A control chart pattern recognition system for feedback-control processes

De la Torre Gutierrez, Hector; Pham, Duc

DOI:
10.1016/j.eswa.2019.112826

Title: A control chart pattern recognition system for feedback-control processes

Authors (SURNAME, FORENAME):

1.- De la Torre-Gutiérrez, Héctor *[a]

[a] Main address: Department of Mechanical Engineering, University of Birmingham, Edgbaston, Birmingham, West Midlands B15 2TT

[a]Present address: High speciality laboratory, Centre for Research in Mathematics, Aguascalientes, Aguascalientes, Mexico, 20200

*Corresponding author (Email: hector.delatorre@cimat.mx, +52 395 1145576)

(ORCID: 0000-0002-8343-989X)

2.- Pham, Duc Truong[b]

[b] Department of Mechanical Engineering, University of Birmingham, Edgbaston, Birmingham, West Midlands B15 2TT (Email: d.t.pham@bham.ac.uk)

Abstract

The automated diagnosis of control charts to detect faults is a problem studied by many researchers. In recent years, they have turned their attention to processes that do not fulfil the condition of having normally, identically and independently distributed (NIID) variables. With those processes, it is common to have one or more manipulatable variables that can affect the quality characteristic under investigation. The Engineering Process Control (EPC) approach is often used to minimise the variance around the target value of the monitored characteristic by adjusting the manipulatable variables. In this work, a control chart pattern recognition (CCPR) system was developed for processes adjusted by EPC (also known as SPC-EPC or feedback-control processes). This issue of simultaneous identification of simple control chart patterns for feedback-control processes had previously not been studied. A Machine Learning algorithm was proposed to train a pattern recognition system. All the possible combinations of factors of the CCPR system were studied to determine the combination yielding the highest recognition accuracy, namely, using raw data as input, generating patterns with significance level α=0.01, monitoring the output signal, and employing a Proportional Integrative Derivative (PID) controller and the Radial Basis Function (RBF) kernel. This combination yielded overall accuracies of 94.18% and 94.14% for the AR(1) and ARMA(1,1) models, respectively.

Comment [HDITG1]: I hope this phrase is understood as "identify any of the seven simple patterns, not only by pairs or a subset of patterns as it was done by other authors.

Keywords: *Control chart pattern recognition, PID control, Support Vector Machine, SPC, EPC*

Abbreviations

ANOVA	Analysis of variance
AR(1)	First-order autoregressive
ARMA(1,1)	First-order autoregressive moving-average
BA	Bees Algorithm
BESSEL	Bessel kernel
CCPR	Control chart pattern recognition
CI	Confidence interval
CYC	Cyclic pattern
D_t	Disturbance magnitude at time t
DS	Downward shift
DT	Downward trend
e_t	White noise at time t
EPC	Engineering process control
HDWT	Haar discrete wavelet transform
IMA (1,1)	First-order integrated moving-average
IRT	Input representation technique
k_D	Coefficient for the derivative part of the controller
k_I	Coefficient for the integral part of the controller
k_P	Coefficient for the proportional part of the controller
MMSE	Minimum mean square error
MSE	Mean square error
n	Sample size
N_t	Inherent noise at time t
NIID	Normally, identically and independently distributed
NN	Neural network
NORM	Normal pattern

PGS	Pattern generation scheme
PGS-1	Conventional pattern generation scheme
PGS-2	Pattern generation scheme with $\alpha = 0.01$
PI	Proportional integral
PID	Proportional integral derivative
RBF	Radial basis function
S_t	Scaled variable at time t
sin	Sine function
SPC	Statistical process control
SVM	Support Vector Machine
SYS	Systematic pattern
T	Target value
t	Time
US	Upward shift
UT	Upward trend
X_t	Controller compensation at time t
Y_t	Output variable at time t
Z_t	Observed quality characteristic before the controller compensation
α	Significance level
β	Abnormal pattern parameter
ϕ	Autoregressive coefficient
σ_e	Standard deviation of white noise
σ_N	Standard deviation of inherent noise
τ	Time when a break point occurs
θ	Moving-average coefficient

1. Introduction

Statistical Process Control (SPC) is a collection of statistical techniques aimed at identifying assignable causes of variations in a process by monitoring the process and analysing the data obtained. If assignable causes are efficiently determined, two benefits can be achieved: reduction of the variance of the output variable and increase of the monitoring capability. One of the most efficient tools used by SPC is the control chart (CC). There are two main approaches to analysing and identifying assignable causes with CC. The first approach is to apply run rules or zone tests. However, there might be more than one assignable cause related to each rule or test, which creates uncertainty. The second approach involves the identification of patterns in the control chart. When the process is running under its intended conditions, the control chart displays a “Normal” (NORM) pattern (see Figure 1). On the other hand, if there are external disturbances (assignable causes), the control chart can exhibit one or more of the fourteen different types of abnormal patterns (Western Electric Company, 1956). Six of these patterns are considered basic patterns: Upward/Downward Trends (UT/DT), Upward/Downward Shifts (US/DS), Cycles (CYC) and Systematic (SYS). Figure 1 outlines these simple patterns. The remaining eight patterns are regarded as either particular cases or combinations of the basic patterns.

[Insert]Figure 1: Seven simple patterns in control charts

Reduction of the variance in the monitored variables is essential in modern manufacturing due to the need to increase quality and reduce scrap. In discrete part manufacturing, SPC has shown to be effective at addressing assignable causes. However, when the aim of monitoring is the reduction of the variance of the process, SPC has not always succeeded. On the other hand, in continuous processes, different process conditions are observed. The most common control charts cannot be used to monitor a continuous process as the assumption of time independence of the monitored quality characteristics is not fulfilled in most continuous processes. For these processes, it is usual that the variance of the output variable (the quality characteristic of interest) is reduced by means of a compensation or regulation scheme acting on manipulatable variables. These process compensation or regulation schemes are known as Engineering Process Control (EPC), stochastic control, or feedback/feedforward control, depending on the nature of the adjustments (Montgomery, 2009). A good quality control system is one that efficiently identifies patterns due to assignable causes and keeps the variance of the process at the minimum level, always around the nominal value of the process. Quality control systems that simultaneously monitor manipulatable variables and compensate for their effects are known as SPC-EPC or synergistic control schemes.

EPC schemes assume that changes in the manipulatable variables will have repercussions on the output variable in accordance with a specific dynamic model that links these variables. If this dynamic model is correct, the variance of the output variable is reduced. However, when certain types of external disturbances or assignable causes occur that are outside the framework of this dynamic model, then the compensation rules will not completely account for them. As a result, variability will be increased. By applying SPC in a specific way, these assignable causes can be detected and the combined SPC-EPC procedure will be more effective than EPC alone (Montgomery, 2009). As the identification of the aforementioned seven simple patterns in SPC-EPC schemes has not been fully studied, it was necessary to develop a control chart pattern recognition (CCPR) system for these process types.

CCPR systems for SPC-EPC schemes must take into account how the seven simple patterns are affected by the control scheme implemented by EPC. The main aim of this work is to develop CCPR systems for processes where the simple patterns are affected by a control scheme, as well as determining which variable - the output variable or the control compensations - is suitable for efficient identification of assignable causes from observed control chart patterns. Two different time series were used to model the inherent disturbance, the first-order autoregressive (AR(1)) and first-order autoregressive moving average (ARMA(1,1)) models, the ARMA(1,1) never studied before when a feedback control scheme is implemented. The simultaneous identification of the seven simple control chart patterns has not previously studied in feedback-control processes as highlighted ahead in the Literature review.

Two of the most common and effective controllers have been implemented and compared, namely, the Proportional Integrative Derivative (PID) and the Minimum Mean Squared Error (MMSE) controllers. As a consequence of applying controllers, two signals are produced: the output of the controller and the process output after the controller action. As aforementioned, determining which signal to monitor in order accurately to recognise patterns is another aim of this work. This comparative study of controllers when developing recognition systems is another contribution of this paper.

CCPR for feedback-control processes has not been much studied and the combination of factors (pattern generation scheme (PGS), input representation technique (IRT) and kernel of the Machine Learning algorithm) that yields the highest recognition accuracies is not known. Thus, the best combination of these factors is determined.

The rest of this paper is organised as follows. Section 2 reviews some of the publications most pertinent to this work. Section 3 presents the proposed CCPR system for feedback-control processes. The results obtained are discussed in Section 4. Finally, Section 5 concludes the paper and suggests areas for further investigation.

2. Literature review

The design of quality systems where SPC is integrated with EPC techniques has been an issue studied by several researchers during the last two decades.

This section reviews the most relevant publications related to SPC-EPC monitoring schemes and CCPR for normally, identically and independently distributed (NIID), autocorrelated and feedback-control processes.

2.1. SPC-EPC schemes

In SPC-EPC schemes, monitoring is typically conducted on the output of a controlled process (Del Castillo, 2006), but which signal to monitor in SPC-EPC control systems is still an unresolved issue. Jiang & Tsui (2002) demonstrated that monitoring either the output or the control action can be more efficient depending on the autocorrelated process dynamics. Other authors such as Box & Kramer (1992) and Capilla, Ferrer, Romero, & Hualda (1999) suggested that monitoring controller actions may improve the chances of early detection of shifts in the mean.

Kandananond (2010) quantified the effect of factors such as types of controllers, control charts and monitored signals on integrated SPC-EPC systems for non-stationary inherent disturbances when the Mean Squared Error (MSE) and average run length are measured as responses. Wang & Tsung (2007) proposed the use of the T^2 control chart for detecting dynamic patterns in mean shifts of Proportional-Integral (PI) controlled and MMSE controlled processes for inherent noise modelled by an ARMA(1,1) time series. For a broader discussion and review of the integration of SPC and EPC, see Jiang & Farr (2007).

2.2. CCPR for NIID processes

Designing CCPR systems that deal effectively with NIID inherent noise has recently been the most commonly studied problem (Hachicha & Ghorbel, 2012).

Xanthopoulos & Razzaghi (2014) proposed the use of weighted Support Vector Machines (SVM) for CCPR. Ranaee, Ebrahimzadeh, & Ghaderi (2010) introduced a CCPR system using a SVM as the recognition system and Particle Swarm Optimisation to improve the overall performance of the SVM by finding the best set of free parameters. Zhao et al. (2017) utilised Genetic Algorithms for searching the best set of free parameters in an improved-SVM-based pattern recognition system.

Pham & Wani (1997) proposed a set of shape features to be extracted directly from the control chart data and to be used as inputs for CCPR systems, increasing the pattern recognition accuracies and recognition stability. Based on these features, Gauri & Chakraborty (2006, 2009) suggested another set of shape features that not only increased pattern recognition accuracies and recognition stability but also were independent of the scale of the control chart data. Zaman & Hassan (2018) developed a two-staged recognition system, where the features are extracted and selected in the first stage, and in the final stage, the patterns are recognised using an adaptive neuro-fuzzy inference system (ANFIS) along with fuzzy c-mean (FCM).

Guh & Tannock (1999) developed a sequential pattern analysis scheme with four networks divided into two sequences in order to identify more detailed information about abnormal patterns. Using a sequence of networks to obtain more detailed information about the pattern was also studied by Guh (2003, 2005); Jiang, Liu, & Zeng (2009) and Shaban & Shalaby (2012). Authors such as Du, Huang, & Lv (2013); Lu, Shao, & Li (2011) and Xie et al.

(2013) have focused on the application of signal analysis techniques to pre-process the control chart data in order to enhance the performance of the CCPR system

2.3. CCPR for autocorrelated processes

(Noorossana, Farrokhi, & Saghaei, 2003) developed a multi-layer neural network-based CCPR system to detect three types of abnormal patterns referred to as level shift, additive outlier and innovation outlier. The inherent disturbance was modelled by an AR(1) model. Bo, Beibei, Yuwei, & Shengran (2018) designed a recognition system based on Random Forest and Classification and Regression Trees, where the inherent disturbance is also modelled by a AR(1).

Guh (2008) was the first author formally to study the identification of simple patterns in processes of which observations are not independent, using the AR(1) model to describe the inherent noise. He developed an on-line CCPR system for each of the nineteen autocorrelation levels studied. The designed on-line CCPR system neglected the biasing effect of the abnormal pattern over the estimated common-cause parameters (Boyles, 2000). Guh’s study showed encouraging results, introducing a new direction in CCPR research.

Other authors (Lin, Guh, & Shiue, 2011; Yang & Zhou, 2015) developed on-line CCPR systems also neglecting how the correlation coefficient is biased when abnormal patterns occur, thus training one CCPR system for each of the studied autocorrelation levels.

Cheng & Cheng (2008) used a multi-resolution analysis approach based on the Haar Discrete Wavelet Transform (HDWT) to denoise, decorrelate and extract features from AR(1) processes. They studied five pattern types and employed a multi-layer neural network as recognition system. The recognition accuracies of the proposed CCPR system were compared with those obtained using raw data as input. The best combination of coefficients of the

HDWT, approximation and detail, was determined by trial and error, causing long processing times and uncertainty. The proposed feature extraction technique increased the accuracy compared to those achieved using raw data as input. Wu & Yu (2010) developed a neural-network-based system for recognising both mean and variance shifts in AR(1) processes, providing additional useful information about process changes.

2.4. CCPR for feedback-control processes

The first authors to discuss the issue of pattern recognition and categorisation for feedback-control processes were Shao & Chiu (1999). A neural network (NN) was used as pattern recognition system. A first-order integrated moving-average (IMA(1,1)) model was adopted to model the inherent noise and a PI controller, to adjust the process. The NN was trained to identify step and linear disturbances and their magnitudes and achieved good recognition accuracies.

Lu, Wu, Keng, & Chiu (2008) developed a neural-network-based model with independent component analysis to recognise shifts in the correlated process parameters. They only considered two pattern types, step and linear changes, and assumed that the process can be modelled by an IMA(1,1) time series. They used a PI controller to make adjustments to the process.

The issue of detecting the start time of some abnormal patterns was addressed by Shao, Lu, & Chiu (2011). The inherent disturbance was modelled with an AR(1) time series and a MMSE controller was employed to tune the process. SVM and NN were used to detect the start time of only step-changes with different magnitudes.

Shao (2014) trained three SVMs to recognise pattern types in pairs, i.e., he studied three pattern types, having three possible pairwise combinations and training one SVM for each pair. He also assumed that the inherent noise could be modelled by an AR(1) time series with a given autocorrelation level (ϕ=0.9) and the process could be adjusted by a MMSE controller. As result, the proposed CCPR systems proposed by the author were able only to recognise patterns that showed that autocorrelation level and only distinguishing between patterns by pair.

The above review has revealed the need to develop CCPR systems for feedback-control processes robust to autocorrelation levels and able to identify the seven simple patterns simultaneously. It was noted that other time series models such as ARMA(1,1) must be considered to model the inherent noise before the controller action. Comparison between the two most efficient EPC controllers, MMSE and PID, is also required.

3. Proposed CCPR for feedback-control processes

3.1. Generation of the feedback-control processes

The proposed scheme for recognising patterns in feedback-control processes comprises three steps:

i. Initial generation of in-control processes and estimation of the controller parameters. An autocorrelated process, N_t, is generated according to one of the two time series models employed in this work (see Appendix). Using N_t, the parameters of the following two controllers are estimated:

- Minimum-Mean-Squared-Error (MMSE) controller (Jiang & Tsui, 2002):

$$X_t = \phi X_{t-1} + (\theta - \phi)(N_t - T) \tag{1}$$

  The parameters ϕ and θ are estimated by fitting an ARMA(1,1) or AR(1) model to N_t. In this research, the target value, T, was set to zero without loss of generality.

- Proportional Integral Derivative (PID) (Montgomery, 2009):

$$X_t = -k_P N_t - k_I \sum_{i=1}^{t} N_i - k_D (N_t - N_{t-1}) \tag{2}$$

The parameters k_P, k_I, k_D are estimated by minimising the MSE of the output variable, N_t, constrained to the following stability region for stationary processes (Box, Jenkins, & Reinsel, 1994; Tsung & Shi, 1999):

$$\begin{cases} k_I \geq 0 \\ k_P + {}^{k_I}/_{2} + 2k_D < 1 \\ -1 < k_D < 1 \\ -k_D(1 + k_P + k_I) - k_P < 1 \end{cases} \tag{3}$$

ii. Using the autocorrelated data, N_t, generated in (i), two methods were followed to produce patterns: the method adopted in most of the work on CCPR (denoted as PGS-1) and the scheme proposed by De la Torre Gutiérrez & Pham (2018) based on testing the statistical significance of the pattern parameters (denoted as PGS-2). In the first scheme, patterns are generated directly from equations (A2) - (A6) in the appendix and no further treatment is made to the data. In the second scheme, by fitting a dynamic regression model to the control chart data, the statistical significance of the pattern parameters is tested. The significance level chosen in this work was $\alpha = 0.01$. This level had been tested in previous work (De La Torre Gutierrez & Pham, 2016, 2018) to yield the best recognition accuracy.

iii. Once the patterns have been generated and the parameters of the PID and MMSE controllers have been estimated, the controller is applied and two different variables are obtained from the original, the feedback-control output, Y_t, and the controller compensations, X_t. Y_t can be obtained from:

$$Y_t = Z_t + X_{t-1} \tag{4}$$

where Z_t represents the disturbance as described in the Appendix.

Determining which of these two signals, Y_t or X_t, to monitor and analyse in order to achieve the highest pattern recognition accuracy is a key point in this work.

3.2. Input factors of the CCPR system

In addition to the pattern generation methods described in the previous subsection, the CCPR scheme also involves applying an IRT and a recognition system.

- ❖ The two IRTs tested in this work were:
  - Normalised raw data: The length of the input vector is preserved and the data are scaled to enable the CCPR system to recognise patterns in processes with any process mean and standard deviation (Zorriassatine & Tannock, 1998). The following expression was used for normalisation:

$$S_t = \frac{O_t - \bar{O}}{\hat{\sigma}_o} \tag{5}$$

    where $\bar{O}$ and $\hat{\sigma}_o$ represent the mean and standard deviation of the output variable, X_t or Y_t, respectively.

  - Shape features: To reduce the dimension of the input vector, the shape features initially proposed by Pham & Wani (1997) and then improved by Gauri (2010) for NIID observations are extracted. These features are independent of the data scale, increase pattern recognition accuracies and reduce training time.
- ❖ Machine Learning kernels: SVM was used as the pattern recognition algorithm in this work. SVM is a relatively recent Machine Learning algorithm. It has many advantages compared to other existing methods: generalisation capacity, ease of use and solution uniqueness (De Tejada & Martìnez-Echevarrìa, 2007). SVMs can also deal with nonlinear formulations, provide a trade-off between dimensionality (space complexity) and accuracy and produce good results in pattern recognition

applications. Three SVM kernels for nonlinear classification were tested, namely, Radial Basis Function (RBF), Laplace (LAPLA) and Bessel.

Figure 2 depicts the proposed scheme for CCPR of feedback-control processes for each inherent noise model.

[Insert]Figure 2: Proposed scheme for CCPR of feedback-control processes

3.3. Training of the pattern recognition system

Two sets of 5600 patterns, 800 of each type, were generated; one of the sets was produced using the methodology proposed by De la Torre Gutiérrez & Pham (2018), and the other following the PGS adopted in most of the CCPR literature (Pham, Otri, Ghanbarzadeh, & Koc, 2006; Pham & Oztemel, 1996). Each synthesised pattern consisted of a random sequence of length $n=60$, sampled at time t_1, t_2,....,t_{60}.

The Bees Algorithm (BA) proposed by Pham et al. (2006) was chosen to determine the best set of SVM parameters that minimise the misclassification rate during training. The misclassification rate under five-fold cross validation was selected as the loss function to be minimised. The BA was chosen for its proven ability to find globally optimal solutions in diverse complex optimisation problems, using both local and global search techniques (Pham, Castellani, & Chen, 2015). Table 1 shows the BA parameter values used. For further information regarding this algorithm and its parameters, see Pham et al. (2006) and Yuce, Packianather, Mastrocinque, Pham, & Lambiase (2013).

Table 1: Parameters of the BA used during SVM training

Parameter	Symbol	Value
Initial population	*nb*	20
Number of “best” sites	*m*	3
Number of “elite” sites	*e*	2

Patch size for Cost parameter *C*	*ngh-c*	0.5
Patch size for Kernel parameters	*ngh-k*	0.02
Number of bees for the elite sites	*ne*	3
Number of bees for the remaining "best" points	*nb*	2

4. Results

For each inherent noise model, 200 test sets of 700 patterns each were generated, 100 sets using PGS-2 and the remaining using PGS-1. For simplicity, the analysis of accuracies has been divided into two parts; in the first part, the best combination of input factors is determined. In the second part, the performance for that combination is studied and disaggregated by controller type and pattern type.

4.1. Analysis of input factors

Figure 3 shows the mean accuracies and the 95% confidence intervals (CIs) found for the AR(1) process for the five studied factors, disaggregated by pattern type. Figure 4 gives the recognition accuracies achieved when the inherent noise was ARMA(1,1) distributed and the 95% CIs for these accuracies for the five factors.

To determine which of the aforementioned five factors affects the recognition accuracy, a 2^4 x3 Analysis of Variance (ANOVA) with up to quintuple interactions was utilised.

Table 2 shows the p-values obtained from the aforementioned ANOVA for the AR(1) and ARMA(1,1) models; the triple, quadruple and quintuple interactions have been omitted.

Table 2: p-values obtained from ANOVA for the five input factors

Factor	**AR(1)**	**ARMA(1,1)**
PGS	≈0	≈0
IRT	≈0	≈0
SIGNAL	≈0	≈0
KERNEL	≈0	≈0
CONTROLLER	≈0	≈0

PGS*CONTROLLER	≈0	≈0
IRT*CONTROLLER	≈0	≈0
SIGNAL*CONTROLLER	≈0	≈0
KERNEL*CONTROLLER	0.4893	≈0
PGS*IRT	0.1723	≈0
PGS*SIGNAL	≈0	≈0
PGS*KERNEL	0.3730	0.2849
IRT*SIGNAL	≈0	≈0
IRT*KERNEL	≈0	≈0
SIGNAL*KERNEL	0.3614	0.0008

[Insert] Figure 3: Results for the five factors of the AR(1) model

[Insert] Figure 4: Results of the five factors for the ARMA(1,1) process

4.2. Analysis of the best factor arrangement

For the analysis of the best arrangement, the controller type was taken as the fixed factor and its interaction with the inherent noise model was studied. The performance of each model-controller type has been analysed by a post-hoc Tukey test. Table 3 presents the results obtained.

Table 3: Best factor arrangements for AR(1) and ARMA(1,1) models

Model-Controller	**Best arrangement**			
	PGS	**IRT**	**Kernel**	**Signal**
AR-PID	PGS-2	Raw data	RBF	Y_t
AR-MMSE	PGS-2	Raw data / Features	RBF	Y_t
ARMA-PID	PGS-2	Raw data	RBF	Y_t
ARMA-MMSE	PGS-2	Raw data / Features	RBF / LAPLA	Y_t

Table 4 shows the accuracies for each optimal arrangement, disaggregated by controller type and pattern. It can be observed that the accuracies for Normal patterns when a PID controller was applied were the lowest. As for the MMSE controller, the worst accuracies were observed for CYC patterns.

Table 4: Accuracies using the best arrangements of factors

	AR		ARMA	
	PID (%)	**MMSE (%)**	**PID (%)**	**MMSE (%)**
TOTAL	94.18	81.53	94.14	76.93
NORM	88.13	82.93	88.95	81.32
UT	93.00	77.66	92.70	70.66
DT	95.99	81.58	96.48	73.24
US	94.12	78.21	93.58	82.79
DS	98.60	90.64	98.04	87.66
CYC	92.63	77.41	93.10	70.12
SYS	96.82	82.25	96.15	72.72

To measure the impact of the controllers, the recognition accuracies achieved in this research were compared with those achieved in De la Torre Gutiérrez & Pham (2018) where no controllers were utilised. The results of the comparison are shown in Table 5.

Table 5: Accuracies with and without controller application (%)

	AR			ARMA		
	PID	**No controller**	**Difference**	**PID**	**No controller**	**Difference**
TOTAL	94.18	90.03	4.15	94.14	89.28	4.86
NORM	88.13	83.92	4.21	88.95	81.04	7.91
UT	93.00	91.08	1.92	92.70	89.81	2.90
DT	95.99	93.60	2.39	96.48	93.30	3.19
US	94.12	79.70	14.42	93.58	83.04	10.54
DS	98.60	96.64	1.96	98.04	95.63	2.41
CYC	92.63	90.97	1.66	93.10	89.47	3.63
SYS	96.82	94.28	2.54	96.15	92.71	3.44

As shown in Table 5, the overall accuracy increased by 4.15% and 4.86% for the AR and ARMA processes, respectively. Regarding the pattern type, US patterns showed the highest rise in recognition accuracy, by 14.42% and 10.54% for the AR and ARMA processes, respectively. This could have been caused by the amplitude effect of the controller on the magnitude of abnormal patterns.

4.3. Real data application

To demonstrate the ability of the proposed CCPR system to handle real data, 60 measurements of the thickness of a very thin metallic film in the early stages of the development of an electronic device taken from Box, Luceño, & Paniagua-Quiñones (2009) were utilised (corresponding to observations 11 to 70), and the SPC-EPC approach was followed to adjust and monitor this quality characteristic (see Figure 5). Box et al. (2009) highlighted the existence of an assignable cause that abruptly increased the metallic film thickness after 30 observations.

[Insert] Figure 5: Thickness of metallic film in the early stages of the development of an electronic device

The CCPR trained with the best arrangement of input factors for the two signals (X_t and Y_t) were used, and NORM and US patterns were identified for Y_t and X_t, respectively (see Figure 6). As mentioned in Box et al. (2009), in the process before the adjustment, a US pattern can be observed. Therefore, this pattern is expected to be recognised in one of the two signals, in this case, X_t.

In order further to categorise the pattern recognised by the aforementioned CCPR system, the methodology proposed for autocorrelated inherent noise was applied, i.e., two NLM-ARMA proposed for autocorrelated patterns were fitted to the original data. The p-value corresponding to the F-test for nested models was 0.0020; therefore, the full model better fitted the data. The most likely breakpoint was detected at τ = 30. Table 6 shows all the values regarding the full model fitted. It can be observed that the parameter related to the Shift pattern is statistically significant and greater than zero. Thus, like the CCPR, the NLM-ARMA classifies the pattern as a US pattern.

[Insert] Figure 6: Output and controller signals obtained from the SPC-EPC process

Table 6: ANOVA of the NLM-ARMA model fitted to the thickness measurements for a metallic film

Parameter	Estimate	Std. Error	t value	p-value
ϕ	0.306	0.1066	2.8701	0.0041
Intercept	80.5090	2.9488	27.3023	0.0000
Slope (Trend)	0.1784	0.0986	1.8093	0.0740
Shift magnitude (Shift)	18.4251	4.0195	4.5839	0.0000
Amplitude (Cyclic)	0.7434	1.4738	0.5044	0.6140
Frequency (Cyclic)	3.2311	1.0233	3.1575	0.0016
Departure (Systematic)	0.4504	1.2484	0.3608	0.7183

5. Conclusion

An important aspect to pay attention to when developing CCPR models is that they must be general, i.e., able to identify a wide variety of patterns. The generation of training patterns to ensure generality of the CCPR model and to create benchmarks for comparing recognition accuracies is an issue studied by De la Torre Gutiérrez & Pham (2016, 2018) who developed PGSs with that specific aim. The PGS proposed for autocorrelated patterns was the one adopted in this work. The control chart patterns, Z_t, were synthesised using two different PGSs, PGS-1 and PGS-2. PGS-2 (De la Torre Gutiérrez & Pham, 2018) ensured that correct decision boundaries were drawn and the patterns were appropriately categorised before the action of the controller. Therefore, the models developed using PGS-2 represent general CCPR models and can be employed in real-world applications.

SPC-EPC is a quality improvement technique that has shown good performance in a variety of production systems. As stated by Western Electric Company (1956), when a process is affected by assignable causes, SPC control charts exhibit patterns that can reveal those causes. However, those patterns have not been fully studied when feedback controllers are used in EPC to reduce the variability of the output. This paper has described the design of CCPR for feedback-control processes. This task involves several factors such as IRT and signals to be monitored, determining the best arrangement of these factors being the focus of this paper. Another factor that can be set by production personnel and that was also studied here is the controller type, PID and MMSE being the two most commonly adopted.

In the case of the AR(1) model, employing a PID controller and monitoring the output variable using the raw data as IRT was the arrangement that yielded the highest pattern recognition accuracies. In the case of the MMSE controller, the raw output data used as IRT also gave the best accuracies. The RBF, LAPLA and Bessel kernels showed similar accuracies for both controllers.

When the ARMA(1,1) model was employed, using raw data also produced the highest pattern recognition accuracy for both controllers. As in the case of the AR(1) model, the RBF, LAPLA and Bessel kernels also showed similar accuracies for both controllers.

As noted the previous section, to achieve the highest recognition accuracies, it is recommended to monitor the raw data of the signal Y_t

It is worth noting how different the recognition accuracies were between the controllers. For the AR(1) model, the overall difference was 12.60% and for the ARMA(1,1) model, it was 17.21%.

The proposed recognition systems only deal with two stationary time series models (AR and ARMA), so the future work will be focused on developing PGS and CCPR systems for non-stationary processes (SARIMA and ARIMA models). Furthermore, another limitation of the proposed schemes is that the recognition accuracies are far to be satisfactory in nowadays industries, so increasing the recognition accuracies is also necessary.

As noted in the Results section, the recognition accuracies achieved when the MMSE controller is applied are low, around 80%, so future work could be focused on how to increase the accuracy, this can be achieved by either applying signal processing techniques or using Deep Learning algorithms as pattern recognisers.

Future research will also focus on studying the identification of patterns in multivariate control charts, not only in the presence of autocorrelation but also in feedback-control processes and where assignable causes can be masked. Another research topic to study is the application of the T^2 control chart to simultaneously monitor the output and controller performance in feedback-control processes.

6. Appendix

Two time series models were used to model the inherent noise of the monitored process, ARMA(1,1) and AR(1).

$$N_t = \phi N_{t-1} - \theta e_{t-1} + e_t \qquad \text{(A1)}$$

where if θ=0, an AR(1) process is obtained. e_t represents white noise which is normally, independently and identically distributed, with mean equal to zero and standard deviation equal to one. For further information about generating stationary processes starting from white noise e_t, see Box, Luceño, & Paniagua-Quiñones (2011).

The seven simple patterns, represented by D_t, were generated using the following expressions:

- Normal:

$$D_t = T \qquad \text{(A2)}$$

❖ Upward / Downward Trends:

$$D_t = \pm\beta_1 t + T \tag{A3}$$

❖ Upward / Downward Shifts:

$$D_t = \pm\beta_2 d + T \tag{A4}$$

❖ Cyclic:

$$D_t = \beta_3 sin\left(\frac{2\pi t}{\beta_4}\right) + T \tag{A5}$$

❖ Systematic:

$$D_t = \beta_5(-1)^t + T \tag{A6}$$

The meaning of the parameters and ranges used in this research are shown in Table A1:

Table A1: Parameter definitions

Pattern	Parameter	Range	Meaning
Target value	T	Set to 0	Nominal value of the quality characteristic under study
Upward trend	β_1	From $0.01\sigma_N$ to $0.30\sigma_N$	Slope
Downward trend	β_1	From $-0.30\sigma_N$ to $-0.01\sigma_N$	Slope
Upward shift / Downward shift	d	0 or 1, 0 when $t < \tau$ and 1 when $t \geq \tau$ τ, from 16 to n-15	τ is the time when the mean shift occurs.
Upward shift	β_2	From $0.01\sigma_N$ to $3.0\sigma_N$	Mean shift magnitude
Downward shift	β_2	From $-3.0\sigma_N$ to $-0.01\sigma_N$	Mean shift magnitude
Cyclic	β_3	From $0.01\sigma_N$ to $3.0\sigma_N$	Cycle amplitude
Cyclic	β_4	From 3 to 16	Frequency
Systematic	β_5	From $0.01\sigma_N$ to $3.0\sigma_N$	Systematic departure

In Table A1 σ_N represents the standard deviation of the ARMA model used for modelling the inherent noise, calculated the following expression:

$$\sigma_N = \sqrt{\frac{1 + \theta^2 - 2\phi\theta}{1 - \phi^2}}\sigma_e \tag{A7}$$

The magnitudes of the patterns were determined to remain in $6\sigma_N$ control in the inspection window. The window length, n, was set to 60. The frequencies of the CYC patterns were such that the patterns had at least four cycles in the inspection window.

The change points of the Shift patterns were randomly chosen between τ=16 and τ = *n-15*. This was due to the number of parameters to be estimated and the degrees of freedom available during the PGS application.

Let Z_t be the quality characteristic under study without the effect of the controller, defined as follows:

$$Z_t = N_t + D_t \tag{A8}$$

Patterns, represented by Z_t, are autocorrelated control chart patterns like those generated and studied in De la Torre Gutiérrez & Pham (2018) (and denoted as Y_t therein).

7. Acknowledgments

The first author wishes to acknowledge the Mexican National Council for Science and Technology, CONACYT, for enabling him to pursue graduate studies at the University of Birmingham – United Kingdom under grant No. 381672. The authors also acknowledge the high performance computing support given by the Birmingham Environment for Academic Research (BEAR).

8. References

Bo, Z., Beibei, L., Yuwei, W., & Shengran, Z. (2018). Recognition of control chart patterns in auto-correlated process based on random forest. In 2018 IEEE International Conference on Smart Manufacturing, Industrial & Logistics Engineering (SMILE) (pp. 53–57). IEEE. https://doi.org/10.1109/SMILE.2018.8353981

Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (1994). Time Series Analysis: Forecasting & Control. Book. Pearson Education India. https://doi.org/10.1016/j.ijforecast.2004.02.001

Box, G. E. P., Luceño, A., & Paniagua-Quiñones, M. D. C. (2011). Statistical Control by Monitoring and Adjustment: Second Edition. John Wiley & Sons Inc. https://doi.org/10.1002/9781118164532

Box, G. E. P., Luceño, A., & Paniagua-Quiñones, M. del C. (2009). Statistical control by monitoring and adjustment. John Wiley & Sons.

Box, G., & Kramer, T. (1992). Statistical Process Monitoring and Feedback Adjustment: A Discussion. Technometrics, 34(3), 251–267. https://doi.org/10.2307/1270028

Boyles, R. A. (2000). Phase I Analysis for Autocorrelated Processes. Journal of Quality Technology, 32(4), 395–409.

Capilla, C., Ferrer, A., Romero, R., & Hualda, A. (1999). Integration of Statistical and Engineering Process Control in a Continuous Polymerization Process. Technometrics, 41(1), 14–28. https://doi.org/10.2307/1270991

Cheng, H. P., & Cheng, C. S. (2008). Denoising and feature extraction for control chart pattern recognition in autocorrelated processes. International Journal of Signal and Imaging Systems Engineering, 1(2), 115–126.

De la Torre Gutiérrez, H., & Pham, D. T. (2016). Estimation and generation of training patterns for control chart pattern recognition. Computers and Industrial Engineering, 95, 72–82. https://doi.org/10.1016/j.cie.2016.02.016

De la Torre Gutiérrez, H., & Pham, D. T. (2018). Identification of patterns in control charts for processes with statistically correlated noise. International Journal of Production Research, 56(4), 1504–1520. https://doi.org/10.1080/00207543.2017.1360530

De Tejada, J. G. S., & Martìnez-Echevarrìa, J. S. (2007). Support Vector Machines. In Computational Intelligence (pp. 147–191). Boston, MA: Springer US. https://doi.org/10.1007/0-387-37452-3_7

Del Castillo, E. (2006). Statistical process adjustment: A brief retrospective, current status, and some opportunities for further work. Statistica Neerlandica, 60(3), 309–326. https://doi.org/10.1111/j.1467-9574.2006.00328.x

Du, S. C., Huang, D. L., & Lv, J. (2013). Recognition of concurrent control chart patterns using wavelet transform decomposition and multiclass support vector machines. Computers & Industrial Engineering, 66(4), 683–695. https://doi.org/DOI 10.1016/j.cie.2013.09.012

Gauri, S. K. (2010). Control chart pattern recognition using feature-based learning vector quantization. International Journal of Advanced Manufacturing Technology, 48(3), 1061–1073. https://doi.org/10.1007/s00170-009-2354-7

Gauri, S. K., & Chakraborty, S. (2006). A study on the various features for effective control chart pattern recognition. The International Journal of Advanced Manufacturing Technology, 34(3–4), 385–398. https://doi.org/10.1007/s00170-006-0591-6

Gauri, S. K., & Chakraborty, S. (2009). Recognition of control chart patterns using improved selection of features. Computers and Industrial Engineering, 56(4), 1577–1588. https://doi.org/10.1016/j.cie.2008.10.006

Guh, R.-S. (2005). A hybrid learning-based model for on-line detection and analysis of control chart patterns. Computers & Industrial Engineering, 49(1), 35–62. https://doi.org/10.1016/j.cie.2005.03.002

Guh, R. S. (2003). Integrating artificial intelligence into on-line statistical process control. Quality and Reliability Engineering International, 19(1), 1–20. https://doi.org/10.1002/qre.510

Guh, R. S. (2008). Real-time recognition of control chart patterns in autocorrelated processes using a learning vector quantization network-based approach. International Journal of Production Research, 46(14), 3959–3991. https://doi.org/10.1080/00207540601011501

Guh, R. S., & Tannock, J. D. T. (1999). A neural network approach to characterize pattern parameters in process control charts. Journal of Intelligent Manufacturing, 10(5), 449–462. https://doi.org/10.1023/A:1008975131304

Hachicha, W., & Ghorbel, A. (2012). A survey of control-chart pattern-recognition literature (1991-2010) based on a new conceptual classification scheme. Computers and Industrial Engineering, 63(1), 204–222. https://doi.org/10.1016/j.cie.2012.03.002

Jiang, P., Liu, D., & Zeng, Z. (2009). Recognizing control chart patterns with neural network and numerical fitting. Journal of Intelligent Manufacturing, 20(6), 625–635. https://doi.org/10.1007/s10845-008-0152-y

Jiang, W., & Farr, J. V. (2007). Integrating SPC and EPC Methods for Quality Improvement. Quality Technology & Quantitative Management, 4(3), 345–363. Retrieved from http://web2.cc.nctu.edu.tw/%7B~%7Dqtqm/qtqmpapers/2007V4N3/2007V4N3_F3.pdf %5Cnhttp://web2.cc.nctu.edu.tw/%7B~%7Dqtqm/

Jiang, W., & Tsui, K.-L. (2002). SPC Monitoring of MMSE- and PI-Controlled Processes. Journal of Quality Technology, 34(4), 384–398. Retrieved from http://asq.org/qic/display-item/index.html?item=18505

Kandananond, K. (2010). Effectively monitoring the performance of integrated process control systems under nonstationary disturbances. International Journal of Quality, Statistics, and Reliability, 2010. https://doi.org/10.1155/2010/180293

Lin, S.-Y., Guh, R.-S., & Shiue, Y.-R. (2011). Effective recognition of control chart patterns in autocorrelated data using a support vector machine based approach. Computers & Industrial Engineering, 61(4), 1123–1134. https://doi.org/10.1016/j.cie.2011.06.025

Lu, C.-J., Shao, Y. E., & Li, P.-H. (2011). Mixture control chart patterns recognition using independent component analysis and support vector machine. Neurocomputing, 74(11), 1908–1914. https://doi.org/10.1016/j.neucom.2010.06.036

Lu, C.-J., Wu, C.-M., Keng, C.-J., & Chiu, C.-C. (2008). Integrated Application of SPC/EPC/ICA and neural networks. International Journal of Production Research, 46(4), 873–893. https://doi.org/10.1080/00207540600943969

Montgomery, D. C. (2009). Introduction to statistical quality control. John Wiley & Sons Inc. https://doi.org/10.1002/1521-3773(20010316)40:6<9823::AID-ANIE9823>3.3.CO;2-C

Noorossana, R., Farrokhi, M., & Saghaei, A. (2003). Using Neural Networks to Detect and Classify Out-of-control Signals in Autocorrelated Processes. Quality and Reliability Engineering International, 19(6), 493–504. https://doi.org/10.1002/qre.535

Pham, D. T., Castellani, M., & Chen, J. (2015). A comparative study of the Bees Algorithm as a tool for function optimisation. Cogent Engineering, 2(1), 1091540. https://doi.org/10.1080/23311916.2015.1091540

Pham, D. T., Ghanbarzadeh, A., Koc, E., Otri, S., Rahim, S., & Zaidi, M. (2006). The Bees Algorithm - A Novel Tool for Complex Optimisation Problems. In Intelligent Production Machines and Systems - 2nd I*PROMS Virtual International Conference 3-14 July 2006 (pp. 454–459). https://doi.org/10.1016/B978-008045157-2/50081-X

Pham, D. T., Otri, S., Ghanbarzadeh, A., & Koc, E. (2006). Application of the Bees Algorithm to the Training of Learning Vector Quantisation Networks for Control Chart Pattern Recognition. 2006 2nd International Conference on Information & Communication Technologies, 1, 0–5. https://doi.org/10.1109/ICTTA.2006.1684627

Pham, D. T., & Oztemel, E. (1996). Intelligent quality systems. Springer Science & Business Media. https://doi.org/10.1007/978-1-4471-1498-7

Pham, D. T., & Wani, M. A. (1997). Feature-based control chart pattern recognition. International Journal of Production Research, 35(7), 1875–1890. https://doi.org/10.1080/002075497194967

Ranaee, V., Ebrahimzadeh, A., & Ghaderi, R. (2010). Application of the PSO-SVM model for recognition of control chart patterns. ISA Transactions, 49(4), 577–586. https://doi.org/10.1016/j.isatra.2010.06.005

Shaban, A., & Shalaby, M. A. (2012). A double neural network approach for the identification and parameter estimation of control chart patterns. International Journal of Quality Engineering and Technology, 3(2), 124. https://doi.org/10.1504/IJQET.2012.049681

Shao, Y. E. (2014). Recognition of Process Disturbances for an SPC / EPC Stochastic System Using Support Vector Machine and Artificial Neural Network Approaches. In Abstract and Applied Analysis (Vol. 2014). Hindawi Publishing Corporation.

Shao, Y. E., & Chiu, C. C. (1999). Developing identification techniques with the integrated use of SPC/EPC and neural networks. Quality and Reliability Engineering International, 15(4), 287–294. https://doi.org/10.1002/(SICI)1099-1638(199907/08)15:4<287::AID-QRE251>3.0.CO;2-5

Shao, Y. E., Lu, C. J., & Chiu, C. C. (2011). A fault detection system for an autocorrelated process using SPC/EPC/ANN AND SPC/EPC/SVM schemes. International Journal of Innovative Computing, Information and Control, 7(9), 5417–5428.

Tsung, F., & Shi, J. (1999). Integrated design of run-to-run PID controller and SPC monitoring for process disturbance rejection. IIE Transactions (Institute of Industrial Engineers), 31(6), 517–527. https://doi.org/10.1023/A:1007698222427

Wang, K., & Tsung, F. (2007). Monitoring feedback-controlled processes using adaptive T2 schemes. International Journal of Production Research, 45(23), 5601–5619. https://doi.org/10.1080/00207540701325488

Western Electric Company. (1956). Statistical Quality Control Handbook.

Wu, B., & Yu, J. B. (2010). A neural network-based on-line monitoring model of process mean and variance shifts. Proceedings of the International Conference on E-Business and E-Government, ICEE 2010, 37(6), 2615–2618. https://doi.org/10.1109/ICEE.2010.661

Xanthopoulos, P., & Razzaghi, T. (2014). A weighted support vector machine method for control chart pattern recognition. Computers & Industrial Engineering, 70, 134–149. https://doi.org/10.1016/j.cie.2014.01.014

Xie, L., Gu, N., Li, D., Cao, Z., Tan, M., & Nahavandi, S. (2013). Concurrent control chart patterns recognition with singular spectrum analysis and support vector machine. Computers & Industrial Engineering, 64(1), 280–289. https://doi.org/10.1016/j.cie.2012.10.009

Yang, W. A., & Zhou, W. (2015). Autoregressive coefficient-invariant control chart pattern recognition in autocorrelated manufacturing processes using neural network ensemble. Journal of Intelligent Manufacturing, 26(6), 1161–1180. https://doi.org/10.1007/s10845-013-0847-6

Yuce, B., Packianather, M. S., Mastrocinque, E., Pham, D. T., & Lambiase, A. (2013). Honey bees inspired optimization method: The bees algorithm. Insects, 4(4), 646–662. https://doi.org/10.3390/insects4040646

Zaman, M., & Hassan, A. (2018). Improved statistical features-based control chart patterns recognition using ANFIS with fuzzy clustering. Neural Computing and Applications, 1–15. https://doi.org/10.1007/s00521-018-3388-2

Zhao, C., Wang, C., Hua, L., Liu, X., Zhang, Y., & Hu, H. (2017). Recognition of Control Chart Pattern Using Improved Supervised Locally Linear Embedding and Support Vector Machine. In Procedia Engineering. https://doi.org/10.1016/j.proeng.2017.01.138

Zorriassatine, F., & Tannock, J. D. T. (1998). A review of neural networks for statistical process control. Journal of Intelligent Manufacturing, 9(3), 209–224. https://doi.org/10.1023/A:1008818817588