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CONTROL CHARTS FOR AUTOCORRELATED PROCESSES: A REVIEW

ABSTRACT

One of the primary tools used in statistical quality control is the control charts. The standard assumptions that are usually cited in justifying the use of control charts are that the data generated by the in control process are independent and identically distributed. However the independency assumption is not realistic in practice. Data sets collected from industrial processes may have correlation among adjacent observations (autocorrelation). In this case control charts are modified to monitor the autocorrelated process observation. Many scientists made contributions in the area of control charts for autocorrelated data. In the present paper, a comprehensive overview for control charts for autocorrelated data is given by discussing both theoretical developments and practical experiences, and identifying research trends. Finally, historical progression in this field was emphasized and recommendations for future research are suggested.
Keywords: Control Charts, Autocorrelation, Literature Review, Residual Control Charts, Neural Network Based Control Charts

OTOKORELASYONLU GÖZLEMLER İÇİN KONTROL KARTLARI: LİTERATÜR TARAMA

ÖZET

İstatistiksel kalite kontrolde öncelikle kullanılan araçlardan biri kontrol kartlarıdır. Kontrol kartlarının kullanımında genellikle atfedilen standart varsayım, kontrol altındaki süreç tarafından üretilen verilerin bağımsız olduğu ve aynı dağılımdan geldiğidir. Ne var ki, bağımsızlık varsayımı uygulamada gerçekçi değildir. Endüstriyel süreçlerden toplanan veri setleri ardışık gözlemler arası korelasyona (otokorelasyon) sahip olabilir. Bu durumda kontrol kartları, otokorelasyonlu süreç gözlemlerini izlemek için modifiye edilirler. Pek çok bilim adamı otokorelasyonlu gözlemler için kontrol kartları alanına katkıda bulunmuştur. Bu çalışmada, otokorelasyonlu gözlemler için kontrol kartları için geniş bir literatür taramasına, hem teorik gelişmeleri hem de uygulamalı deneyimleri ve araştırma eğilimlerini göz önüne alarak, yer verilmiştir. Son olarak, bu alandaki tarihsel gelişim üzerinde durulmuş ve gelecek araştırmalar için tavsiyelerde bulunulmuştur.
Anahtar Kelimeler: Kontrol Kartları, Otokorelasyon, Literatür Taraması, Artık Terimler İçin Kontrol Kartları, Yapay Sinir Ağı Tabanlı Kontrol Kartları

1. INTRODUCTION (GİRİŞ)

Since the first control chart has been proposed by Shewhart in 1931, lots of charts have been developed and then improved to use for different process data. In its basics form, a control chart compares process observations with a pair of control limits. The standard assumptions that are usually cited in justifying the use of control charts are that the data generated by the in control process are normally and independently distributed by mean of μ and standard deviation of σ [1]. However the independency assumption is not realistic in practice. The most frequently reported effect on control charts of violating such assumptions is the erroneous assignment of the control limits. Alwan & Roberts (1995) showed that about 85% of a sample of 235 control chart applications displayed incorrect control limits [2]. More than half of these displacements were due to violation of the independence assumption, that is, due to serial correlation in the data. However, many processes such as those found in refinery operations, smelting operations, wood product manufacturing, waste-water processing and the operation of nuclear reactors have been shown to have autocorrelated observations.

When there is significant autocorrelation in a process, traditional control charts with independent and identically distributed (iid) assumption will be ineffective. In addition to various control charts developed for monitoring autocorrelated processes, three general approaches are recommended; (i) fit ARIMA model to data then apply traditional control charts such as Shewhart, CUSUM, EWMA to process residuals, (ii) monitor the autocorrelated observations by modifying the standard control limits to account for the autocorrelation (iii) eliminate the autocorrelation by using an engineering controller [1].

A variety of control charts are introduced for autocorrelated data. The purpose of this paper is to give a comprehensive survey of works on various control chart applications for autocorrelated processes. Through the following section the significance of this research and review studies on control charts are discussed. In section 3, a comprehensive review of control chart applications for autocorrelated processes are given. Finally, historical progression in this field was emphasized and recommendations for future researches are suggested in section 4.

2. RESEARCH SIGNIFICANCE (ÇALIŞMANIN ÖNEMİ)

The purpose of this paper is to give a comprehensive review of works on various control chart applications for autocorrelated processes. When the literature reviewed the following review studies on control chart applications are considerable. Ho & Case reviewed literature for 1981-1991 and presented the studies on economic design of control charts [3]. Lowry & Montgomery (1995) presented a review of the literature on control charts for multivariate quality control (MQC), with a concentration on developments occurring since the mid-1980s. Multivariate cumulative sum (MCUSUM) control procedures and a multivariate exponentially weighted moving average (MEWMA) control chart were reviewed and recommendations were made regarding their use [4]. DelCastillo & Hurwitz (1997) reviewed run to run control methods from a statistical and control engineering point of view [5]. Zorriassatine & Tannock (1998) reviewed the literature on application of Neural Networks (NNs) to the analysis of Shewhart's traditional statistical process control (SPC) charts [6]. Ganesan, Das, & Venkataraman (2004) reviewed the multiscale monitoring of both univariate and multivariate processes [7]. Jensen, Farmer, & Champ (2006) reviewed the literature that explicitly considers the effect of parameter estimation on control chart properties [8]. Bersimis, Psarakis, & Panaretos (2007) reviewed multivariate extensions for all kinds of univariate control charts, such as multivariate Shewhart-type control charts, multivariate CUSUM control charts and multivariate EWMA control charts. In addition, they reviewed unique procedures for the construction of multivariate control charts, based on multivariate statistical techniques such as principal components analysis (PCA) and partial least squares (PLS). Also, they described the most significant methods for the interpretation of an out-of-control signal [9]. Koutras, Bersimis, & Maravelakis (2007) reviewed the well known Shewhart type control charts supplemented with additional rules based on the theory of runs and scans. The motivation for their article stems from the fact that during the last decades, the performance improvement of the Shewhart charts by exploiting runs rules has attracted continuous research interest [10]. Topalidou & Psarakis (2009) reviewed multinominal and multiattribute quality control charts [11].

It is clearly observed that there is no presented study that reviews the recent literature on control charts for autocorrelated data. In this study, an attempt to review the research previously conducted on control charts for autocorrelated data is made in order to help the interested researchers and practitioners get informed about the references on the relevant research in this field, regarding the design, performance and applications of control charts for autocorrelated data.

3. APPLICATION OF CONTROL CHARTS IN AUTOCORRELATED PROCESSES (KONTROL KARTLARININ OTOKORELASYONLU SÜREÇLERDE UYGULANMASI)

3.1. Residual Control Charts (Artık Terimler için Kontrol Kartları)

A common approach to detect a possible process mean shift is to use residual control charts, also known as the special cause chart (SCC), which are constructed by applying traditional SPC charts (such as Shewhart, cumulative sum (CUSUM), exponentially weighted moving average (EWMA)) to the residuals from a time series model of the process data [12]. The basic idea in the SCC method is to transform the original autocorrelated data to a set of "residuals" and monitor the residuals. Shewhart charts proposed by Shewhart in 1931 and they are usually effective for detecting large shifts but ineffective for detecting small shifts (about 1.5 or less) in process parameters. To overcome this disadvantage two different control charts, cumulative sum (CUSUM) and exponentially weighted moving average (EWMA), are proposed [1]. The CUSUM chart was firstly introduced by Page in 1954. The basic purpose of a CUSUM chart is to track the distance between the actual data point and the grand mean. Then, by keeping a cumulative sum of these distances, a change in the process mean can be determined, as this sum will continue getting larger or smaller. The EWMA chart was proposed by Roberts in 1959. The EWMA is a statistic for monitoring the process that averages the data in a way that gives less and less weight to data as they are further removed in time. CUSUM and EWMA are appropriate for detecting small shifts, because they give smaller weight to the past data. However, they do not react to large shifts as quickly as the Shewhart chart. Yourstone & Montgomery (1989) studied on geometric moving average (GMA) and geometric moving range (GMR) control charts. The geometric moving range between successive pairs of residuals is used to track the dispersion of the process quality data in the real-time SPC algorithm [13]. The geometric moving range allows the user of the algorithm to alter the sensitivity of the moving range filter through adjustments to the smoothing constant. Two years later, in 1991, they proposed two innovative control charts, the sample autocorrelation chart (SACC) and the group autocorrelation chart (GACC) which are shown to be particularly effective control schemes when used control chart for the residuals of the time series model of the real time process data [14]. These charts are based on the autocorrelation function of autocorrelated data. The SACC as well as the GACC detect shifts in the mean as well as shifts in the autocorrelative structure. The GACC chart detects the shift before the SACC since the GACC detects fluctuations over all lags of the sample autocorrelation. The SACC will signal shifts through a change in the pattern of the plots of the sample autocorrelation as well as through plots meeting or exceeding the control limits. The GACC will detect shifts that impact the sample autocorrelations as a group [14]. When compared with the previous methods, SACC is less sensitive in detecting mean and variance shifts but very competitive in detecting changes in the parameters of ARMA model [15].

Today, many industrial products are produced by several dependent process steps not just one step. However, conventional SPC techniques focus mostly on individual stages in a process and do not consider disseminating information throughout the multiple stages of the process. They are shown to be ineffective in analyzing multistage processes. A different approach to this problem is the cause-selecting chart (CSC), proposed by Zhang (1984). The CSC based on the output adjusted for the effect of the incoming quality shows promise for increasing the ability to analyze multistage processes [16].

On the other hand, the traditional practice in using the control charts to monitor a process is to use a fixed sampling rate (FSR) which takes samples of fixed sample size (FSS) with a fixed sampling interval (FSI). In recent years, several modifications adopting the variable sampling interval (VSI), variable sample size (VSS) and variable sampling rate (VSR) or variable sampling interval and sampling size (VSSI) in the $\overline{X}$ control chart have been suggested to improve traditional FSI policy and have been shown to give better performance than the conventional $\overline{X}$ charts in the sense of quick response to process change in the quality control literature. The VSSI features are extended to CUSUM and EWMA charts. Zou, Wang, & Tsung (2008) [17] suggested using a variable sampling scheme at fixed times (VSIFT) to enhance the efficiency of the $\overline{X}$ control chart for the autocorrelated data. Two charts are under consideration, that is, the VSIFT $\overline{X}$ chart and variable sampling rate with sampling at fixed times VSRFT $\overline{X}$ charts. These two charts are called $\overline{X}$-VSFT charts.

Traditional residual based charts, such as a Shewhart, CUSUM, or EWMA on the residuals, do not make use of the information contained in the dynamics of the fault signature. In contrast, methods such as the Cumulative Score (Cuscore) charts which are presented by Box & Ramirez (1992) or Generalized Likelihood Ratio Test (GLRT) do incorporate this information [18].

Traditional control charts are intended to be used in high volume manufacturing. In a short run situation, there is not enough data available for the estimation purposes. In processes where the length of the production run is short, data to estimate the process parameters and control limits may not be available prior to the start of production, and because of the short run time, traditional methods for establishing control charts cannot be easily applied. Many sampling difficulties arise when applying standard control charts in low volume manufacturing horizon. Q charts have been proposed to address this problem by Quesenberry (1991) [19].

The basic idea in the SCC method is to transform the original, autocorrelated data to a set of "residuals" and monitor the residuals. The minimum mean squared error (MMSE) predictor used in the SCC chart is optimal for reducing the variance of the residuals but is not necessarily best for the purposes of process monitoring. Furthermore, the MMSE predictor is closely tied to a corresponding MMSE scheme in feedback control problems. Despite a huge literature on MMSE-based feedback control, the class of proportional integral derivative (PID) control schemes is more common in industry (see Box, Jenkins, & Reinsel, 1994; Astrom & Hagglund, 1995 refered from [20]). Jiang et al. (2002) use an analogous relationship between PID control and the corresponding PID predictor to propose a new class of procedures for process monitoring. As in SCC charts, they transform the autocorrelated data to a set of "residuals" by subtracting the PID predictor and monitoring the residuals [20].

When the literature is reviewed for 1997-2010 year range, it is clearly observed that the following studies are remarkable. Kramer & Schmid (1997) [21] discussed the application of the Shewhart chart to residuals of AR(1) process and in the same year Reynolds & Lu (1997) [22] compared performances of two different types of EWMA control charts for residuals of AR(1) process. Yang & Makis (1997) [23] compared the performances of Shewhart, CUSUM, EWMA charts for the residuals of AR(1) process. Zhang (1997) [24] remarked that the detection capability of an x residual chart was poor for small mean shifts compared to the traditional x chart, EWMA, and CUSUM charts for AR(2) process. Two years later Reynolds & Lu (1999) [25] compared the performances of EWMA control chart based on the residuals from the forecast values of AR(1) process and EWMA control chart based on the original observations. Luceno & Box (2000) [26] studied the One-sided CUSUM chart. Rao, Disney & Pignatiello (2001) [27] focused on the integral equation approach for computing the ARL for CUSUM control charts for AR(1) process. They studied the ARL performance versus length of the sampling interval between consecutive observations for residuals of AR(1) process. Jiang et al. (2002) [20] proposed proportional integral derivative (PID) charts for residuals of ARMA(1,1) process. Kacker & Zhang (2002) [28] studied the run length performance of Shewhart $\overline{x}$ for residuals of IMA(λ,σ) processes. Shu, Apley, & Tsung (2002) [29] proposed a CUSUM-triggered Cuscore chart to reduce the mismatch between the detector and fault signature. A variation to the CUSUM-triggered Cuscore chart that uses a GLRT to estimate the mean shift time of occurrence is also discussed. They used ARMA(1,1) process to test the performance of proposed chart. It is shown that the triggered Cuscore chart performs better than the standard Cuscore chart and the residual-based CUSUM chart. Ben-Gal Morag, & Shmilovici (2003) [30] presented context-based SPC (CSPC) methodology for state-dependent discrete-valued data generated by a finite memory source and tested the performance of this new modified chart for AR(1), AR(2), MA(1) processes. Snoussi, Ghourabi, & Limam (2005) [31] studied on residuals for short run autocorrelated data of autocorrelated process. They compared the performances of Shewhart $\overline{x}$, CUSUM, and EWMA control charts for residuals of AR(1) process. They also compared the performances of CUSUM, and EWMA control charts with Q statistics (EWMA Q chart and CUSUM Q chart) for residuals of AR(1) process. Kim, Alexopoulos, Goldsman, & Tsui (2006) [32] considered a CUSUM process as their monitoring statistic that is a bit different than that of Johnson & Bagshaw (1974), and they approximate this CUSUM process by a Brownian motion process. Noorossana & Vaghefi (2006) [33] investigated the effect of autocorrelation on performance of the

MCUSUM control chart. Triantafyllopoulos (2006) [34] has developed a new multivariate control chart based on Bayes' factors. This control chart is specifically aimed at multivariate autocorrelated and serially correlated processes and tested for AR(1) process. Yang & Yang (2006) [16] considered the problem of monitoring the mean of a quality characteristic *x* on the first process step and the mean of a quality characteristic *y* on the second process step, in which the observations *x* can be modeled as an AR(1) model and observations *y* can be modeled as a transfer function of *x* since the state of the second process step is dependent on the state of the first process step. To effectively distinguish and maintain the state of the two dependent process steps, the Shewhart control chart of residual and the cause selecting chart (CSC) are proposed. They showed that the proposed control charts are much better than the misused Hotelling T^2 control chart and the individual shewhart chart. Ghourabi & Limam (2007) [35] proposed a new method of residual process control, the Pattern Chart and tested this new chart for AR(1) process and compared its ARL values with SCC chart. Costa & Claro (2008) [36] considered the double sampling (DS) $\overline{X}$ control chart for monitoring processes in which the observations can be represented as ARMA(1,1) model. Zou, wang, & Tsung (2008) [17] suggested using a variable sampling scheme at fixed times (VSIFT) to enhance the efficiency of the $\overline{X}$ control chart for the autocorrelated data. Two charts are under consideration, that is, the VSIFT $\overline{X}$ and variable sampling rate with sampling at fixed times (VSRFT $\overline{X}$) charts. These two charts are called $\overline{X}$-VSFT charts. The authors used AR(1) model as representative model for their study. An integration equation method combined with a Markov process model was developed to study the performance of these charts. Sheu & Lu (2009) [37] examined a GWMA with a time-varying control chart for monitoring the mean of a process based on AR(1) process and they compared ARL performance of GWMA and EWMA charts. Weiss & Testik (2009) [38] investigated the CUSUM control chart for monitoring autocorrelated processes of counts modeled by a Poisson integer-valued autoregressive model of order 1 (Poisson INAR(1)). Knoth, Morais, Pacheco, & Schmid (2009) [39] discussed the impact of autocorrelation on the probability of misleading signals (PMS) of simultaneous Shewhart and EWMA residual schemes for the mean and variance of a AR(1) process.

Use of a residual chart has the advantage that it can be applied to any autocorrelated data even if the data from a nonstationary process. It needs time series modeling efforts [12]. Although the residual charts have some advantages by using them for autocorrelated processes, there are some problems due to the detection capability of the residual chart. Harris & Ross (1991) [40] recognized that the CUSUM control chart and EWMA control chart for the residuals from a first-order autoregressive (AR(1)) process may have poor capability to detect the process mean shift. Wardell, Moskowitz, & Plante (1994a) [41] showed that Shewhart charts are not completely robust to deviations from the assumption of process randomness; namely when observations are correlated. EWMA chart is very good at detecting small shifts, and performs well for large shifts at only the case when the autoregressive parameter is negative and the moving average parameter is positive. No other chart is obviously dominant under every condition. They showed that when the processes were positively autocorrelated (at the first lag), the residual chart did not perform very well. Zhang (1997a) also studied on detection capability of residual chart for autocorrelated data. In his study, Zhang defined a measure of the detection capability of the residual *x*-chart for the general stationary process and showed that the detection capability of a residual chart for AR(2) process was small compared to the detection capability of the *x* chart [42]. One of the most important disadvantages of residual charts is that the time series modeling knowledge is needed for constructing the ARIMA model and some residual charts which based on two valid time series models signal differently. To overcome the disadvantages of residual-based control charts, monitoring the autocorrelated observations by modifying the standard control limits to account for the autocorrelation is suggested. These modified control charts for autocorrelated data are described in the next section.

3.2. Modified Control Charts (Modifiye Edilmiş Kontrol Kartları)

Modified control charts such as moving centerline exponentially weighted moving average (MCEWMA),exponentially weighted moving average for stationary process (EWMAST), autoregressive moving average (ARMA) control charts and other modified control charts are introduced to deal with the disadvantages of the residual charts. MCEWMA control chart is used for individual observations. The MCEWMA chart is based on the familiar EWMA chart that is also standard in the literature; however, it adapts the EWMA for the autocorrelated data given by the ARIMA disturbance model [43]. Montgomery & Mastrangelo (1991) [44] point out that it is possible to combine information about the state of statistical control and process dynamics on a single control chart. EWMAST control chart has been introduced by Zhang in 1998 to deal with the disadvantages of the residual charts. EWMAST chart is an extension of the traditional EWMA chart and basically constructed by charting the EWMA statistics for stationary process. EWMAST chart is a EWMA chart for stationary processes. Zhang (1998) [42] remarked that the limits of the EWMAST chart are different from that of the traditional EWMA chart when the data are autocorrelated. When the process is positively autocorrelated, the limits of the EWMAST chart are wider than that of the ordinary EWMA chart. Zhang showed that a EWMA of a stationary process is asymptotically a stationary process. The autocovariance function of EWMA is derived when the process is stationary. Then the EWMAST chart for general stationary process is established. The control limits of the EWMAST chart are analytically determined by the process variance and autocorrelation. When the process is nonstationary or near nonstationary with strong and positive autocorrelations, residual charts can be used. When the mean shifts are small, however, the performance of the residual chart is still satisfactory. Actually, no process control chart performs well in this case. In general, nonstationarity or near nonstationarity with positive autocorrelation is likely to occur when the data are acquired at high frequency. In this case the large in-control ARLs (such as those of the EWMAST chart) are often desirable, and the corresponding large out-of-control ARLs are much less a problem [42]. SCC chart is shown to be effective when detecting large shifts. The EWMAST chart performs better than the SCC chart when the process autocorrelation is not very strong and the mean changes are not large. On the other hand, the EWMAST chart applies the EWMA statistic directly to the autocorrelated process without identifying the process parameters and shown to be efficient in some parameter regions [45]. An obvious advantage of using EWMAST chart is that there is no need to build a time series model. The EWMAST chart is easy to implement just like its special case, ordinary EWMA chart. On the other hand, implementation of a residual chart needs a time series modeling algorithm [42].

By integrating the advantages of SCC chart and EWMAST chart and taking into account the autocorrelation structure of the underlying process, a family of control charts, the ARMA chart is proposed by Jiang, Tsiu, & Woodal (2000) [45]. This charting technique based on an autoregressive moving average (ARMA) statistic and provides a more flexible choise of parameters to relate the autocorrelation structure of the statistic to the chart performance and includes the special cause chart (SCC) chart and the EWMAST chart as special cases. It is shown that an ARMA chart with appropriate parameter values will outperform both the SCC and EWMAST charts for autocorrelated processes. Jiang et al. (2000) [45] use the same notation of the EWMAST chart proposed by Zhang (1998) [42], and denote the ARMA chart as the ARMAST chart that is proposed for stationary processes.

On the other hand, the limitations of distribution-based procedures can be overcome by distribution-free SPC charts. Runger & Willemain (R&W) (1995) [46] organized the sequence of observations of the monitored process into adjacent nonoverlapping batches of equal size; and their SPC procedure called unweighted batch means (UBM) is applied to the corresponding sequence of batch means. They choose a batch size larger enough to ensure that the batch means are approximately iid normal, and then they apply to the batch means one of the classical SPC charts developed for iid normal data, including the Shewhart and Tabular CUSUM charts. In contrast to this approach, Johnson & Bagshaw (J&B) (1974) [47] and Kim, Alexopoulos, Goldsman, & Tsui (2006) [32] presented CUSUM based methods that use raw (unbatched) observations instead of batch means. Computing the control limits for the latter two procedures requires an estimate of the variance parameter of the monitored process that is the sum of covariances at all lags (see [32] for experimental evaluations of R&W chart and J&B chart)

Kim et al. (2006) [32] considered a CUSUM process as their monitoring statistic that is a bit different than that of Johnson & Bagshaw (1974) [47], and they approximate this CUSUM process by a Brownian motion process. By exploiting the known properties of Brownian motion, they derive a new model-free CUSUM chart called the MFC Chart. The proposed SPC procedure requires the asymptotic variance constant which is the sum of covariances of all lags, the procedure is completely model-free - including the design of control limits and chart parameters - with the help of non-parametric variance estimation techniques popular in the simulation community. The MFC chart can be used with raw observations or batch means of any size, so using large batches can be avoided. Also this procedure provides a convenient way to compute control limits like the Shewhart chart does [32]. Another distribution-free chart is rum sum chart proposed by Willemain & Runger (1998) [48]. Their use of run sums is revival of an earlier idea. The use of coded run sums for iid data was described by Roberts (1996), who cited earlier work by Toda (1958), who in turn cited Imaizuma (1955) and Reynolds (1971) presented a simplified overview [48]. The Run Sum chart proposed by Willemain & Runger (1998) [48] differs from these earlier works in two significant ways. First, they consider the autocorrelated data characteristic of data-rich environments. Second, they use the sums of the observations directly, whereas earlier work coded the data values into integer scores before summing. Most SPC methods are not suitable for monitoring nonlinear and state-dependent processes. Another approach to developing distribution-free SPC charts is taken by Ben-Gal, Morag, & Shmilovici (2003) [30]. They presented context-based SPC (CSPC) methodology for state-dependent discrete-valued data generated by a finite memory source. The key idea of the CSPC is to monitor the statistical attributes of a process by comparing two context trees at any monitoring period of time. The first is a reference tree that represents the "in-control" reference behavior of the process; the second is a monitored tree, generated periodically from a sample of sequenced observations that represents the behavior of the process at that period. The Kullback–Leibler (KL) statistic is used to measure the relative "distance" between these two trees, and an analytic distribution of this statistic is derived. Monitoring the KL statistic indicates whether there has been any significant change in the process that requires intervention. The proposed CSPC extends the scope of conventional SPC methods. It allows the operators to monitor varying-length state-dependent processes as well as independent and linear ones. The CSPC is more generic and less model-biased with respect to time series modeling. The major drawback of CSPC is relatively large sample size required during the monitoring stage. Therefore, it should be applied primarily to processes with high sampling frequency, such as the buffer-level monitoring process. The CSPC is currently limited to discrete and single-dimensional processes [30]. For distribution free processes "distribution free charts" are suggested. Kim, Alexopoulos, Tsui, & Wilson (2007) [49] proposed a distribution free tabular CUSUM (DFTC) chart to detect mean shifts of autocorrelated observations. The authors defined the proposed chart as "a generalization of the conventional tabular CUSUM chart that is designed for iid normal random variables".

When the literature is reviewed for 1997-2010 year range, it is clearly observed that the following studies are remarkable. As refered before, Zhang (1998) [42] proposed exponentially weighted moving average for stationary process (EWMAST) control chart, which is a modified control chart for autocorrelated data, and tested this new chart for AR(1), AR(2), ARMA(1,1) processes. Willemain & Runger (1998) [48] proposed Run sum chart which is a distribution-free chart and examined the residuals of AR(1) and ARMA(1,1) processes. Apley & Shi (1999) [50] presented an on-line SPC technique, based on a GLRT, for detecting and estimating mean shifts in autocorrelated processes that follows a normally distributed ARIMA(4,0,3) model. The GLRT is applied to the uncorrelated residuals of the appropriate time-series model. The performance of GLRT is compared to Shewhart and CUSUM charts. By integrating the advantages of SCC chart and EWMAST chart and taking into account the autocorrelation structure of the underlying process, a family of control charts, the autoregressive moving average (ARMA) chart is proposed by Jiang, Tsiu, & Woodal (2000) [45]. They compared the performances of ARMA, ARMAST, EWMAST, EWMA, CUSUM and Shewhart control charts for AR(1), ARMA(1,1) processes. Later in (2001) [51] jiang performed the average run length computation of ARMA charts for stationary processes and developed a Markow chain model for evaluating the run length performance of the ARMA chart applied to an ARMA (p,q) process. By exploiting the known properties of Brownian motion, they derive a new model-free CUSUM chart called the MFC Chart and tested this new chart for AR(1) process. Winkel & Zhang (2004) [53] compared the performances of EWMA for the residuals of AR(1) process and EWMAST control charts for AR(1) process. Brence & Mastrangelo (2006) [52] explored the capabilities of the tracking signals and the MCEWMA when the smoothing constants are varied and a shift is introduced into the AR(1) and ARMA(1,1) processes. Kim et al. (2007) [49] proposed a distribution free tabular CUSUM (DFTC) chart to detect mean shifts in autocorrelated and normal distributed process observations. Stationary AR(1) and AR(2) processes are used to test its performance. Cheng & Chou (2008) [54] used ARMA control chart in a real-time inventory decision system using Western Electric run rules. They monitored the data of demand that presents a pattern of time series. They employed ARMA chart to monitor the market demand that is autocorrelated and used individual control chart to monitor the inventory level. Issam & Mohamed (2008) [55] proposed to apply support vector regression (SVR) method for construction of a residual multivariate CUSUM (MCUSUM) chart, for monitoring changes in the process mean vector. Koksal, Kantar, Ula, & Testik (2008) [56] investigated the effect of Phase I sample size on the run length performance of Residual chart, modified Shewhart chart, EWMAST chart and ARMA chart for monitoring the changes in the mean of AR(1) process.

3.3. Neural Network Based Control Charts (Yapay Sinir Ağı Tabanlı Kontrol Kartları)

A neural network is an approach to data processing that does not require model or rule development. Researchers have been investigating the use of artificial neural networks (NNs) in the application of control chart pattern (CCP) recognition with encouraging results in recent years. When compared to other methodologies the neural network approach has certain advantages. The model development is much simpler than that for most other approaches. Instead of theoretical analysis and development for a new model the neural network tailors itself to the training data. The model can be refined at any time with the addition of new training data [57]. Also note that, a traditional control chart considers only the current sample when determining the status of a process and hence does not provide any pattern related information. NN based process control charts can classify patterns that the traditional charting methods for autocorrelated data cannot properly handle [58]. Because of these advantages application of NNs to SPC has great interest in recent years. The application of NNs to SPC can be commonly classified into two categories: (i) control chart pattern recognition and (ii) detection of unnatural behavior [2]. In the second category, NN used to diagnose the shift in the mean of a manufacturing process.

Few studies on mean shift detection of autocorrelated processes by a neural-based approach were presented. West, Mangiameli, & Chen (1999) [59] investigated the ability of radial basis function NNs to monitor and control complex manufacturing processes that exhibit both auto and cross-correlation. They demonstrated that the radial basis function network is superior to three control models proposed for complex manufacturing processes: multivariate Shewhart, MEWMA, and a feed forward NN with logistic units trained by backpropagation (often called a back propagation neural network (BPN)). They used VAR(1) model as the representative process model for their work. Chiu, Chen, & Lee (2001) [60] used BPN to identify shifts in process parameter values from AR(1) process. Pacella & Semeraro (2007) [2] proposed Elman recurrent neural network for manufacturing processes quality control. For a wide range of possible shifts and autocorrelation coefficients, performance comparisons between the neural-based algorithm and SCC chart, X chart, EWMAST chart are presented for ARMA(1,1) model. Guh (2008) [58] presented a learning vector quantization (LVQ) based system that can effectively recognize CCPs in real time for various levels of autocorrelation for AR(1) model and compared its ARL performance with SCC chart, X chart and EWMA chart. Hwarng & Wang (2010) [61] proposed a neural network based identifier (NNI) for multivariate autocorrelated processes. A rather extensive performance evaluation of the proposed scheme is carried out, benchmarking it against three statistical control charts, namely the Hotelling T^2 control chart, the MEWMA chart and the Z chart.

4. CONCLUSION AND SUGGESTIONS (SONUÇ VE ÖNERİLER)

Over the last two decades, control charts for autocorrelated observations have been applied to an increasing number of real-world problems. In the present paper, control chart applications for the autocorrelated processes were reviewed, and the historical progression in this field was emphasized in order to help the interested researchers and practitioners get informed about the references on the relevant research in this field, regarding the design, performance and applications of control charts for autocorrelated processes. Recent research studies for autocorrelated data are summarized in Table 1 in a chronological order, in order to see the gradual development in these works. This survey aimed to review publications appearing in refereed journals between 1997 and 2009.

A summary of some unanswered questions and future research ideas for control chart applications on autocorrelated process observations are listed below:

- VAR(1) processes prevalently inspected for multivariate autocorrelated processes. Higher order multivariate cases may be considered in the future researches.
- In general, control chart performances for ARIMA (1,1,1) model are studied but performances for higher orders have not been studied prevalently. Future research may focus on this area.
- In recent years, several modifications adopting the variable sampling interval (VSI), variable sample size (VSS) and variable sampling rate (VSR) or variable sampling interval and sampling size (VSSI) in the $\overline{X}$ control, CUSUM and EWMA charts, have been suggested to improve traditional FSI policy. These VSSI features may be extended to other control charts.
- Shewhart, EWMA and CUSUM charts for residuals for short run autocorrelated data of AR(1) process have been investigated. The performance of modified control charts for short run can be investigated extensively for autocorrelated processes.
- Control chart applications to different areas such as real-time inventory decision systems are presented (see [54]). According to Cheng & Chou (2008) [54] the future research may be focused on the study of the effect of lead time on the performance of the inventory decision systems. This study is a good case for applying control charts to different scientific areas. Similar studies can be performed on different scientific areas where the process observations are needed to be observed between upper-lower limits and had to have a mean value.
- Investigating the impact of estimators of mean and variance (namely based on an auxiliary and independent random sample) on probability of misleading signals (PMS), or the influence of trends on PMS can be studied (see [39]).
- One-sided Poisson INAR(1) CUSUM control chart is proposed by Weiss & Testik (2009) [38] and performance of this chart is presented. According to the authors, analysis of the performance of this CUSUM scheme in the case when the chart design is based on estimated parameters is a particularly important issue for future work. Furthermore, it should be investigated how the proposed one-sided CUSUM chart can be extended to a two-sided chart, and if an exact ARL computation would still be possible in this case.

Table 1. Evolution of control charts for autocorrelated data
(Tablo 1. Very otokorelasyon kontrol kartlarının gelişimi)

Year	Author(s)	Control Charts	Autocorrelation Structure
1974	Johnson & Bagshaw	J&B	AR(1)
1988	Alwan & Roberts	Shewhart $\bar{X}$, CCC, SCC	IMA(1,1), ARMA(1,1)
1989	Yourstone & Mongomery	GMA, GMR	ARMA(2,1), AR(2)
1991	Harris & Ross	EWMA, CUSUM	AR(1)
1991	Montgomery & Mastrangelo	MCEWMA	AR(1)
1991	Yourstone & Mongomery	SACC, GACC	AR(4), ARMA(2,4)
1992	Wardell et al.	EWMA	ARMA(1,1)
1994	Wardell et al.	Shewhart $\bar{X}$, EWMA	AR(1)
1995	Mastrangelo & Montgomery	MCEWMA	IMA(1,1), ARIMA(1,1,1), AR(1), AR(2), ARMA(1,1)
1995	Runger & Willemain	R&W	AR(1)
1997	Kramer & Schmid	Shewhart $\bar{X}$	AR(1)
1997	Reynolds & Lu	EWMA	AR(1)
1997	Yang & Makis	Shewhart $\bar{X}$, CUSUM, EWMA	AR(1)
1997	Zhang	Shewhart $\bar{X}$	AR(2)
1997	Atienza et al.	SACC, SCC, CUSUM	AR(1), MA(1)
1998	Willemain & Runger	Run sum chart	AR(1), ARMA(1,1)
1998	Zhang	EWMAST	AR(1), AR(2), ARMA(1,1)
1999	Apley & Shi	Cuscore charts	ARIMA(4,0,3)
1999	Reynolds & Lu	EWMA	AR(1)
1999	West et al.	Multivariate Shewhart, MEWMA, BPN	VAR(1)
2000	Jiang et al.	ARMA, ARMAST, EWMAST, EWMA, CUSUM, Shewhart $\bar{X}$	AR(1), ARMA(1,1)
2000	Luceno & Box	One-sided CUSUM	AR(1)
2001	Jiang	ARMA	ARMA(1,1)
2001	Rao et al.	CUSUM	AR(1)
2001	Chiu et al.	BP Neural Network	AR(1)
2002	Jiang et al.	PID	ARMA(1,1)
2002	Kacker & Zhang	Shewhart $\bar{X}$	IMA(λ, σ)
2002	Shu et al.	CUSUM-triggered Cuscore	ARMA(1,1)
2003	Ben-Gal et al.	CSPC	AR(1), AR(2), MA(1)
2004	Winkel & Zhang	EWMA, EWMAST	AR(1)
2005	Snoussi et al.	Shewhart $\bar{X}$, CUSUM, EWMA, EWMA Q, CUSUM Q	AR(1)
2005	Winkel & Zhang	EWMAST, EWMA	AR(1)
2005	Kim et al.	MFC	AR(1)
2006	Yang & Yang	CSC, Shewhart-$\bar{X}$, Hottelling T^2	AR(1)
2006	Brence & Mastrangelo	MCEWMA	AR(1), ARMA(1,1)
2006	Noorossana & Vaghefi	MCUSUM	AR(1)
2006	Triantafyllopoulos	A new Multivariate Control Chart	AR(1)
2007	Kim et al.	DFTC	AR(1), AR(2)
2007	Ghourabi & Limam	Pattern Chart, SCC	AR(1)
2007	Pacella & Semeraro	SCC, X chart, EWMAST, Elman NN	ARMA(1,1)
2008	Costa & Claro	DS $\bar{X}$	ARMA(1,1)
2008	Zou et al.	VSIFT $\bar{X}$, VSRFT $\bar{X}$	AR(1)
2008	Cheng & Chou	ARMA	ARMA(1,1)
2008	Issam & Mohamed	MCUSUM	VAR(1)
2008	Koksal et al.	Residual chart, modified Shewhart, EWMAST, ARMA	AR(1)
2008	Guh	SCC, X chart, EWMA, LVQ NN	AR(1)
2009	Weiss & Testik	CUSUM	Poisson INAR(1)
2009	Sheu & Lu	GWMA, EWMA	AR(1)
2009	Knoth et al.	Shewhart, EWMA	AR(1)
2010	Hwarng & Wang	Hotelling T^2, MEWMA, Z chart, NN Identifier	VAR(1)

- The effect of parameter estimation has not been considered for many types of control charts, especially the charts with VSS and/or VSI. Researches for these charts are needed in order to have good recommendations on how to best design the charts with estimated parameters.
- The combined effect of model misspecifications and parameter estimation on control charts for autocorrelated data may be investigated widely, because of being strongly dependent on the correctness of the assumed time series model.
- The study of Yang & Yang (2006) [16] can be extended to the process control for autocorrelated observations with the ARMA model under two dependent process steps and the adaptive process control for correlated observations with the ARMA model under two dependent process steps.
- A major advantage of the approach that is proposed by Triantafyllopoulos (2006) [34] as compared with other multivariate control charts is that once the log Bayes' factors have been obtained, any appropriate univariate control chart can be applied. This important area of SPC is an interesting research area for future research and the work performed by Triantafyllopoulos (2006) [34] can be extended to other control charts such as modified CUSUM and non-parametric control charts that do not require any knowledge about the underlying distribution of the variable.
- The pattern chart's performance that is proposed by Ghourabi & Limam [35] for residuals of autocorrelated process observations is compared with SCC chart. The performance of proposed chart can be compared with other control charts for residuals.
- Different neural network based approaches are presented for multivariate processes. However all these works considered VAR(1) processes. Further researches may be focus on higher-order multivariate cases for identifying a shift.
- Adapting neural networks to real-time is a problem. The researches may direct their work to design more efficient training regime, including the use of training data and training time.
- Neural network based pattern recognizers for autocorrelated data are applied to first order autocorrelated processes. Further researches may focus on higher order autoregressive and autoregressive moving average cases.
- Much recent neural network based research for identifying shift in mean focused on most commonly used control chart patterns (natural pattern, upward-downward shift, increasing-decreasing trend, cycle). More empirical work can be done for other patterns, such as systematic variation or mixture.

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