03610920008832642>
- [50] W. H. Woodall and B. M. J. Q. E. Adams, "The statistical design of CUSUM charts," *Quality Engineering*, 5:4, 559-570, 1993. <https://doi.org/10.1080/08982119308918998>
- [51] B. K. Lad and M. S. Kulkarni, "A parameter estimation method for machine tool reliability analysis using expert judgement," *International Journal of Data Analysis Techniques and Strategies*, vol. 2, pp. 155-169, 2010. <https://doi.org/10.1504/ijdots.2010.032455>
- [52] T. J. Lorenzen and L. C. Vance, "The economic design of control charts: a unified approach," *Technometrics*, vol. 28, pp. 3-10, 1986. <https://doi.org/10.1080/00401706.1986.10488092>
- [53] D. C. Montgomery, *Introduction to statistical quality control*: John Wiley & Sons (New York), 2009.

Submitted: 17.8.2020

Accepted: 19.11.2020

Mohammed A. Noman*
Industrial Engineering Department,
College of Engineering, King Saud
University, P. O. Box 800, Riyadh 11421,
Saudi Arabia.
Department of Industrial and
Manufacturing Systems Engineering,
College of Engineering & IT, Taiz
University, Taiz 6803, Yemen.
Adel AL-Shayea
Husam Kaid
Abdulrahman Al-Ahmari
Industrial Engineering Department,
College of Engineering, King Saud
University, P. O. Box 800, Riyadh 11421,
Saudi Arabia.
Emad Abouel Nasr
Haitham A. Mahmoud
Industrial Engineering Department,
College of Engineering, King Saud
University, P. O. Box 800, Riyadh 11421,
Saudi Arabia.
Faculty of Engineering, Mechanical
Engineering Department, Helwan
University, Cairo 11732, Egypt.
Ali K. Kamrani
Industrial Engineering Department,
College of Engineering, University of
Houston, 213 Engineering Building 2,
Houston, TX 77204 4008, USA.
Corresponding author
*mmohammed1@ksu.edu.sa