Chapter 4
Special Control Charts Using Intelligent Techniques: EWMA Control Charts

Bulut Aslan, Yeliz Ekinci and Ayhan Özgür Toy

Abstract In this chapter we consider the economical design of EWMA zone control charts for set of machines operating under JPS (Jidoka Production System). We provide an extensive literature review of intelligent systems in quality control deductively to fit our purposes. It starts with an overview of quality control charts; then, reviews charts designed for special purposes such as EWMA, CUSUM and zone control charts. Finally, as particularly related to this study, reviews of economical design and intelligent applications of EWMA are provided. We discuss and review Jidoka Production System and motivation of operating such a system. We suggest an intelligent control and repair system such that in a production system, machines are individually controlled and repaired when an out-of-control signal is triggered in the zone with the tight control limits, however a system-wide shut down and repair is conducted when the out-of-control signal is from beyond the inner (tight) control limits which is considered as an opportunity for repair and calibration of all machines. We illustrate and investigate the behaviour of control parameters, namely sample size, sampling interval and control limits, via a numerical study of a three-machine system through simulation. We also provide insights for implementation of several metaheuristics for the system setting discussed in this chapter.

Keywords Control charts · EWMA · CUSUM · Intelligent · Jidoka production system

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C. Kahraman and S. Yanık (eds.), *Intelligent Decision Making in Quality Management*, Intelligent Systems Reference Library 97,
DOI 10.1007/978-3-319-24499-0_4

4.1 Introduction

This study suggests an intelligent system approach to the quality control problem of a production environment. This intelligent system provides controlling particular decisions automatically, which are once made manually by operators at the job level. An Exponentially Weighted Moving Average (EWMA) quality control chart, integrated with zone control policy, is intelligently controlled at the system level to minimize the rate of total cost. This intelligent system will be useful for the companies which use Jidoka Production System and implement statistical process control tools. The statistical process control (SPC) is a widely used method in quality control. SPC has been introduced by Walter Shewhart (Shewart, 1924) in 1920s and it is defined as a technique of monitoring, controlling, and improving a process through statistical analysis. The advantages of SPC are listed by Parkash et al. (2013) among which there are *improving process performance by reducing product variability*, *minimizing rework and loss of sales*, and *elimination of unnecessary quality checks and higher quality product by reducing variability and defects*. De Vries and Reneau (2010) state that there are two aspects of the SPC approach: (i) to assist the continuous improvement of performance by further reduction of unexplained variability; (ii) to detect any variability in the system as quickly as possible.

Benneyan et al. (2003) define the basic principles of SPC as: (i) individual measurement from any process exhibits variation (ii) variability due to common cause can be predicted and represented by statistical models such as Gaussian, binomial, or Poisson distribution, (iii) variability due to assignable cause displays deviation in some observable way from the aforementioned random distribution models, (iv) statistical limits can be established to test the data in order to provide evidence of any change. We refer the reader to Montgomery (1991) for a detailed description and explanation of SPC.

There are seven basic tools for quality improvement that are used for statistical process control. These are; check sheet, defect concentration diagram, histogram, Pareto chart, scatter diagram/chart, cause and effect or fishbone diagram, control chart. Quality control charts are the most widely used technique and are of concern in this study.

Quality control charts started to be used in the manufacturing industries in the 1920s, but later implemented in lots of other application areas such as health care management, epidemiology, animal production systems, service, financial and agriculture systems, (see De Vries and Reneau 2010; Woodall 2006; Thor et al. 2007; Quesenberry 1997; Montgomery 2009; Solodky et al. 1998 and Diaz and Neuhauser 2005 for various applications of SPC). We will dwell into control charts in subsequent sections.

In some processes it may be required to implement more sensitive control charts, i.e., to detect smaller or moderate sized shifts in the process mean, for which Exponentially Weighted Moving Average (EWMA) control charts and Cumulative Sum (CUSUM) control charts have been developed. A large body of literature has been built on EWMA control charts following the pioneering work by Roberts (1959).

We will present some of recent works on EWMA control charts in the subsequent sections. We also refer the reader to Page (1954) for CUSUM control charts.

Recognition of any systematic or non-random patterns in observations is of interest in some cases. In order to pinpoint these patterns, establishment of control limits at different expanding levels in multiples of process standard deviation is necessary. Zone control charts are the choice when the concern is to detect systematic patterns. The zone control charts can be traced back to The *Statistical Quality Control Handbook* (Western Electric 1956).

Implementation of control charts in production systems generally assumes that machines are individually operated and controlled. Therefore, control charts are designed for each machine considered in isolation. However, this assumption does not always hold. Recent trends in manufacturing view machines operating in coordination as a single system, and hence, suggest a central control mechanism. *Jidoka* (translated as autonomation) is such a defect detection system, which automatically or manually stops the production operation whenever an abnormal or defective condition arises. In the concept of jidoka when a team member encounters a problem in his or her workstation, he/she is responsible for indicating the problem by pulling an *andon cord*, which can stop the line. Hence, when any machine issues an alarm, a system-wide shut down is triggered and the production is ceased until the inspection/restoration of the triggering machine. Here, we assume that holding WIP (Work-In-Process) inventory between the machines, that keeps upstream and downstream of the line working during restoration of an intermediate machine, is not feasible or undesirable. Such a production system is denoted as *Jidoka Production System* (JPS) by Berk and Toy (2009).

Designing a control chart means to determine the operating parameters, (i.e., when to sample, how much to sample and the reference values (control limits) for an inference about the sample) of a control chart. There are economical, statistical and economic-statistical procedures of determining these operating parameters (refer to Montgomery 1980a, b for explanation of these procedures). Our focus in this chapter is on the economical design of control charts, specifically economically designing EWMA zone control charts for set of machines operating under JPS.

We suggest a control and repair policy such that in a production system, machines are individually controlled and repaired when an out-of-control signal is triggered in the zone with the tight control limits, however a system-wide shut down and repair is conducted when the out-of-control signal is from beyond the inner (tight) control limits which is considered as an opportunity for repair and calibration of all machines. We illustrate and investigate the behaviour of control parameters, namely sample size, sampling interval, control limits and EWMA smoothing parameter.

In the sequel, we will provide literature review on intelligent systems in quality control. Then, we introduce Jidoka Production System as an intelligent QC approach with our assumptions and the model prior to presenting our methodology and numerical study. Finally we present our conclusions.

4.2 Intelligent Systems in Quality Control

Intelligent systems (IS) is a broad term, covering a range of computing techniques that have emerged from research into artificial intelligence (Hopgood 2012). It is about generating representations, procedures and strategies to handle tasks that were once thought only do-able by humans (Schalkoff 2009). The tools of particular interest are roughly divided among *knowledge-based systems*, *computational intelligence* and *hybrid* systems (Schalkoff 2009; Negnevitsky 2011; Hopgood 2012). Knowledge-based systems include expert and rule-based systems, object-oriented and frame-based systems, and intelligent agents. Computational intelligence includes neural networks, genetic algorithms and other optimization algorithms (i.e., metaheuristics). Techniques for handling uncertainty, such as fuzzy logic, fit into both categories. Knowledge-based systems, computational intelligence, and their hybrids are collectively referred to here as IS. When knowledge is not explicitly stated but represented by numbers, computational intelligence takes place to improve any system accuracy; where numerical techniques such as genetic algorithms and neural networks.

This study brings in an IS approach to the quality control problem of a production environment. Particular decisions, which are once made manually by operators at the job level, are now automatically controlled and taken into consideration at the system-level. An EWMA chart, integrated with zone control policy, is intelligently controlled at the system level to minimize the rate of total cost.

The following literature review is organized in a deductive way to clearly underline this study's contribution. It starts with a generic introduction to quality control charts; then, an overview of QC charts designed for special purposes such as EWMA, CUSUM and zone control charts is provided. Subsequently, as particularly related to this study, studies on economical design and finally intelligent applications of EWMA are reviewed. Each subsection is chronologically organized on its own.

4.2.1 Quality Control Charts

Quality control charts, developed by Shewhart (1924), is a statistical tool applied to detect a shift on the process. In this tool observations are plotted over time to see whether a process is running as it should be. In this context, a process is said to be "in-control" if the probability distribution representing the quality characteristic is constant over time. If there is some change in this distribution the process is said to be "out-of-control". Control charts help to distinguish between common causes and assignable causes and quickly detect occurrences of unplanned assignable causes so corrective action may be undertaken and the assignable causes are removed.

Quality control charts are commonly classified into two types: (i) if a control chart is used to track a quality characteristic which can be measured and expressed as a number on some continuous scale of measurement, it is usually called a *variable control chart*. Conveniently, the quality characteristic is described with a measure of central tendency (e.g., mean) and a measure of dispersion (e.g., range or standard deviation). The $\bar{X}$ chart is the most widely used chart for controlling the former, whereas the charts based on the latter, such as R-chart or s-chart, are used to control process variability; (ii) In cases where quality characteristics are not measured on a continuous or quantitative scale, control charts are constructed based on quality conformances and called *attribute control charts*. Each unit is categorized as either conforming or nonconforming on the basis of possession of certain attributes or the number of nonconformities (defects) appearing on a unit of product.

De Vries and Reneau (2010) state that good design of control charts depends on grouping of observations, *the distribution of the process observations*, *the size of the process shift of interest*, and *the costs of Type I and Type II errors*. There are two types of variable control charts that are widely used, namely, $\bar{X}$ chart and R-chart. The $\bar{X}$ chart is used to monitor the process mean and the R-chart is used to monitor variability. For both of them, samples are taken over time and values of a statistic are plotted. The first quality control chart developed by Shewhart is of type $\bar{X}$ and is slow in detecting the smaller mean shifts. The "variable sampling intervals (VSI) $\bar{X}$ charts" and "variable parameters (VP) $\bar{X}$ charts" detect small shifts in the process mean faster than the standard $\bar{X}$ chart (see Costa 1999; Reynolds et al. 1988; Lee et al. 2012 for discussion). CUSUM and EWMA charts are also good alternatives when the aim is detecting small shifts. However Lee et al. (2012) argue that their control procedures are not as easy to set up as Shewhart control chart.

A control chart consists of two parts: (i) a series of measurements plotted in time order, and (ii) the control chart "template" which consists of three horizontal lines called the center line (typically, the mean), the upper control limit (UCL), and the lower control limit (LCL) The values of the UCL and LCL are usually calculated from the inherent variation in the data. The lower control limit and the upper control limit determine the bounds of the in-control region, i.e. as long as the measurement of the sample taken falls in between these two lines the process is assumed to be in the in-control status. Only random causes exist if the sample data points fall between the two control limits. If the process shifts to the out-of-control status then we expect that most of the observations are outside the control limits. Moreover, when in-control, the data points plotted on the chart should be distributed without a pattern between the control limits. Sometimes the data points are located only on one side of the center line and close to each other. This also may be an evidence for a systematic variation, hence, out-of-control state. It is assumed that, at the start of a production run after the last restoration, the production process is in the in control status, producing items of acceptable quality. After a period of time in production, the process may shift to the out-of-control status.

The placing of the control limits on a control chart depends on the cost of false alarms (i.e., Type I errors) and the cost after a shift occurs but not detected (i.e., Type II errors). The optimal placing of control limits and the optimal frequency of collecting observations has triggered much research (Montgomery 2009). If the limits are set too narrow there is a high probability of a "Type I error"—mistakenly inferring assignable cause variation exists when, in fact, a predictable extreme value is being observed which is expected periodically from common cause variation. On the other hand, if the limits are set too wide there is a high probability of a "Type II error".

The control limits are usually set at ±3 standard errors of the plotted statistic from a center line at its historical average value. Conventionally, "control limits at 3-standard errors from the mean" is robust for observations from most kinds of distributions but could result in poor performance when unplanned changes are costly and need to be detected quickly. The formula for the calculation of the standard error is usually based on a distributional assumption. The control limits for the Shewhart charts are relatively easy to calculate. Finding the control limits for the CUSUM and EWMA given a desired rate of false alarms requires special software or tables. Hawkins and Olwell (1998) present algorithms for control limits on CUSUM charts.

Process engineers prefer to evaluate the effectiveness of a control procedure in terms of cost-based performance rather than risk-based performance measures such as the Type I and Type II errors. A typical example of the cost- based approach for a control chart is the economic design of the control chart (Park 2013).

4.2.2 EWMA and CUSUM Quality Control Charts

Alluded to above, EWMA and CUSUM control charts are implemented to detect small and moderate-sized shifts in the process. In EWMA, each point represents the weighted average of current and certain number of previous observation values, giving weight on the observations based on the recency. Shewart-type control charts are not very efficient in detecting small shifts since they only consider the final observation and do not consider accumulated information of the multiple observations; EWMA and CUSUM control charts are the methods to overcome this difficulty.

Neubauer (1997) discusses the properties of EWMA control charts and comparison with other quality control procedures. He specifically states, "*The EWMA chart offers a flexible instrument for visualizing imprecision and inaccuracy*". The properties of the EWMA chart with the constant control limits have also been studied by Robinson and Ho (1978), Waldmann (1986), Lucas and Saccucci (1990) and Gan (1991). The four-step procedure for implementing the EWMA chart established by Crowder (1989) has been discussed in Neubauer (1997).

The smoothing operation in EWMA control charts is achieved through a "smoothing parameter, λ" which guarantees giving less and less weight to observations as they are further removed in time. In brief, after multiplication by a factor λ, the current measurement is added to the sum of all former measurements, which is weighted with (1−λ). Thus, at each time epoch $t (t = 1,2,\ldots)$, the test statistic Z_t can be obtained by Eq. 4.1:

$$Z_t = [\lambda \bar{X}_t + (1 - \lambda) Z_{t-1}] \tag{4.1}$$

where $\bar{X}_t$ is the mean of current sample and $\lambda \in [0, 1]$. The computed Z_t values are displayed on a control chart over time. Since the statistic used is the sample mean in this particular example, this control chart is called the EWMA-$\bar{x}$ chart. Note that setting the smoothing parameter to unity ($\lambda = 1$) in EWMA control chart yields a Shewhart-type control chart.

In EWMA control charts test statistic computed above is plotted on a chart and compared with the control limits. A common approach to determining the control limits (see e.g. Montgomery 1991, p. 300) first requires the calculation of the variance of the test statistic, Z_t, which is given in Eq. 4.2:

$$\sigma_t^2 = [\sigma^2/n][\lambda/(2 - \lambda)][1 - (1 - \lambda^{2t}) \tag{4.2}$$

where we assume that the individual observations (sample mean) are independent random variables with variance σ^2.

The variance calculation above enables us to derive the following control limits for the EWMA control chart (Eqs. 4.3 and 4.4):

$$UCL = \mu_0 + L\sigma \sqrt{\left(\frac{\lambda}{2 - \lambda}\right)[1 - (1 - \lambda)^{2t}]} \tag{4.3}$$

$$LCL = \mu_0 - L\sigma \sqrt{\left(\frac{\lambda}{2 - \lambda}\right)[1 - (1 - \lambda)^{2t}]} \tag{4.4}$$

where L is the coefficient which defines "the width of the control limits". As the sample number, t, gets larger control limits converges to, so called, the steady-state EWMA control limits, which are given by Eqs. 4.5 and 4.6:

$$UCL = \mu_0 + L\sigma \sqrt{\left(\frac{\lambda}{2 - \lambda}\right)} \tag{4.5}$$

$$LCL = \mu_0 - L\sigma \sqrt{\left(\frac{\lambda}{2 - \lambda}\right)} \tag{4.6}$$

It is important to note, however, that the expression for the variance of Z_t for $t > 1$ is derived by ignoring the truncation effects of the control limits employed at the previous $t-1$ samples. Thus, using a constant multiple of the standard deviation to give the control limits is done somewhat arbitrarily.

Vargas et al. (2004) provides insights for choosing smoothing parameter, λ, and for the coefficient of the width of the control limit interval, L. They state that, in practice, values between 0.05 and 0.25 for the smoothing parameter work well, with the popular choices being 0.05; 0.10 and 0.20; and the usual three-sigma limits ($L = 3$) work reasonably well particularly with the larger values of λ. Montgomery (1996) suggests that when λ is small, ($\lambda \leq 0.1$), there is an advantage in reducing the width of limits, using a value of L between 2.6 and 2.8.

We next provide a brief review of CUSUM control charts. The CUSUM and EWMA control charts differ from each other in incorporation of the smoothing parameter in EWMA control charts, which allows the adjustment of shift sensitivity. The CUSUM control chart was initially proposed by Page (1954) and has been widely studied and implemented then on. CUSUM chart attributes equal weight to all observations independent of their recency.

Like EWMA control charts CUSUM control charts also incorporate past observations and are therefore sensitive to detecting small shifts in the process. The CUSUM charts are available for distributions such as the Normal, Binomial, Poisson, and Weibull.

In CUSUM charts, each plotted point represents the algebraic sum of the previous observations and the most recent deviation from the target (Parkash et al. 2013). Assuming that samples of size $n \geq 1$ are collected, $\bar{x}_j$ is the average of the jth sample and μ_0 is the value wanted for the process average, the CUSUM control chart is formed by the formula resulting quantity along with sample i (Vargas et al. 2004) (Eq. 4.7):

$$C_i = \sum_{j=1}^{i} (\bar{x}_j - \mu_0) \tag{4.7}$$

where C_i is the cumulative sum including the ith sample, since they combine information from several samples. If the process keeps in control at the target value μ_0, the cumulative sums describe a random way. On the other hand, if the average changes to any value above $\mu_1 > \mu_0$, then an ascendant tendency will develop at the cumulative sum C_i. Reciprocally, if the average changes to some value below $\mu_1 < \mu_0$, the cumulative sum C_i will have a negative direction. Considering this, if at the demarcated points a tendency up or down appears, it must be considered as an evidence of process average change, and a search for the assignable causes must be done (Vargas et al. 2004). The main advantage of CUSUM charts is that it is very effective for small shifts and samples of size $n = 1$. The main disadvantage is that they are relatively slow to respond to large shifts and special patterns are hard to see and analyze.

Montgomery (2013) states that the general consensus is that the practical performances of the CUSUM and EWMA are quite similar and neither of them has a clear advantage over the other. Thus, users only need to implement one or the other to monitor their process. The CUSUM chart has a well-known optimality property: if a shift occurs in steady state, the CUSUM to which it is tuned has a faster average response than does any other chart (Hawkins and Olwell 1998; Hawkins and Wu 2014). Vargas et al. (2004) present a comparative study of the performance of the CUSUM and EWMA control charts. Their objective is to verify when CUSUM and EWMA control charts do the best control region, in order to detect small changes in the process mean. One of the results they come up with after several simulations is that the CUSUM control chart practically does not sign points out of control for the levels of variation between ±1.0 standard deviation; for these variation levels the EWMA control chart is more efficient. In a recent study, Hawkins and Wu (2014) conclude that, though the CUSUM outperforms the EWMA, if the actual shift is smaller than that used in the design, the EWMA may respond faster. Recently, synthetic EWMA (SynEWMA) and synthetic CUSUM (SynCUSUM) control charts have been proposed based on simple random sampling (SRS) by integrating the EWMA and CUSUM control charts with the conforming run length control chart, respectively. Haq et al. (2014) state that these synthetic control charts provide overall superior detection over a range of mean shift sizes.

Recently, Abbas et al. (2012) introduced the design structure of a mixed EWMA-CUSUM (MEC) control chart for improved monitoring of the process parameters. In their study, the EWMA statistic is used as the input for the CUSUM structure. Zaman et al. (2014) propose a reverse version of this mixing, that is, a mixed CUSUM-EWMA (MCE) control chart. In this new setup, the CUSUM statistic will serve the input for the EWMA structure. MCE control chart is used to monitor the location of a process. The performance of the proposed mixed CUSUM-EWMA control chart is measured through the average run length, extra quadratic loss, relative average run length, and a performance comparison index study. The analysis has revealed that the proposed MCE control chart is very sensitive for the detection of small and moderate shifts and offers a quite efficient structure as compared with existing counterparts. The relative performance of the proposed chart as compared with the other charts varies depending on the amounts of shifts.

4.2.3 Zone Control Charts

It may be of interest to recognize any systematic or non-random patterns in observations. Establishing control limits at different expanding levels in multiples of process standard deviation facilitates to pinpoint any patterns. Zone control charts are the choice when the concern is to detect systematic patterns. The zone control charts can be traced back to The *Statistical Quality Control Handbook* (Western Electric 1956) in which it has been suggested that the process is concluded to be out-of-control if either (1) one point plots outside the three-sigma control limits, (2) two out of three consecutive points plot beyond the two-sigma warning limits, (3) four out of five consecutive points plot at a distance of one sigma or beyond from the center line, or (4) eight consecutive points plot on one side of the center line.

Jaehn (1987, 1989) suggests a zone chart with eight zones, four on each side of the center line. Scores are assigned to each zone, and the procedure signals an out-of-control status when the total score exceeds a threshold value. Likewise, Flaig (2004) proposed a zone control chart that partitions the normal process distribution into regions and assigns a score to each region. A normal process distribution is partitioned as follows (Table 4.1):

An illustration of the above rules is depicted in Fig. 4.1 (excerption from Flaig 2004). In the figure, the chart starts with current score of zero and a cumulative score of zero. As additional observations are recorded, the cumulative score is adjusted using the following rules (Flaig 2004).

1. if observation i and observation $i-1$ are on different sides of the center line, then the cumulative score at i is set to the zone score at i
2. if observation i and observation $i-1$ are on the same side of the center line, then add the current score at i to the cumulative score at $i-1$.
3. If the cumulative score reaches 8, then an out of control signal is generated.

Performance of zone control charts, in the presence of a constant process mean, has been studied by Davis et al. (1990, 1994). The latter paper showed that in the presence of a constant process mean, a zone control chart with appropriate parameters has superior performance compared to the corresponding Shewhart chart with some combination of supplementary runs rules (Davis and Krehbiel 2002). Davis et al. (1994) proposed a general model for the zone control chart. In this model, any zone control chart is based on a cumulative score, which begins at zero. The cumulative score for the zone control chart with score vector S = (A1, A2, A3, M) is incremented based on how many standard errors (s.e.) a sample mean is away from the target mean, with zone scores assigned as follows (Table 4.2):

Table 4.1 Zone control chart scores

Zone	Score
Centerline	0
Between center and one sigma	1
Between one and two sigma	2
Between two and three sigma	4
Beyond three sigma	8

Table 4.2 Zone control chart scores in the study of Davis et al. (1994)

Zone	Score
Within one s.e. of target	A_1
Between one and two s.e. from target	A_2
Between two and three s.e.from target	A_3
Beyond three s.e. from target	M

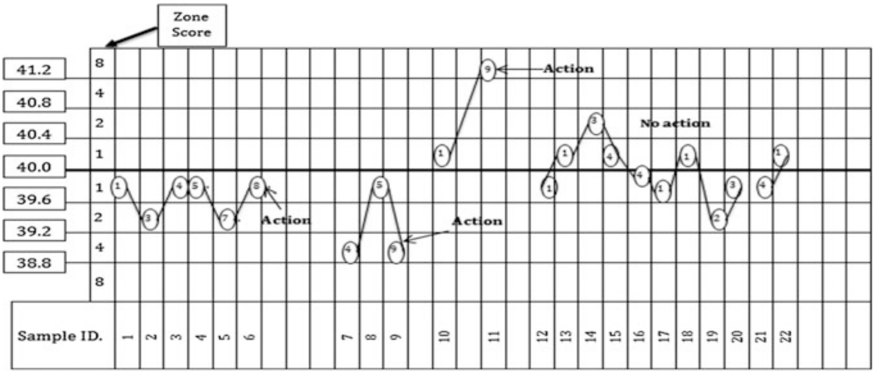


Fig. 4.1 Zone chart (Flaig 2004)

The cumulative score after any given sample consists of the score for the most recent sample mean added to the previous cumulative score. The only exception is when two successive sample means fall on opposite sides of the target; in this case, the cumulative score is reset to the score for only the most recent sample mean. Thus, if the process is in control, the sample means will fall on either side with a probability of 1/2 and the cumulative score will reset fairly frequently instead of continuing to get larger. If the cumulative score reaches or exceeds M, the chart generates an out-of-control signal (Davis and Krehbiel 2002; Davis et al. 1994).

In another paper, Davis and Krehbiel (2002) studied the average run length performances of Shewhart charts with supplementary runs rules and zone control charts when the process mean changes linearly over time. Shewhart charts with all possible combinations of the typical runs rules are compared to zone control charts with identical false alarm rates. The zone control charts generally outperform the Shewhart charts in detecting a process mean that is changing linearly over time.

4.2.4 Economical Design of Quality Control Charts

Economic design of control charts has been extensively studied since the pioneering work of Duncan (1956). Duncan (1956) studied on the economic design of $\bar{X}$ charts used to maintain current control of process, developed a cost model and solved for the design parameters (sample size, sampling interval, and control limit coefficient). Since then, there has been an increased interest in the economic design of the control charts in the late 1980s and early 1990s in accordance with developments in lean management of production systems (e.g., Montgomery 1980a, b; Vance 1983; Woodall 1986; Pignatiello and Tsai 1988; Niaki et al. 2010, 2013). A detailed explanation of construction of economically designed control charts is provided by Montgomery (1980a, b) and Ho and Case (1994b).

In economic design, parameters are determined such that the total cost associated with the implementation of quality control policy is minimized. In a regular $\bar{X}$ control chart, these parameters consist of the sample size, the time interval between two consecutive sampling, the coefficient (multiple of standard deviation) that specifies the Upper Control Limit, and the Lower Control Limit.

The economic models are generally formulated using the total cost per unit time function. Overall production time is divided into stochastically identical cycles. Each cycle starts with the production in the in-control status. When, at some sampling instance, control chart indicates an out-of-control status (denoted as an alarm) a search for the assignable cause is conducted and if discovered the process is stored to the in-control status. The time between these two time points is called a cycle. Hence the expected cost within this cycle is computed and divided by the expected duration of the cycle. Minimization of this cost rate yields the design parameters of the control chart.

The study of Lorenzen and Vance (1986) proposed a general cost model that applied to all control charts, regardless of the statistic used. Later, several studies (Montgomery et al. 1995; Reynolds et al. 1988; Costa 1993;Torng et al. 2009a, b; Nenes 2011; Lee et al. 2012) focused on the design of various control charts and minimize the costs of process control (Niaki et al. 2011).

The weaknesses of the economic design of control charts approach have been highlighted by Woodall et al. (1986) and Woodall (1987). Despite the problems, the economic design of control charts is appealing to process engineers since the effectiveness of the control chart procedure is explained in terms of cost (Park 2013).

There have been studies in the literature, which consider economical design of control charts other than $\bar{X}$ charts. Next we will dwell into economic design of EWMA control charts by providing reviews of some milestone and recent papers. The very first work on the economical design of EWMA control charts is by Ho and Case (1994b). Tolley and English (2001) studied the economic design of EWMA control chart and EWMA-$\bar{X}$ chart, and provide a comparison of the two. One of the studies in the last decade belongs to Park et al. (2004), who looked into the economic design of an adaptive EWMA chart. In this study, the user changes the sampling interval and/or sample size dynamically based on the current chart statistic. Chou et al. (2008) presented economic design of Variable Sampling Intervals EWMA (VSI EWMA) control charts with sampling at fixed times. The two more recent studies dealing with joint economic design of EWMA charts for the process mean and dispersion have been performed by Serel and Moskowitz (2008) and Serel (2009). In the study of Serel (2009) the case where the assignable cause changes only the process mean or dispersion is explored. The economic design of the single control chart used for monitoring the process parameter (mean or variance) influenced by the assignable cause is the main concern in this study. It suggests that using a different type of quality loss function (linear versus quadratic) leads to a significant change in sampling interval while affecting the sample size and control limits very little. It is also observed that the overall costs are insensitive to the choice of Shewhart or EWMA charts. Various authors have and studied meta-heuristic applications in economical design of EWMA control chart, we discuss these works in later sections.

To the best of our knowledge, the only work that considers economic design of zone control charts is by Ho and Case (1994a). In their study, based on factors such as performance, simplicity, efficiency, ease of use, and ease of understanding, they recommend the joint Zone Control Chart.

4.2.5 Intelligent Applications of Ewma QC Chart

In this study and in most of the studies on economical design of quality control charts, classical optimization methods are used. Typically, the optimization problem of EWMA charts contains both, continuous (e.g., smoothing parameter) and discrete (e.g., sample size) decision variables. This produces a discontinuous non-convex solution space exists, standard non-linear programming techniques may prove to be ineffective (He et al. 2002; Aparisi and Garcia-Diaz 2007). Hence, here comes the computational intelligence into place which is employed in order to solve that optimization problem. Among several intelligent applications of EWMA quality control charts, metaheuristic applications have outnumbered the rest in the quality control area. Besides, we review a few but worthwhile efforts deploying evolutionary methods and neural networks in EWMA quality control chart design.

In the recent years metaheuristic approaches have been widely used to investigate the economic design of EWMA control charts. For instance, a study by Niaki et al. (2011) models and solves the economic and the economic-statistical design problems of Multivariate EWMA (MEWMA) control charts by a Particle Swarm Optimization (PSO) approach. Yet another economical design was conducted by Chou et al. (2008) who focused on variable sampling intervals of EWMA charts with sampling at fixed times using genetic algorithms. In fact, Genetic Algorithms are one of the most widely used heuristics. Aparisi and García-Díaz (2004) employed an GA optimization of Average Run Length (ARL) of EWMA and multivariate EWMA charts with respect to *smoothing parameter* and *control limits,* given that *sample size* n is 1. The authors further improved this setting where detection of small shifts is not necessary, while shift detecting is still important (Aparisi and García-Díaz 2007).

Sample size is added as another integer decision variable; and a third zone is defined where it is insignificant whether the process shift is detected or not.

Seeking a different heuristic approach, Niaki and Ershadi (2012) applied an ant-colony optimization of the economic-statistical design model of the MEWMA control chart in which the main parameters of the employed ant colony algorithm are tuned by means of a response surface methodology approach. Similarly, Zhou and Zhu (2008) used Grid Search minimization of the (hourly) cost of the integrated model (SPC and Preventive Maintenance) with respect to *sample size*, *sampling interval*, *control limits*, and *inspection interval*. To improve that Charongrattanasakul and Pongpullponsak (2011) contributed to the usual zone control policy, by adding another zone, called *warning zone*, and increased the set of four decision variables of Zhou and Zhu (2008) to six variables. In other words, the (hourly) cost of the integrated model (SPC and Preventive Maintenance) was minimized using GA with respect to the decision variables of *sample size*, *sampling interval*, *warning control limits*, *the number of subintervals between two consecutive sampling times,* and *the number of samples taken before Planned Maintenance*. This case revealed an interesting point such that the addition of the warning zone caused an overall increase of the total costs, due to increased ability of defective product detection which resulted to the increase of repairing and maintenance of machines; thus the hourly cost got higher. Other successful applications of Genetic Algorithms (GA) in the economic designs of control charts can be found in Saghaei et al. (2013), Celano and Fichera (1999), Chou and Chen (2006), Vommi and Seetala (2007), Torng et al. (2009a, b), and Lin et al. (2012). Besides these heuristics widely used in several areas of Operations Management, the real AI applications of EWMA charts achieved their potential in the semiconductor industry.

Since early 90s, EWMA has been popular in the semiconductor industry to maintain process targets over extended periods for improved product quality and decreased machine downtime (Spanos 1992; Su and Hsu 2004b). However, the several process factors (alternating in time) are thought to determine the 'best' value for an EWMA smoothing parameter. Smith and Boning (1997a, 1997b) proposed a self-tuning EWMA controller which dynamically updates its smoothing parameter by estimating the disturbance state and using the Artificial Neural Network (ANN) function mapping to provide updates to the controller parameters. Similarly, Su and Hsu (2004a) applied ANN for online tuning of EWMA smoothing parameter. The underlying approach indicated that the network learns very quickly when taking autocorrelation function and sample partial autocorrelation function patterns as the input features. Fan and Wang (2008) further contributed to this setting by incorporating a multivariate double EWMA component (i.e., EWMA having two smoothing parameters, coined for semiconductor industry by Butler and Stefani 1994). All these studies were conducted and results obtained in a simulation environment.

The next section introduces the concept of *jidoka* and its use within the model of this study as an intelligent quality control procedure.

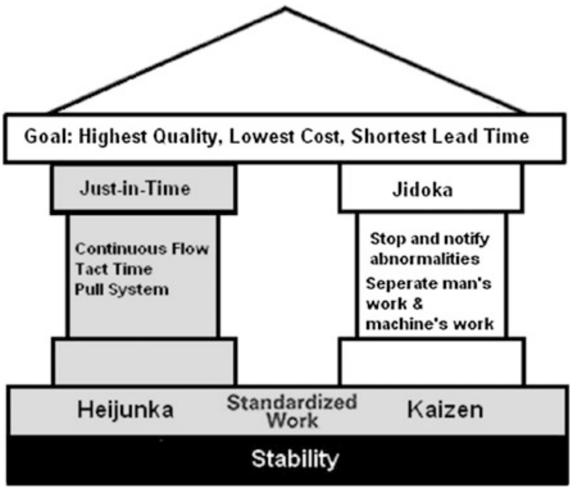
4.3 Jidoka Production System as an Intelligent QC Approach

The proposed intelligent system provides controlling particular decisions automatically, which are once made manually by operators at the job level in a Jidoka Production System. The entrance of Japanese goods in western markets was a subject of discussion in American business in the 1970s (Schonberger 2007) and since then, academia has used many terms to explain this phenomenon, including Toyota Production System (TPS) also known as Lean Manufacturing (Monden 1983; Hoss and ten Caten 2013). Toyota Production System proposes factory designers to combine inspections with operations (Kim and Gershwin 2005). By this way, the production quality is increased and much more benefits are gained. Hoss and ten Caten (2013)suggest implementation of functions such as just in time (JIT) and *jidoka* to achieve high quality, low cost, and low lead time.

TPS is frequently modelled as a house with two pillars (see Fig. 4.2). The top of the house consists "highest quality, lowest cost, shortest lead time", whereas one of the two pillars represents just-in-time (JIT), and the other pillar the concept of jidoka. Jidoka (translated as autonomation) is a defect detection system, which automatically or manually stops the production operation whenever an abnormal or defective condition arises. The manufacturing system introduced will not stand without both of the pillars. Yet many researchers and practitioners focus on the mechanisms of implementation—one piece flow, pull production, tact time, standard work, kanban—without linking those mechanisms back to the pillars that hold up the entire system. While the majority of the studies in the literature have focused on the problems of the first pillar (JIT), two research articles by Kim and Gershwin (2005) and Berk and Toy (2009) are two notable exceptions for the other pillar (Hoss and ten Caten 2013). We can state that a lot of failed implementations can be traced back to not building this second pillar. In the concept of *jidoka* when a team member encounters a problem in his or her workstation, he/she is responsible for correcting the problem by pulling an andon cord, which can stop the line. The objective of jidoka can be summed up as: Ensuring quality 100 % of the time, preventing equipment breakdowns, and working efficiently.

TPS advocates think that mechanical and human *jidoka* prevent the waste that would result from producing a series of defective items. Hence, *jidoka* can be

Fig. 4.2 The house of toyota production system (Ohno 1988)



defined as a means to improve quality and increase productivity at the same time (Shingo 1989; Toyota Motor Corporation 1996; Kim and Gershwin 2005). Berk and Toy (2009)consider design of control charts in the presence of machine stoppages that are exogenously imposed (as under *jidoka* practices). Here, each stoppage creates an opportunity for inspection/repair at reduced cost. They first model a single machine facing opportunities arriving according to a Poisson process, develop the expressions for its operating characteristics and construct the optimization problem for economic design of a control chart. Afterwards, they consider a multiple machine setting where alarms about the quality status of the machines cause system-wide stoppages as it is the case under *jidoka* practices. Their findings indicate that ignoring exogenous inspection/repair opportunities and employing the classical QC chart parameters may result in significant cost increases.

4.3.1 Model Description

In the model described herein, we consider a multiple machine environment. In this environment, machines are operated and controlled individually. Each machine is controlled through a separate control chart. EWMA procedure is employed with multiple control limits; hence there are zones in the control charts. We use 2-zone control chart. We specify tight control limits (UCL_t and LCL_t) and loose control limits (UCL_l and LCL_l). The zone between the tight control limits is the inner zone and the zone between tight and loose control limits identifies the outer zone. Inner zone is where the process is considered to be in-control. A different inspection and repair policy is defined for outer zone and outside the control limits. A test statistic, Z_t, (exponentially weighted moving-average values of the sample means) which lies in the outer zone and outside the control limits is denoted as an *alarm* for the system.

Production system considered herein is assumed to be part of *Jidoka* Production System. Whenever a machine raises an alarm, all the system stops, i.e. the production is ceased. In the policy we suggest, these overall system stoppages due to individual machine alarms create opportunities for other machines to be inspected and repaired. This opportunity is taken only if the test statistic, Z_t lies beyond the loose control limits. That is, all the machines in the system are inspected and repaired, yielding in-control machines at the next system re-start instance. The time and cost of inspection/repair for each machine at a system stoppage are computed as follows: The alarm-raising machine(s) incur the downtime cost related to its own inspection/repair time. Among the remainder, the machine(s) with the longest inspection/repair time will have an available duration (as an opportunity for preventive maintenance) equal to the inspection/repair time of the alarm-raising machine(s). There will be no additional delay if these durations are equal to each other; otherwise, there will be some extra delay and machine experiencing the longest inspection/repair time will incur the additional downtime cost. However, when the system is stopped due to a $Z_t$value in the outer zone, only the machine(s) raising alarm is (are) inspected and repaired. As shutdowns are not utilized for inspecting other machines, the downtime cost is charged only to the self-stopping machine in this case.

In the model description below we retain the notation used in Berk and Toy (2009). Let M be the set of machines working in coordination, and let m denote the number of machines. The set of machines may comprise non-identical machines. Hence, when the machines have different reliability, restoration times, sampling interval etc., inspection opportunities may be beneficial, i.e., resulting in cost reduction, for some machines, it may be not beneficial, i.e., increasing the cost for the others.

Every machine $i(\in \mathrm{M})$, is subject to control with an EWMA control chart. A sample of size $y^{(i)}$ is taken with $h^{(i)}$ time intervals, test statistic Z_t is computed. The EWMA values of the quality specification of the sample weighted by λ, is plotted on a control chart. If the EWMA value of machine i falls outside the loose control limits (k_2) defined by Eq. 4.8.

$$\mu_0^{(i)} \pm k_2^{(i)} \frac{\sigma^{(i)}}{\sqrt{y^{(i)}}} \sqrt{\frac{\lambda}{2-\lambda}} \tag{4.8}$$

all machines are stopped. If it falls between the loose and tight control limits (k_1) for machine i, the latter defined by

$$\mu_0^{(i)} \pm k_1^{(i)} \frac{\sigma^{(i)}}{\sqrt{y^{(i)}}} \sqrt{\frac{\lambda}{2-\lambda}} \tag{4.9}$$

only that particular machine is stopped. A sample results in a false alarm with probability α (Type I error) and a true alarm with probability $(1-\beta)$ (complement of Type II error). Clearly, α and β are related to k_1, k_2, λ, y and for a normal variate Z. If the process faces an exogenous shutdown triggered by another alarm-raising machine, its operator uses this stoppage as an opportunity to carry out an inspection of the process although no signals have been received from the control chart to initiate one. On inspection, if the process is found to be in the out-of-control status, the opportunity is said to be a true opportunity, which is followed by a complete restoration of the process to the in-control status; otherwise, the opportunity is a false opportunity, which requires no adjustment. Type I and Type II errors for multiple machine with two zone control limits (α_1, α_2 and β_1, β_2) are as follows (Eqs. 4.10, 4.11, 4.12, 4.13):

$$\alpha_1 = 2\Phi\left[-\mathrm{k}_1\sqrt{\frac{\lambda}{2-\lambda}}\right] \tag{4.10}$$

$$\alpha_2 = 2\Phi\left[-\mathrm{k}_2\sqrt{\frac{\lambda}{2-\lambda}}\right] \tag{4.11}$$

$$\beta_1 = \Phi\left[k_1\sqrt{\frac{\lambda}{2-\lambda}} - \delta\sqrt{y^{(i)}}\right] - \Phi\left[-k_1\sqrt{\frac{\lambda}{2-\lambda}} - \delta\sqrt{y^{(i)}}\right] \tag{4.12}$$

$$\beta_2 = \Phi\left[k_2\sqrt{\frac{\lambda}{2-\lambda}} - \delta\sqrt{y^{(i)}}\right] - \Phi\left[-k_2\sqrt{\frac{\lambda}{2-\lambda}} - \delta\sqrt{y^{(i)}}\right] \tag{4.13}$$

Next we define the costs associated with the quality control of the systems. We consider three categories of quality costs: (i) sampling cost, (ii) the cost of operating in the out-of-control state, and (iii) the inspection and repair cost.

Sampling Cost: The sampling cost has two components, fixed and variable. Fixed component is denoted by u and is incurred at each sampling instance whereas variable component, y, is associated with the sample size and incurred at each sampling instance, as well. Hence, the total sampling cost is given by $u + by$.

Cost of Operating in out-of-control state: once the process shifts to the out-of-control state, any product processed in a stage (machine) is considered to be defective hence requires rework. The cost associated with these sub-standard products is denoted by a per time unit.

Inspection and repair cost: When a machined is stopped by an alarm, an inspection is conducted immediately and if shift is detected a repair operation is conducted. Since the system stops until inspection and repair operations completed we assume that there is a lost profit cost associated with idle time. The idle time is related with the system status at the stoppage instance; i.e., if the process has shifted it requires a time for both inspection and repair, however if the process has not shifted the idle time is only as much as the inspection time. The elapsed time until the process shift is distributed exponentially with mean θ. This cost component is computed as πL_s, where π is the profit (lost) per unit of time and L_s denotes the downtime of the process. Depending on the status of the machine at the stoppage instance repair cost varies, as well. Such that shifted process costs more than the non-shifted process, in terms of labour hours and spare parts.

Our objective is to economically and jointly design the control charts of all machines resulting a minimum system-wide cost rate. Control parameters of this system are same as the regular control charts. Specifically, we decide on the sample size (y), sampling frequency (h), control limits (k_1, k_2) and smoothing parameter (λ) which minimizes the expected cost per unit time.

4.4 Numerical Study

Three-machine setting with two zone control policy is simulated using the parameter sets below which results in 54 experimental instances. In each combination, an exhaustive search over the variable set (within the provided intervals) has been performed in order to find the 'best (minimum)' overall system cost rate.

The results are compared with the case where autonomation (or JPS) is not applied. Namely, the same experimental instances are simulated for the three independent machine system, i.e., for each machine a separate control chart is maintained, hence only self-stoppages are allowed.

The parameter ranges for our experimental set: variable cost (per sample) cost of sampling, $b = 0.1$; fixed cost of sampling $u = 5$; true and false alarm repair costs, $R_T = R_F = 0$; true and false alarm idle times, $L_T = L_F = L$, with $L \in \{0.05, 0.10, 0.15\}$; profit per unit time, $\pi \in \{500, 1500\}$; process mean shift rate, $\theta \in \{0.01, 0.05, 0.1\}$; and the per time cost of operating in out-of-control state, $a \in \{50, 250, 500\}$.

The domains for our decision variables, in which we performed an exhaustive search, are as follows: [1, 10] for the sample size (y), [0.01, 10] for sampling frequency (h), [1, 2] and [k_1, 3] for the control limits (k_1, k_2), and [0, 0.5] for

Table 4.3 Comparative results with improvement percentage for $\pi = 500$

Case #	L	θ	a	No JPS policy	System cost Under JPS policy	Improvement (%)
1	0.05	0.01	50	10.98	8.58	22
2			250	24.01	18.45	23
3			500	31.76	25.25	20
4		0.05	50	23.72	21.44	10
5			250	55.68	44.59	20
6			500	77.11	59.89	22
7		0.1	50	34.38	29.34	15
8			250	71.77	59.86	17
9			500	107.2	100.12	7
10	0.1	0.01	50	14.36	10.98	24
11			250	32.2	25.38	21
12			500	44.62	31.7	29
13		0.05	50	32.65	25.43	22
14			250	72.24	58.1	20
15			500	103.4	74.33	28
16		0.1	50	44.46	37.03	17
17			250	96.78	77.19	20
18			500	131.3	106.34	19
19	0.15	0.01	50	17.86	14.28	20
20			250	36.26	28.03	23
21			500	52.54	37.77	28
22		0.05	50	37.3	33.54	10
23			250	85.05	67.31	21
24			500	119.05	91.13	23
25		0.1	50	51.2	47.07	8
26			250	117.05	106.56	9
27			500	152.72	116.2	24

smoothing parameter (λ). Considering the time-related variables and parameters, the cases were simulated for a reasonably long final simulation run time and replicated 4.5 times on average. On the completion of each replication (50,000 time units), the domains of all decision variables were shrunk to narrower domains and another replication was performed. An improvement in total quality cost was generally observed after each replication, yet whenever the cost got worse the simulation was run for 150,000 time units using the parameter set resulting the lowest cost. Therefore, the number of replications depended on the quality cost of the penultimate replication.

Tables 4.3 and 4.4 presents the resulting costs of 54 different cases, which are the combinations of different parameters explained above. The costs under JPS policy and classical policy are given in the tables together with the percentage

Table 4.4 Comparative results with improvement percentage for π = *1000*

Case #	L	θ	a	No JPS policy	System cost Under JPS policy	Improvement (%)
28	0.05	0.01	50	17.16	13.54	21
29			250	38.97	29.4	25
30			500	55.03	42.03	24
31		0.05	50	37.63	33.26	12
32			250	87.45	71.43	18
33			500	126.63	102.17	19
34		0.1	50	54.96	45.72	17
35			250	122.83	102.7	16
36			500	166.72	142.92	14
37	0.1	0.01	50	25.6	21.99	14
38			250	54.66	43.9	20
39			500	76.06	56.73	25
40		0.05	50	50.23	46.87	7
41			250	121.21	95.68	21
42			500	170.32	127.29	25
43		0.1	50	65.93	62.76	5
44			250	167.55	135.66	19
45			500	235.49	188.66	20
46	0.15	0.01	50	30.94	28.9	7
47			250	66.65	51.57	23
48			500	91.31	67.88	26
49		0.05	50	59.35	54.61	8
50			250	148.03	130.6	12
51			500	207.68	175.27	16
52		0.1	50	76.29	80.94	−6
53			250	198.38	169.32	15
54			500	276.1	225.02	19

of improvement. It can be clearly observed that, only one case does not show improvement under the JPS policy. The reason for this specific case is that, the computation time was significantly long for this parameter set and an adequate exhaustive search was not performed. The minimum improvement is 5 %, average improvement is 18 % and maximum is 29 % for all 54 cases. Hence we can conclude that JPS policy is significantly superior than the classical policy. The minimum improvement (5 %) is obtained in the case where $L = 0.10$, $\pi = 1500$, $\theta = 0.10$, and $a = 50$. The maximum improvement (29 %) is obtained in the case where $L = 0.10$, $\pi = 500$, $\theta = 0.01$, and $a = 500$.

We observe that system costs increase when a increases while other parameters are kept constant. Another result that can be derived from Table 4.4 is that improvement in the cost decreases when π increases from 500 to 1500 except for the cases where $L = 0.05$. Table 4.3 shows the results where $\pi = 500$ and Table 4.4 shows the results where $\pi = 1000$. The average improvement in Table 4.3 is 19 % while it is 16 % in Table 4.4. It is also seen from the results that, the improvement percentage decreases when θ increases. For instance, the average improvement percentage for the first three combinations, where $\theta = 0.01$ is approximately 22 % while it is 17 % for the next three cases where $\theta = 0.05$, and 13 % for the cases where $\theta = 0.1$. Similar pattern can be seen for the other case groups. However, we do not observe any significant pattern in the improvement percentages with respect to L.

4.5 Conclusion

In this article, we give an extensive literature review on quality control charts and we specifically consider the intelligent systems of economical design of EWMA zone control charts in the presence of machine stoppages that are exogenously imposed. Each stoppage creates an opportunity for inspection/repair at reduced cost. We consider a multiple machine setting where alarms about the quality status of the machines cause system-wide stoppages as it is the case under *Jidoka* practices. In a numerical study for three machine setting to investigate the cost advantages of employing the models herein versus the classical model where JPS is not used. Our findings indicate that ignoring exogenous inspection/repair opportunities and employing the classical QC chart parameters may result in significant cost increases. The average improvement percentage in cost under classical policy and JPS policy is 18 %, which shows that the performance of our model is really high. Hence we can conclude that JPS policy is significantly successful than the classical policy.

There are a number of extensions to our basic model. Herein, we consider only the design of $\bar{X}$ control charts in our numerical study, but our model can be applied to other variable and attribute-control charts. Similarly, different design criteria (semieconomic and statistical) can be considered, as well. For the future research, further applications of metaheuristics are also encouraged for the economic design of quality control charts.

References

Abbas, N., Riaz, M., Does, R.J.M.M.: Mixed exponentially weighted moving average–cumulative sum charts for process monitoring. Qual. Reliab. Eng. Int. **29**(3), 345–356 (2012)

Aparisi, F., García-Díaz, J.C.: Optimization of univariate and multivariate exponentially weighted moving-average control charts using genetic algorithms. Comput. Oper. Res. **31**(9), 1437–1454 (2004)

Aparisi, F., García-Díaz, J.C.: Design and optimization of EWMA control charts for in-control, indifference, and out-of-control regions. Comput. Oper. Res. **34**(7), 2096–2108 (2007)

Benneyan, J.C., Lloyd R.C., Plsek, P.E.: Statistical process control as a tool for research and healthcare improvement. Qual. Saf. Health Care **12**, 458–464 (2003)

Berk, E., Toy, A.O.: Quality control chart design under jidoka. Naval Res. Logist. **56**, 465–477 (2009)

Butler, S.W., Stefani, J.A.: Supervisory run-to-run control of polysilicon gate etch using in situ ellipsometry. IEEE Trans. Semicond. Manuf. **7**(2), 193–201 (1994)

Celano, G., Fichera, S.: Multiobjective economic design of an X control chart. Comput. Ind. Eng. **37**, 129–132 (1999)

Charongrattanasakul, P., Pongpullponsak, A.: Minimizing the cost of integrated systems approach to process control and maintenance model by EWMA control chart using genetic algorithm. Expert Syst. Appl. **38**(5), 5178–5186 (2011)

Chou, C.-Y., Chen, C.-H.: Economic design of variable sampling intervals T2 control charts using genetic algorithms. Expert Syst. Appl. **30**, 233–242 (2006)

Chou, C.Y., Cheng, J.C., Lai, W.T.: Economic design of variable sampling intervals EWMA charts with sampling at fixed times using genetic algorithms. Expert Syst. Appl. **34**, 419–426 (2008)

Costa, A.F.B.: Joint economic design of $\bar{X}$ and R control charts for process subject to two independent assignable causes. IIE Trans. **25**, 27–33 (1993)

Costa, A.F.B.: Joint X chart with variable parameters. J. Qual. Technol. **31**, 408–416 (1999)

Crowder, S.V.: Design of exponentially weighted moving average scheme. J. Qual. Technol. **21**, 155–162 (1989)

Davis, R.B., Krehbiel, T.C.: Shewhart and zone control chart performance under linear trend. Commun. Stat. —Simul. Comput. **31**(1), 91–96 (2002)

Davis, R.B., Jin, C., Guo, Y.: Improving the performance of the zone control chart. Commun. Stat. —Theory Methods **23**, 3557–3565 (1994)

Davis, R.B., Homer, A., Woodall, W.H. Performance of the zone control chart. Commun. Stat.—Theory Methods **19**, 1581–1587 (1990)

De Vries, A., Reneau, J.K.: Application of statistical process control charts to monitor changes in animal production systems. J. Anim. Sci. **88**, E11–E24 (2010)

Diaz, M., Neuhauser, D.: Pasteur and parachutes: when statistical process control is better than a randomized controlled trial. Qual. Saf. Health Care **14**, 140–143 (2005)

Duncan, A.J.: The economic design of $\bar{\mathrm{X}}$ charts used to maintain current control of process. J. Am. Stat. Assoc. **51**, 228–242 (1956)

Fan, S.-K.S., Wang, C.-Y.: On-line tuning system of multivariate dEWMA control based on a neural network approach. Int. J. Prod. Res. **46**(13), 3459–3484 (2008)

Flaig, J.J.: Zone control charts. http://www.e-AT-USA.com (2004)
Gan, F.F.: Computing the percentage points of the run length distribution of an exponentially weighted moving average control chart. J. Qual. Technol. **23**, 359–362 (1991)
Haq, A., Brown, J., Moltchanova, E.: New synthetic EWMA and synthetic CUSUM control charts for monitoring the process mean. Qual. Reliab. Eng. Int. (2014). doi:10.1002/qre.1747
Hawkins, D.M., Olwell, D.H.: Cumulative Sum Charts and Charting for Quality Improvement. Springer, New York (1998)
Hawkins, D.M., Wu, Q.: The CUSUM and the EWMA head-to-head. Qual. Eng. **26**, 215–222 (2014)
He, H., Grigoryan, A., Sigh, M.: Design of double- and triple-sampling X-bar control charts using genetic algorithms. Int. J. Prod. Res. **40**(6), 1387–1404 (2002)
Ho, C., Case, K.E.: An economic design of the zone control chart for jointly monitoring process centering and variation. Comput. Ind. Eng. **26**(2), 213–221 (1994a)
Ho, C., Case, K.E.: Economic design of control charts: a literature review for 1981–1991. J. Qual. Technol. **26**, 39–53 (1994b)
Hopgood, A.A. Intelligent Systems for Engineers and Scientists, CRC Press, Boca Raton (2012)
Hoss, M., ten Caten, C.S.: Lean schools of thought. Int. J. Prod. Res. **51**(11), 3270–3282 (2013)
Jaehn, A.H.: Zone control charts—SPC made easy. Quality **26**, 51–53 (1987)
Jaehn, A.H.: Zone control charts find new applications. ASQC Qual. Congr. Trans. 890–895 (1989)
Kim, J., Gershwin, S.B.: Integrated quality and quantity modeling of a production line. OR Spectrum **27**, 287–314 (2005)
Lee, P.-H., Torng, C.-C., Liao, L.-F.: An economic design of combined double sampling and variable sampling interval X control chart. Int. J. Prod. Econ. **138**, 102–106 (2012)
Lin, S.-N., Chou, C.-Y., Wang, S.-L., Liu, H.-R.: Economic design of autoregressive moving average control chart using genetic algorithms. Expert Syst. Appl. **39**, 1793–1798 (2012)
Lorenzen, T.J., Vance, L.C.: The economic design of control charts: a unified approach. Technometrics **28**, 3–10 (1986)
Lucas, J.M., Saccucci, M.S.: Exponentially weighted moving average control schemes: properties and enhancements (with discussion). Technometrics **32**, 1–29 (1990)
Monden, Y.: Toyota Production System: Practical Approach to production Management. Management Institute Engineering and Management Press, Norcross (1983)
Montgomery D.C.: The economic design of control charts: a review and literature survey. J. Qual. Technol. **1**, 24–32 (1980a)
Montgomery, D.C.: The economic design of control charts: a review and literature survey. J. Qual. Technol. **12**, 75–81 (1980b)
Montgomery, D.C.: Introduction to Statistical Quality Control. Wiley, New York (1996)
Montgomery, D.C.: Introduction to Statistical Quality Control, 2nd edn. Wiley, New York (1991)
Montgomery, D.C., Torng, J.C.-C., Cocgran, J.K., Lawrence, F.P.: Statistically constrained economic design of the EWMA control chart. J. Qual. Technol. **27**(3), 250–256 (1995)
Montgomery D.C.: Introduction to Statistical Quality Control, 6th edn. Wiley, New York (2009)
Montgomery, D.C.: Introduction to Statistical Quality Control, 7th edn. Wiley, New York (2013)
Nenes, G.: A new approach for the economic design of fully adaptive control charts. Int. J. Prod. Econ. **131**(2), 631–642 (2011)
Neubauer, A.S.: The EWMA control chart: properties and comparison with other quality-control procedures by computer simulation. Clin. Chem. **43**(4), 594–601 (1997)
Negnevitsky, M. Artificial Intelligence: a Guide to Intelligent Systems, Addison-Wesley, Boston (2011)
Niaki, S.T.A., Ershadi, M.J., Malaki, M.: Economic and economic-statistical designs of MEWMA control charts, a hybrid taguchi loss, markov chain and genetic algorithm approach. Int. J. Adv. Manuf. Technol. **48**, 283–296 (2010)

Niaki, S.T.A., Gazaneh, F.M. Toosheghanian, M. Economic design of variable sampling interval $\bar{X}$ control charts for monitoring correlated non normal samples. Commun. Stat.—Theory Methods **42**(18), 3339–3358 (2013)

Niaki, S.T.A., Malaki, M., Ershadi, M.J.: A particle swarm optimization approach on economic and economic-statistical designs of MEWMA control charts. ScientiaIranica E **18**(6), 1529–1536 (2011)

Niaki, S.T.A., Ershadi, M.J.: A hybrid ant colony Markov chain, and experimental design approach for statistically constrained economic design of MEWMA control charts. Expert Syst. with Appl. **39**(3), 3265–3275 (2012)

Ohno, T.: Toyota Production System, Productivity Press, Boca Raton (1988)

Page, E.S.: Continuous inspection schemes. Biometrika **41**, 100–115 (1954)

Park, C.: Economic design of charts when signals may be misclassified and the bounded reset chart. IIE Trans. **45**(4), 436–448 (2013)

Park, C., Lee, J., Kim, Y.: Economic design of a variable sampling rate EWMA chart. IIE Trans. **36**, 387–399 (2004)

Parkash, V., Kumar, D., Rajoria, R.: Statistical Process Control. IJRET: Int. J. Res. Eng. Technol. **2**(8), 70–72 (2013)

Pignatiello, J.J., Tsai, A.: Optimal economic design of control chart when cost model parameters are not known. IIE Trans. **20**, 103–110 (1988)

Quesenberry, C.P.: SPC Methods for Quality Improvement. Wiley, New York (1997)

Reynolds Jr, M.R., Amin, R.W., Arnold, J.C., Nachlas, J.A.: X charts with variable sampling intervals. Technometrics **30**, 181–192 (1988)

Roberts, S.W.: Control chart tests based on geometric moving averages. Technometrics **1**, 239–250 (1959)

Robinson, P.B., Ho, T.Y.: Average run lengths of geometric moving average charts by numerical methods. Technometric **20**, 85–93 (1978)

Saghaei, A., Ghomi, S.M.T.F., Jaberi, S.: Economic design of exponentially weighted moving average control chart based on measurement error using genetic algorithm. Reliab. Eng. Int. Qual. doi:10.1002/qre.1538

Schonberger, R.J.: Japanese production management: an evolution—with mixed success. J. Oper. Manag. **25**(2), 403–419 (2007)

Serel, A.S.: Economic design of EWMA control charts based on loss function. Math. Comput. Model. **49**, 745–759 (2009)

Serel, D.A., Moskowitz, H.: Joint economic design of EWMA control charts for mean and variance. Eur. J. Oper. Res. **184**, 157–168 (2008)

Schalkoff, R.J.: Intelligent Systems: Principles. Jones & Bartlett Publishers, Paradigms and Pragmatics (2009)

Shewhart, W.A.: Some Applications of Statistical Methods. ASQ Publications (1924)

Shingo, S.: A Study of the Toyota Production System from an Industrial Engineering Viewpoint. Productivity Press, Portland (1989)

Smith, Taber H., Boning, Duane S.: Artificial neural network exponentially weighted moving average controller for semiconductor processes. J. Vac. Sci. Technol. A **15**, 1377–1384 (1997a)

Smith, T.H., Boning, D.S.: A self-tuning EWMA controller utilizing artificial neural network function approximation techniques. Compon. Packag. Manuf. Technol. Part C, IEEE Trans. **20** (2), 121–132 (1997b)

Solodky, C., Chen, H., Jones, P.K., Katcher, W., Neuhauser, D.: Patients as partners in clinical research: a proposal for applying quality improvement methods to patient care. Med. Care 36 (Suppl.):AS13 AS20 (1998)

Spanos, C.J.: Statistical process control in semiconductor manufacturing. Proc. IEEE 819–830 (1992)

Su, C.-T., Hsu, C.-C.: On-line tuning of a single EWMA controller based on the neural technique. Int. J. Prod. Res. **42**(11), 2163–2178 (2004a)

Su, C.-T., Hsu, C.-C.: A time-varying weights tuning method of the double EWMA controller. Omega **32**(6), 473–480 (2004b)
Thor, J., Lundberg, J., Ask, J., Olsson, J., Carli, C., PukkHarenstam, K., Brommels, M.: Application of statistical process control in healthcare and improvement: a systematic review. Qual. Saf. Health Care **16**(387), 399 (2007)
Tolley, G.O., English, J.R.: Economic designs of constrained EWMA and combined EWMA-X-bar control schemes. IIE Trans. **33**, 429–436 (2001)
Torng, C.-C., Lee, P.-H., Liao, N.-Y.: An economic-statistical design of double sampling $\bar{\mathrm{X}}$ control chart. Int. J. Prod. Econ. **120**(2), 495–500 (2009a)
Torng, C.-C., Lee, P.-H., Liao, H.-S., Liao, N.-Y.: An economic design of double sampling $\bar{\mathrm{X}}$ charts for correlated data using genetic algorithms. Expert Syst. Appl. **36**(10), 12621–12626 (2009b)
Toyota Motor Corporation (1996). The Toyota production system
Vance, L.C.: A bibliography of statistical quality control chart techniques, 1970–1980. J. Qual. Technol. **15**, 59–62 (1983)
Vargas, V.C.C., Lopes, L.F.D., Souza, A.M.: Comparative study of the performance of the CuSum and EWMA control charts. Comput. Ind. Eng. **46**(4), 707–724 (2004)
Vommi, V.B., Seetala, S.N.: A simple approach for robust economic design of control charts. Comput. Oper. Res. **34**(7), 2001–2009 (2007)
Waldman, K.H.: Bounds for the distribution of the run length of geometric moving average charts. J. Roy. Statist. Soc. Ser. B (Appl. Statist.), **35**, 151–158 (1986)
Electric, Western: Statistical Quality Control Handbook. AT& T, Indianapolis (1956)
Woodall, W.H.: Weakness of the economic design of control charts. Technometrics **28**, 408–409 (1986)
Woodall, W.H.: Conflicts between Deming's philosophy and the economic design of control charts. In: Lenz, H.J., Wetherill, G.B., Wilrich, P.T. (eds.) Frontiers in Statistical Quality Control 3, pp. 155–168. Physica-Verlag, Heidelberg (1987)
Woodall, W.H.: The use of control charts in health-care and public-health surveillance. J. Qual. Technol. **38**, 89–104 (2006)
Woodall, W.H., Lorenzen, T.J., Vance, L.C.: Weaknesses of the economic design of control charts. Technometrics **28**, 408–410 (1986)
Zaman, B., Riaz, M., abbas, N., Does, R.J.M.M.: Mixed cumulative sum–exponentially weighted moving average control charts: an efficient way of monitoring process location. Qual. Reliab. Eng. Int. doi:10.1002/qre.1678
Zhou, W.-H., Zhu, G.-L.: Economic design of integrated model of control chart and maintenance. Math. Comput. Model. **47**, 1389–1395 (2008)