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Bivariate quality control using two-stage intelligent monitoring scheme

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ABSTRACT

In manufacturing industries, it is well known that process variation is a major source of poor quality products. As such, monitoring and diagnosis of variation is essential towards continuous quality improvement. This becomes more challenging when involving two correlated variables (bivariate), whereby selection of statistical process control (SPC) scheme becomes more critical. Nevertheless, the existing traditional SPC schemes for bivariate quality control (BQC) were mainly designed for rapid detection of unnatural variation with limited capability in avoiding false alarm, that is, imbalanced monitoring performance. Another issue is the difficulty in identifying the source of unnatural variation, that is, lack of diagnosis, especially when dealing with small shifts. In this research, a scheme to address balanced monitoring and accurate diagnosis was investigated. Design consideration involved extensive simulation experiments to select input representation based on raw data and statistical features, artificial neural network recognizer design based on synergistic model, and monitoring–diagnosis approach based on two-stage technique. The study focused on bivariate process for cross correlation function, ρ = 0.1–0.9 and mean shifts, μ = ±0.75–3.00 standard deviations. The proposed two-stage intelligent monitoring scheme (2S-IMS) gave superior performance, namely, average run length, ARL_1 = 3.18–16.75 (for out-of-control process), ARL_0 = 335.01–543.93 (for in-control process) and recognition accuracy, RA = 89.5–98.5%. This scheme was validated in manufacturing of audio video device component. This research has provided a new perspective in realizing balanced monitoring and accurate diagnosis in BQC.

1. Introduction

In manufacturing industries, when quality feature of a product involves two correlated variables (bivariate), an appropriate SPC charting scheme is necessary to monitor and diagnose these variables jointly. Specifically, process monitoring refers to the identification of process condition either in a statistically in-control or out-of-control, whereas process diagnosis refers to the identification of the source variable(s) for out-of-control condition. In addressing this issue, the traditional SPC charting schemes for BQC such as χ^2 (Hotelling, 1947), multivariate cumulative sum (MCUSUM) (Crosier, 1988), and multivariate exponentially weighted moving average (MEWMA) (Lowry, Woodall, Champ, & Rigdon, 1992; Prabhu & Runger, 1997) are known to be effective in monitoring aspect. Unfortunately, they are merely unable to provide diagnosis information, which is greatly useful for a quality practitioner in finding the root cause error and solution for corrective action. Since then, major researches have been focused on diagnosis aspect. Shewhart-based control charts with Bonferroni-type control limits (Alt, 1985), principle component analysis (PCA) (Jackson, 1991), multivariate profile charts (Fuchs & Benjamini, 1994), T^2 decomposition (Mason, Tracy, & Young, 1995) and Minimax control chart (Sepulveda & Nachlas, 1997), among other, have been investigated for such purpose. Further discussions on this issue can be found in Lowry and Montgomery (1995), Kourti and MacGregor (1996), Mason, Tracy, and Young (1997) and Bersimis, Psarakis, and Panaretos (2007).

In the related study, development in soft computing technology has motivated researchers to explore the use of machine learning (ML) technology for automatically recognizing SPC chart patterns towards improving capability in monitoring and diagnosis. Identification of these patterns coupled with engineering knowledge of the process would lead to more specific diagnosis information. Expert systems (ES) (Chih & Rollier, 1994; Chih & Rollier, 1995), Fuzzy inference system (FIS) (Wang & Chen, 2001), artificial neural network (ANN), decision tree learning (DT) (Guh & Shiue, 2005), and support vector machine (SVM) (Cheng & Cheng, 2008) methods, among others, have been studied in designing the advanced SPC pattern recognition schemes. Extensive literature review revealed that most of the proposed schemes were developed based on

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research in ANN models such as an integrated bivariate SPC-ANN (Chen & Wang, 2004; Niaki & Abbasi, 2005; Yu, Xi, & Zhou, 2009), novelty detector ANN (Zorriassatine, Tannock, & O'Brien, 2003), modular ANN (Guh, 2007), ensemble ANN (Yu & Xi, 2009), multi-module-structure ANN (El-Midany, El-Baz, & Abd-Elwahed, 2010), hybrid learning ANN (Salehi, Bahreininejad, & Nakhai, 2011), an integrated ANN-SVM (Salehi, Kazemzadeh, & Salmasnia, 2012), and feature-based ANN (Masood & Hassan, 2013).

The integrated bivariate SPC-ANN schemes combined the traditional SPC chart(s) with an ANN model. The traditional SPC chart(s) role for monitoring the existence of unnatural variation in bivariate process, whereas an ANN model roles for diagnosing the sources of variation. In that case, an ANN model is utilized only when necessary, that is, when an out-of-control signal is triggered. Inversely, the other schemes such as novelty detector ANN consist of fully ANN or fully ML-based model for monitoring and diagnosing simultaneously. In that case, an ANN model is continuously utilized, that is, for triggering out-of-control signal and then, for identifying the sources of variation. Further discussion on these schemes can be found in (Masood & Hassan, 2010; Hachicha & Ghorbel, 2012).

1.1. Problem situation and solution concept

When dealing with monitoring and diagnosis of bivariate process variation in mean shifts, based on process monitoring viewpoint, an effective bivariate SPC scheme should be able to identify out-of-control condition as quickly as possible at the shortest ARL_1 (average run length for out-of-control process, $ARL_1 \Rightarrow 1$). Concurrently, it should be able to maintain small false alarm at the longest ARL_0 (average run length for in-control process, $ARL_0 \gg 200$). Nevertheless, the existing traditional SPC schemes were mainly designed by focusing on rapid detection of out-of-control condition ($ARL_1 \Rightarrow 1$) but it has limited capability in avoiding false alarm ($ARL_0 \leqslant 200$). Fig. 1 illustrates the concepts of imbalanced monitoring vs. balanced monitoring as the central theme for this investigation.

Based on diagnosis viewpoint, an effective bivariate SPC scheme should be able to identify the source variable(s) of out-of-control condition as accurate as possible. Nevertheless, it is difficult to correctly recognize when dealing with small shifts ($\leqslant$1.0 standard deviation). Chih and Rollier (1994), Chih and Rollier (1995), Zorriassatine, Tannock, and O'Brien (2003), Chen and Wang (2004) and Yu and Xi (2009), for examples, have reported less than 80% accuracy for diagnosing mean shifts at 1.0 standard deviation. Among others, only Guh (2007) and Yu et al. (2009) reported the satisfied results ($\geqslant$90% accuracy).

The imbalanced monitoring and lack of diagnosis capability as mentioned above need further investigation. In order to minimize erroneous decision making in BQC, it is essential to enhance the overall performance towards achieving balanced monitoring (rapidly detect process variation/mean shifts with small false alarm as shown in Fig. 1) and accurate diagnosis (accurately identify the sources of variation/mean shifts). Additionally, the BQC applications are still relevant in today's manufacturing industries. In solving this issue, a two-stage intelligent monitoring scheme (2S-IMS) was designed to deal with dynamic correlated data streams of bivariate process. This paper is organized as follows. Section 2 describes a modeling of bivariate process data streams and patterns. Section 3 presents the framework and procedures of the 2S-IMS. Section 4 discusses the performance of the proposed scheme in comparison to the traditional SPC. Section 5 finally outlines some conclusions.

2. Modeling of bivariate process data streams and patterns

A large amount of bivariate samples is required for evaluating the performance of the 2S-IMS. Ideally, such samples should be tapped from real world. Unfortunately, they are not economically available or too limited. As such, there is a need for modeling of synthetic samples based on Lehman (1977) mathematical model. Further discussion on data generator can be found in Masood and Hassan (2013).

In bivariate process, two variables are being monitored jointly. Let $X_{1\text{-}i} = (X_{1\text{-}1},\ldots,X_{1\text{-}24})$ and $X_{2\text{-}i} = (X_{2\text{-}1},\ldots,X_{2\text{-}24})$ represent 24 observation samples for process variable 1 and process variable 2 respectively. Observation window for both variables start with samples $i = (1,\ldots,24)$. It is dynamically followed by $(i+1)$, $(i+2)$ and so on. When a process is in the state of statistically in-control, samples from both variables can be assumed as identically and independently distributed (*i.i.d.*) with zero mean ($\mu_0 = 0$) and unity standard deviation ($\sigma_0 = 1$). Depending on process situation, the bivariate samples can be in low correlation ($\rho = 0.1$–0.3), moderate correlation ($\rho = 0.4$–0.6) or high correlation ($\rho = 0.7$–0.9). Data correlation (ρ) shows a measure of degree of linear relationship between the two variables. Generally, this data relationship is difficult to be identified using Shewhart control chart as shown in Fig. 2. On the other hand, it can be clearly indicated using scatter diagram. Low correlated samples yield a circular pattern (circular distributed scatter plot), moderate correlated samples yield a perfect ellipse pattern, whereas high correlated samples yield a slim ellipse pattern.

Disturbance from assignable causes on the component variables (variable-1 only, variable-2 only, or both variables) is a major source of process variation. This occurrence could be identified by various causable patterns such as mean shifts (sudden shifts), trends, cyclic, systematic or mixture. In this research, investigation was focused on sudden shifts patterns (upward and downshift shifts) with positive correlation ($\rho > 0$). Seven possible categories of bivariate patterns were considered in representing the bivariate process variation in mean shifts as follows:

- N (0,0): both variables $X_{1\text{-}i}$ and $X_{2\text{-}i}$ remain in-control.
- US (1,0): $X_{1\text{-}i}$ shifted upwards, while $X_{2\text{-}i}$ remains in-control.
- US (0,1): $X_{2\text{-}i}$ shifted upwards, while $X_{1\text{-}i}$ remains in-control.
- US (1,1): both variables $X_{1\text{-}i}$ and $X_{2\text{-}i}$ shifted upwards.
- DS (1,0): $X_{1\text{-}i}$ shifted downwards, while $X_{2\text{-}i}$ remains in-control.
- DS (0,1): $X_{2\text{-}i}$ shifted downwards, while $X_{1\text{-}i}$ remains in-control.
- DS (1,1): both variables $X_{1\text{-}i}$ and $X_{2\text{-}i}$ shifted downwards.

Reference bivariate shift patterns based on mean shifts ±3.00 standard deviations are summarized in Fig. 3. Their structures are unique to indicate the changes in process mean shifts and data correlation. The degree of mean shifts can be identified when the center position shifted away from zero point (0,0).

3. Two-stage intelligent monitoring scheme

As noted in Section 1, an integrated MSPC-ANN was combined in a single-stage monitoring scheme (direct monitoring–diagnosis) as proposed in Chen and Wang (2004), Niaki and Abbasi (2005), and Yu et al. (2009). The other schemes based on fully ANN-based models as proposed in Zorriassatine, Tannock, and O'Brien (2003), Guh (2007), Yu and Xi (2009) and El-Midany et al. (2010) also can be classified as a single-stage monitoring scheme. In this research, two-stage monitoring scheme was investigated by integrating the powerful of MEWMA control chart and Synergistic-ANN model for improving the monitoring-diagnosis performance. Framework and pseudo-code (algorithm) for the proposed scheme are summarized in Figs. 4 and 5 respectively. It should be noted that an initial setting as follows needs to be performed before it can be put into application:

- Load the trained raw data-ANN recognizer into the system.

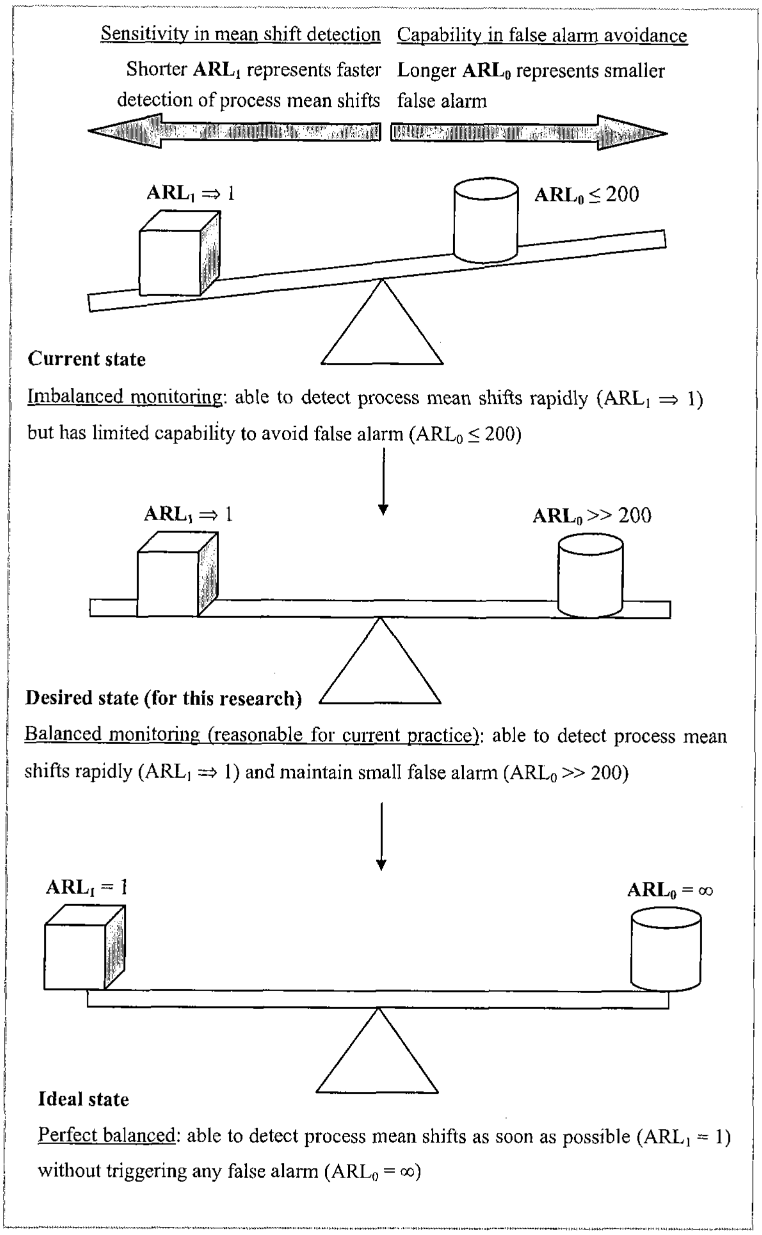


Fig. 1. Current state and desired state towards balanced monitoring.

- Set the values of means (μ_{01}, μ_{02}) and standard deviations (σ_{01}, σ_{02}) of bivariate in-control process (for variables $X_{1\text{-}i}$ and $X_{2\text{-}i}$). These parameters can be obtained based on historical or preliminary samples.
- Perform in-process quality control inspection until 24 observation samples (individual or subgroup) to begin the system.

Recognition window size is set to 24 observation samples (for variables $X_{1\text{-}i}$ and $X_{2\text{-}i}$) since it provided sufficient training results and statistically acceptable to represent normal distribution. Preliminary experiments suggested that a smaller window size (<24) gave lower training result due to insufficient pattern properties, while a larger window size (>24) does not increase the training result but burden the ANN training.

Rational to integrate the MEWMA control chart and the Synergistic-ANN model are based on preliminary experiments. Generally, the MEWMA control chart is known to be effective for detecting bivariate process mean shifts more rapidly compared to the χ^2 control chart. Furthermore, it is very sensitive when dealing with small shifts ($\leqslant$1.00 standard deviations). Unfortunately, based on one point out-of-control detection technique, it gave limited capability to avoid false alarm ($ARL_0 \leqslant 200$). This becomes more critical when the variables are highly correlated. In the related study, pattern recognition scheme using a Synergistic-ANN model gave better capability in avoiding false alarm ($ARL_0 > 200$). As such, it can be concluded that process identification based on recognition of process data stream patterns (Synergistic-ANN model) is more effective compared to detection of one point out-of-control (MEWMA control chart). Nevertheless, different techniques should have their respective advantages in terms of point/pattern discrimination properties. In order to further improve the monitoring performance ($ARL_1 \Rightarrow 1$, $ARL_0 \gg 200$), it is useful to combine both discrimination properties (MEWMA control chart and Synergistic-ANN recognizer) by approaching

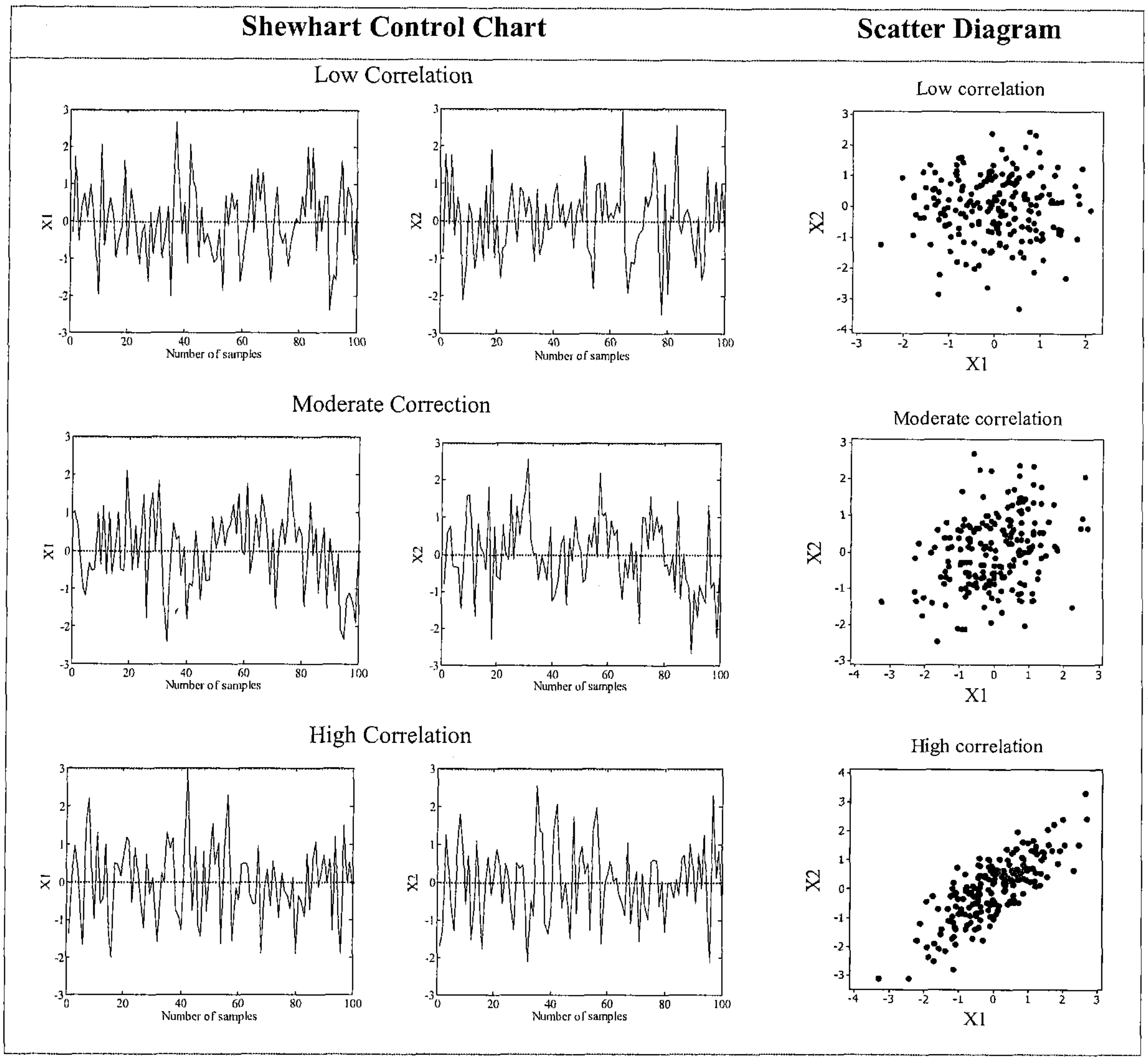


Fig. 2. Shewhart control charts and its respective scatter diagrams.

two-stage monitoring and diagnosis. In the first stage monitoring, the MEWMA control chart is used for triggering bivariate process mean shifts based on 'one point out-of-control' as per usual. Once the shift is triggered, the Synergistic-ANN recognizer will perform second stage monitoring and diagnosis through recognition of process data stream patterns that contain one of several out-of-control points. This approach is suited for 'recognition only when necessary' concept, that is, it is unnecessary to perform recognition while the process lies within a statistically in-control state. Besides, recognition is only necessary for identifying patterns suspected to a statistically out-of-control state. Besides producing smaller false alarm, this approach will also reduce computational efforts and time consumes for pattern recognition operation.

3.1. MEWMA control chart

The MEWMA control chart developed by Lowry et al. (1992) is a logical extension of the univariate EWMA control chart. In the bivariate case, the MEWMA statistics can be defined as follows:

$$\text{MEWMA}_i = \frac{\left[\sigma_2^2(\text{EWMA}_{1i}-\mu_1)^2+\sigma_1^2(\text{EWMA}_{2i}-\mu_2)^2-2\sigma_{12}^2(\text{EWMA}_{1i}-\mu_1)(\text{EWMA}_{2i}-\mu_2)\right]n}{(\sigma_1^2\sigma_2^2-\sigma_{12}^2)} \quad (1)$$

$$\text{EWMA}_{1i} = \lambda Z_{1i} + (1-\lambda)\text{EWMA}_{1(i-1)} \quad (2)$$

$$\text{EWMA}_{2i} = \lambda Z_{2i} + (1-\lambda)\text{EWMA}_{2(i-1)} \quad (3)$$

Covariance matrix of MEWMA:

$$\sum_{\text{MEWMA}} = \frac{\lambda}{(1-\lambda)}\begin{bmatrix}\sigma_1^2 & \sigma_{12}\\ \sigma_{12} & \sigma_2^2\end{bmatrix} \quad (4)$$

The standardized samples (Z_{1i}, Z_{2i}) with cross correlation function (ρ) were used. Thus, $\sigma_1 = \sigma_2 = 1$; $\sigma_{12} = \rho$. Notations λ and i represent the constant parameter and the number of samples. The starting value of EWMA (EWMA_0) was set as zero to represent the process target (μ_0). The MEWMA statistic samples will be out-of-control if it exceeded the control limit (H). In this research, three sets of design parameters (λ, H: 0.05, 7.35; 0.10, 8.64; 0.20, 9.65) as reported in Prabhu and Runger (1997) were investigated.

3.2. Synergistic-ANN model pattern recognizer

Synergistic-ANN model as shown in Fig. 6 was developed for pattern recognizer. It is a parallel combination between two

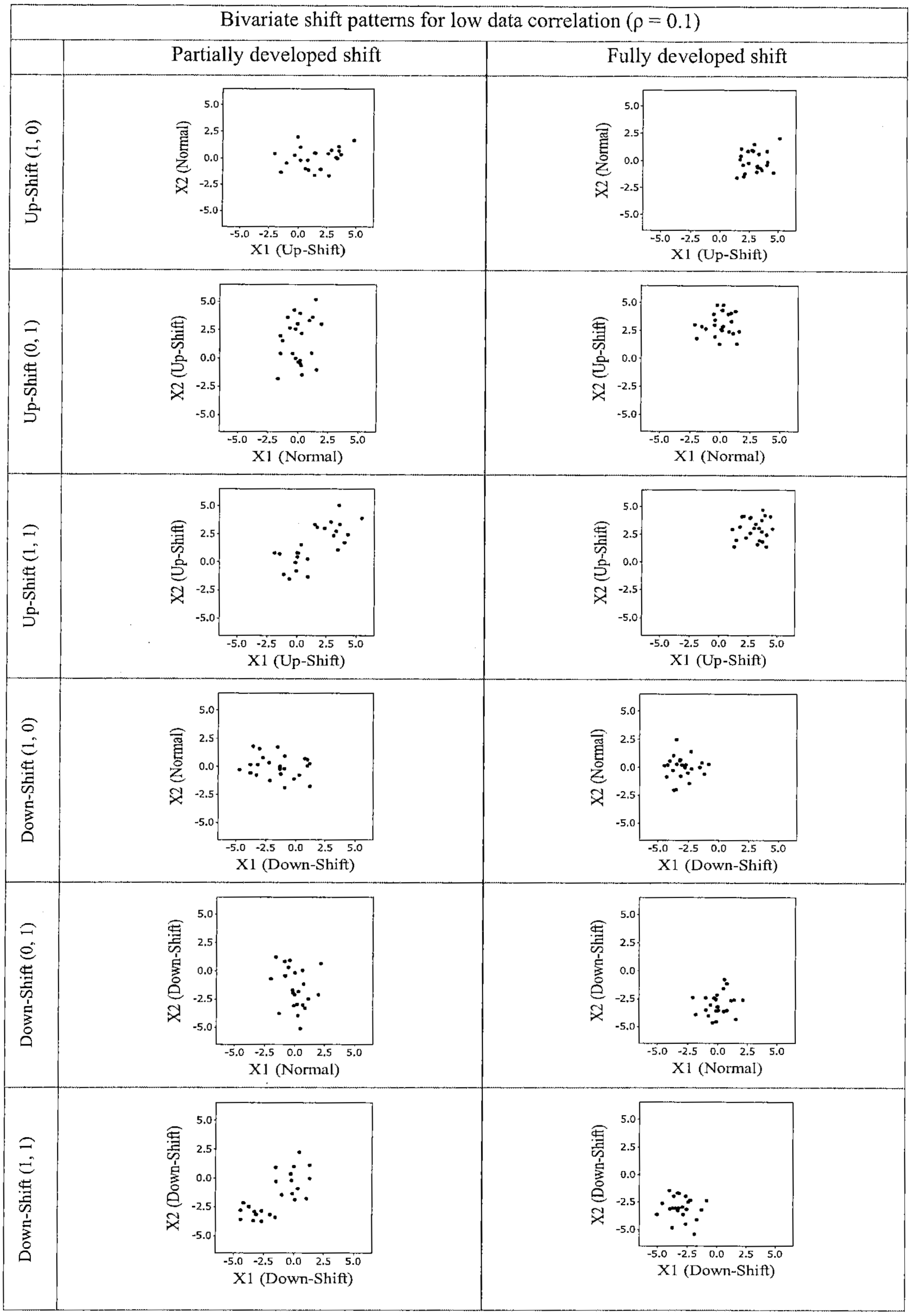


Fig. 3. Summary of bivariate shift patterns for $\rho = 0.1$, 0.5 and 0.9.

individual ANNs that are: (i) raw data-based ANN, and (ii) statistical features-ANN as shown in Fig. 7.

Let $O_{RD} = (O_{RD\text{-}1}, \ldots, O_{RD\text{-}7})$ and $O_F = (O_{F\text{-}1}, \ldots, O_{F\text{-}7})$ represent seven outputs from raw data-based ANN and statistical features-ANN recognizers respectively. Outputs from these individual recognizers can be combined using simple summation: $OI_i = \Sigma(O_{RD\text{-}i}, O_{F\text{-}i})$, where $i = (1, \ldots, 7)$ are the number of outputs. Final decision ($O_{synergy}$) was determined based on the maximum value from the combined outputs:

$$O_{synergy} = \max(OI_1, \ldots, OI_7) \quad (5)$$

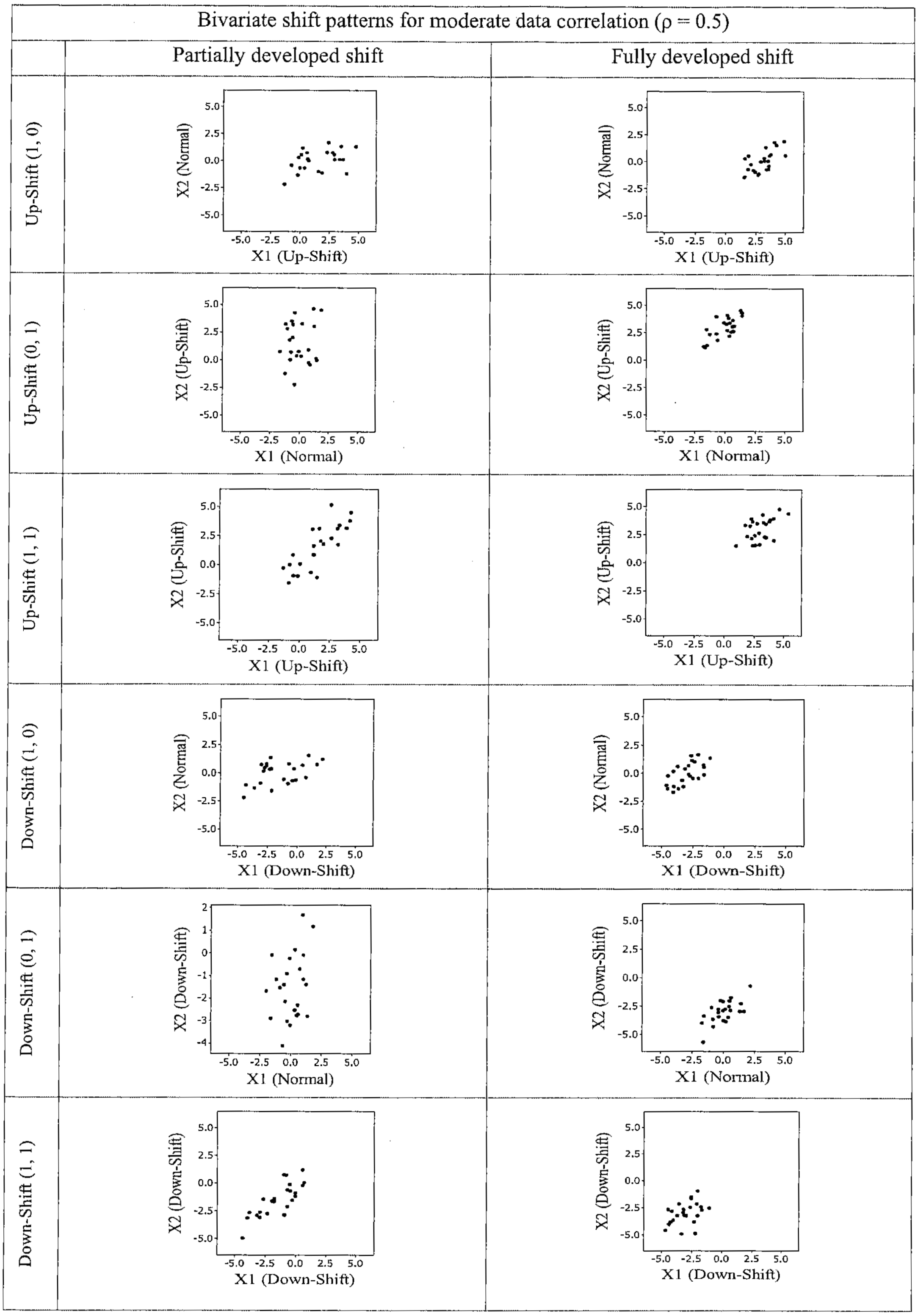


Fig. 3 (*continued*)

Multilayer perceptrons (MLP) model trained with back-propagation (BPN) algorithm was applied for the individual ANNs. This model comprises an input layer, one or more hidden layer(s) and an output layer. The size of input representation determines the number of input neurons. Raw data input representation requires 48 neurons, while statistical features input representation requires only 14 neurons. The output layer contains seven neurons, which was determined according to the number of pattern categories. Based on preliminary experiments, one hidden layer with 26 neurons and 22 neurons were selected for raw

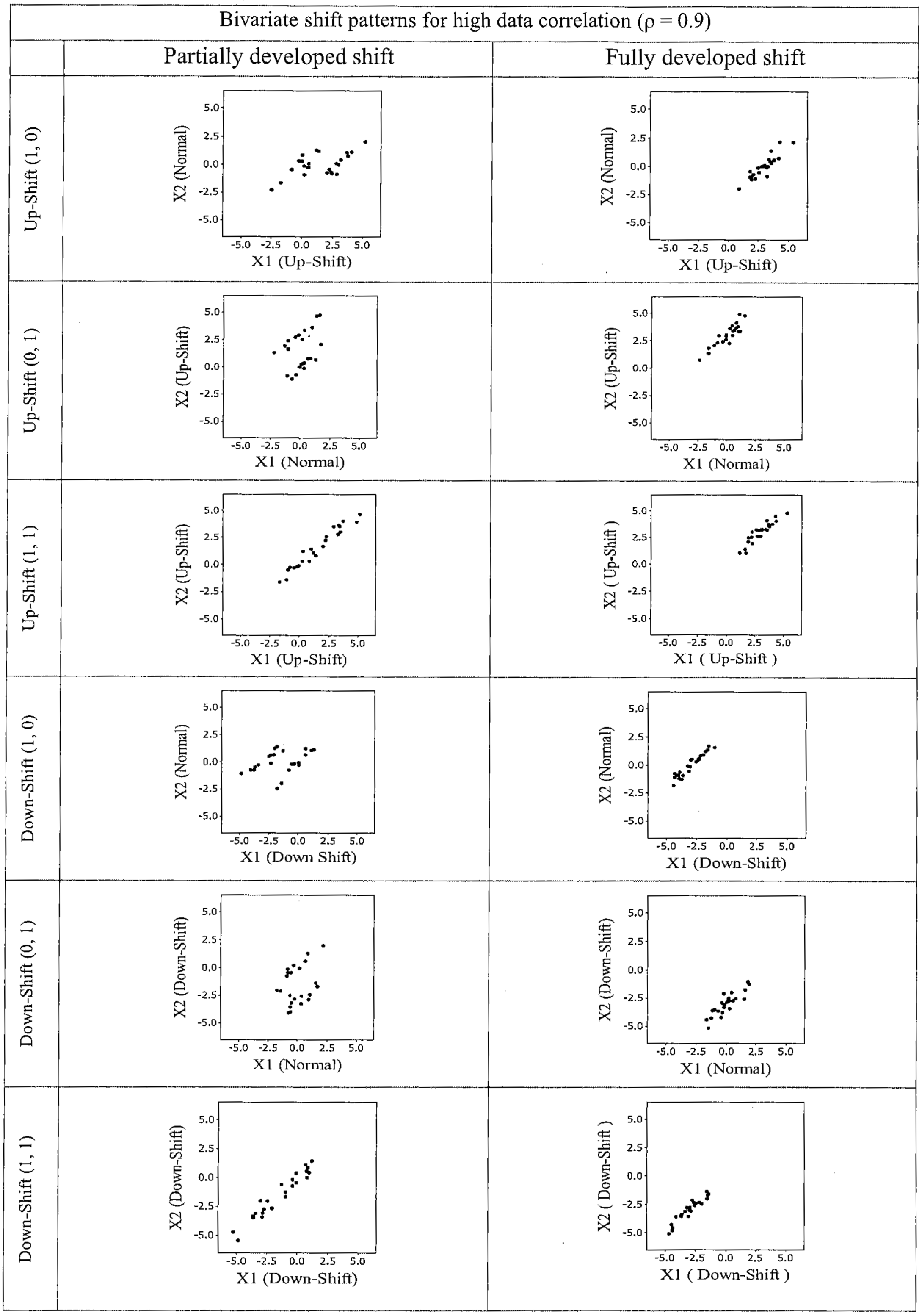


Fig. 3 (*continued*)

data-based ANN and statistical features-ANN. The experiments revealed that initially, the training results improved in-line with the increment in the number of neurons. Once the neurons exceeded the required numbers, further increment of the neurons did not improve the training results but provided poorer results. These excess neurons could burden the network computationally, reduces the network generalization capability and increases the training time.

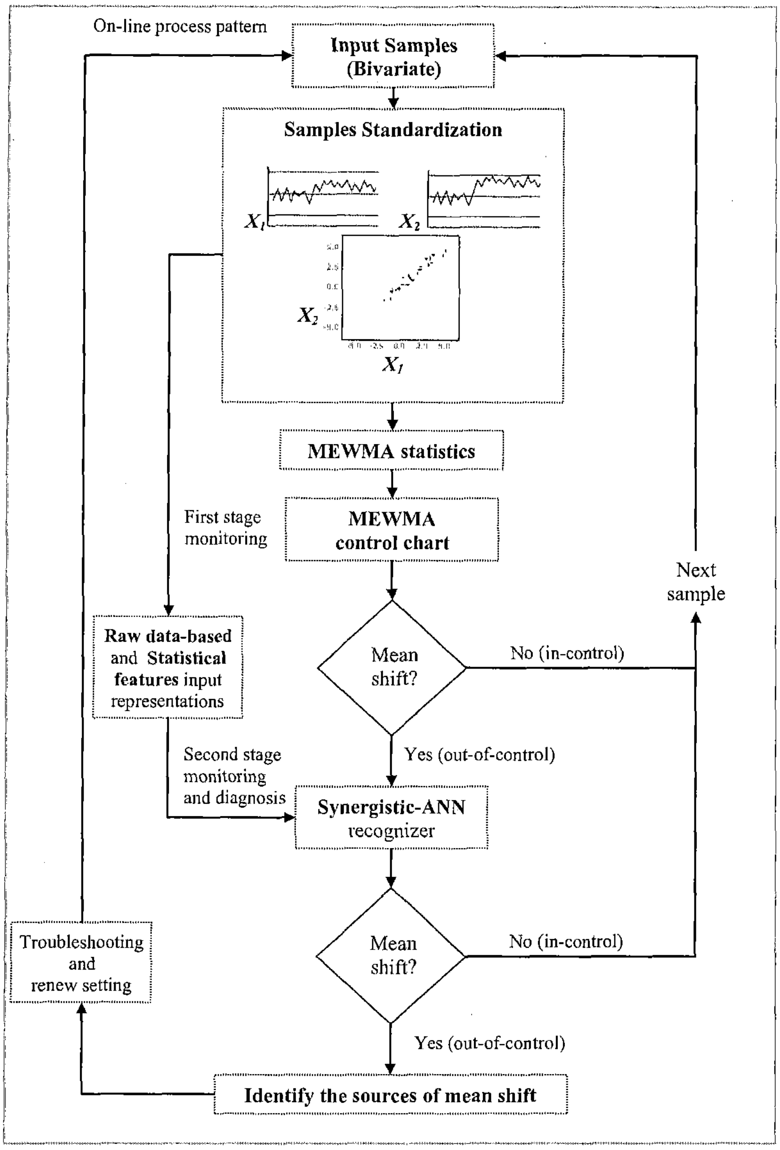


Fig. 4. Framework for the 2S-IMS.

3.3. Input representation

Input representation is a technique to represent input signal into ANN for achieving effective recognition. There are various approaches could be used to represent input signal. Raw data (standardized samples) is the basic approach (Zorriassatine, Tannock, & O'Brien, 2003). Besides raw data, feature-based approach that involves extracted features from raw data is one of the successful technique in image processing (Brunzell & Eriksson, 2000; Klosgen & Zytkow, 2002). This approach has also been applied in the area of univariate quality control (UQC), which is aim to improve accuracy for recognizing univariate control chart patterns (i.e., normal, upward shifts, upward trends, downward shifts, downward trend, and cyclic) by reducing network size, computational efforts and training time of an ANN (Gauri & Chakraborty, 2006; Gauri & Chakraborty, 2008; Guh, 2010; Hassan, Nabi Baksh, Shaharoun, & Jamaludin, 2003; Pham & Wani, 1997). Pham and Wani (1997) firstly investigated nine shape features. Then, it was improved by Gauri and Chakraborty (2006) and Gauri and Chakraborty (2008). In the related study, Hassan et al. (2003) proposed six statistical features comprising of mean, standard deviation, skewness, mean-square value, autocorrelation, and last value of CUSUM. Guh (2010) proposed another six statistical features comprising of mean, standard deviation, skewness, kurtosis, slope, and Pearson correlation coefficient. More recently, Masood and Hassan (2013) proposed another set of statistical features for BQC.

A few researchers have combined features and raw data in a serial form, i.e., χ^2-statistics with raw data (Guh, 2007) and statistical features with raw data (Yu & Xi, 2009; Yu et al., 2009), for strengthening pattern properties in BQC. Nevertheless, this approach has increased network size, computational effort, and training time. This becomes more difficult to implement in a complex case.

The other approach in UQC is using multi-resolution wavelet analysis (MRWA) for denoising or filtering raw data through several decomposition levels without changing the network size (Al-Assaf, 2004; Assaleh & Al-Assaf, 2005), concurrent pattern recognition (Chen, Lu, & Lam, 2007), and image processing (Wang, Kuo, & Qi, 2007). The MRWA has played a crucial role for process

Step 1: Input samples (bivariate). Window size = 24, starting observation samples are: $X_{1\text{-}i} = (X_{1\text{-}1}, \ldots, X_{1\text{-}24})$ and $X_{2\text{-}i} = (X_{2\text{-}1}, \ldots, X_{2\text{-}24})$. It is followed by ($i^{th}$ + 1), (i^{th} + 2) and so on.

Step 2: Samples standardization. Rescale observation samples into a standardized range within [−3, +3]: $Z_1 = (X_1 - \mu_{01})/\sigma_{01}$ and $Z_2 = (X_2 - \mu_{02})/\sigma_{02}$

Input samples (original) and standardized samples can be represented graphically using Shewhart control charts and scatter diagram.

Step 3: First stage monitoring (MEWMA control chart):

Standardized samples (Z_1, Z_2) are converted into MEWMA statistics (T^2_{MEWMA}).

Decision rule: *If* T^2_{MEWMA} < Upper control limit (h)

Proceed to the next samples

else

Proceed to the second stage monitoring.

end

Step 4: Input representation.

(i) Raw data-based input representation: $Z_{1\text{-}P1}, Z_{2\text{-}P1}, \ldots, Z_{1\text{-}P24}, Z_{2\text{-}P24}$
(ii) Statistical features input representation:

- Feature extraction: the standardized samples (Z_1, Z_2) are converted into statistical features, namely, the last value of exponentially weighted moving average ($LEWMA_\lambda$) with λ = (0.25, 0.20, 0.15, 0.10), mean (μ), multiplication of mean with standard deviation (MSD), and multiplication of mean with mean square value (MMSV).
- Fourtheen extracted features are represented as follows: ($LEWMA_{0.25\_P1}$, $LEWMA_{0.20\_P1}$, $LEWMA_{0.15\_P1}$, $LEWMA_{0.10\_P1}$, μ_{P1}, MSD_{P1}, $MMSV_{P1}$, $LEWMA_{0.25\_P2}$, $LEWMA_{0.20\_P2}$, $LEWMA_{0.15\_P2}$, $LEWMA_{0.10\_P2}$, μ_{P2}, MSD_{P2}, $MMSV_{P2}$). Number of samples is denoted by P.

Step 5: Second stage monitoring and diagnosis (synergistic-ANN recognizer):

Decision rule: *If* Maximum output of ANN belongs to N(0, 0):

Process is "in-control"; proceed to the next samples

else Process is "out-of-control"; identify the sources of mean shifts; perform diagnosis, troubleshooting; renew setting and return to Step 1 (out of scopes of this research).

end

Fig. 5. Pseudo-code for the 2S-IMS.

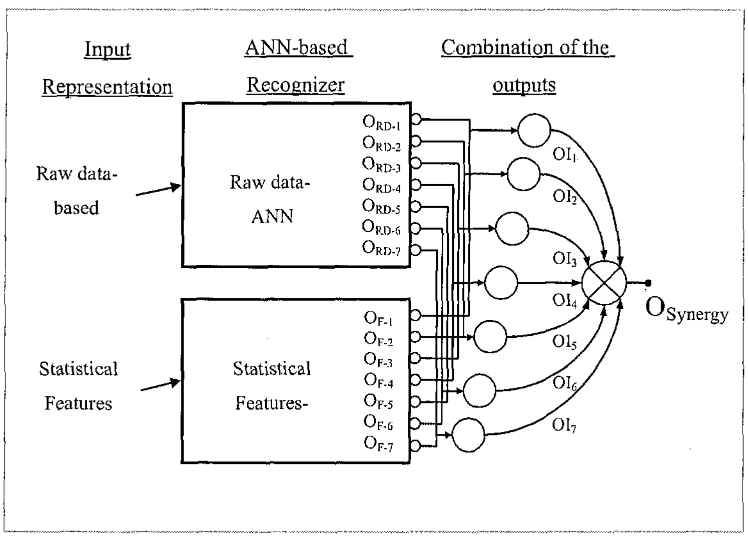


Fig. 6. Synergistic-ANN model.

controlling or monitoring. Insufficient denoising will distort waveforms and introduce errors. Inversely, excessive denoising will over-smooth the sharp features of underlying signals by recognizing them as noise or outliers.

In this research, raw data and improved set of statistical features were applied separately into training of the Synergistic-ANN recognizer for improving pattern discrimination capability. Raw data input representation consists of 48 data, i.e., 24 consecutive standardized samples of bivariate process ($Z_{1\text{-}P1}$, $Z_{1\text{-}P2}, \ldots, Z_{24\text{-}P1}$, $Z_{24\text{-}P2}$). Statistical features input representation consists of last value of exponentially weighted moving average ($LEWMA_\lambda$) with λ = [0.25,0.20,0.15,0.10], mean (μ), multiplication of mean with

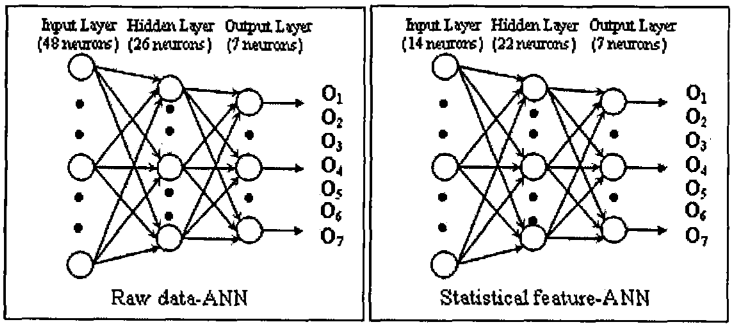


Fig. 7. Individual ANN recognizer.

standard deviation (MSD), and multiplication of mean with mean square value (MMSV). Each bivariate pattern was represented by 14 data as follows: $LEWMA_{0.25\text{-}P1}$, $LEWMA_{0.20\text{-}P1}$, $LEWMA_{0.15\text{-}P1}$, $LEWMA_{0.10\text{-}P1}$, μ_{P1}, MSD_{P1}, $MMSV_{P1}$, $LEWMA_{0.25\text{-}P2}$, $LEWMA_{0.20\text{-}P2}$, $LEWMA_{0.15\text{-}P2}$, $LEWMA_{0.10\text{-}P2}$, μ_{P2}, MSD_{P2}, $MMSV_{P2}$.

$LEWMA_\lambda$ features were taken based on observation window = 24. The EWMA-statistics as derived using Eq. (6) incorporates historical data in a form of weighted average of all past and current observation samples (Lucas & Saccucci, 1990):

$$EWMA_i = \lambda\, X_i + (1-\lambda)EWMA_{i-1} \qquad (6)$$

X_i represents the original samples. In this study, the standardized samples (Z_i) were used instead of X_i so that Eq. (6) becomes:

$$EWMA_i = \lambda\, Z_i + (1-\lambda)EWMA_{i-1} \qquad (7)$$

where $0 < \lambda \leqslant 1$ is a constant parameter and $i = [1,2,\ldots,24]$ are the number of samples. The starting value of EWMA ($EWMA_0$) was set as zero to represent the process target (μ_0). Four value of constant parameter ($\lambda = 0.25, 0.20, 0.15, 0.10$) were selected based on a range within [0.05,0.40] recommended by Lucas and Saccucci (1990). Besides resulting longer ARL_0, these parameters could influence the performance of EWMA control chart in detecting process mean shifts. Preliminary experiments suggested that the EWMA with small constant parameter ($\lambda = 0.05$) were more sensitive in identifying small shifts ($\leqslant$0.75 standard deviations), while the EWMA with large constant parameter ($\lambda = 0.40$) were more sensitive in identifying large shifts ($\geqslant$2.00 standard deviations). The MSD and MMSV features were used to magnify the magnitude of mean shifts (μ_1, μ_2):

$$MSD_1 = \mu_1 \times \sigma_1 \qquad (8)$$

$$MSD_2 = \mu_2 \times \sigma_2 \qquad (9)$$

$$MMSV_1 = \mu_1 \times (\mu_1)^2 \qquad (10)$$

$$MMSV_2 = \mu_2 \times (\mu_2)^2 \qquad (11)$$

where (μ_1, μ_2), (σ_1, σ_2) (μ_1^2, μ_1^2) are the means, standard deviations and mean square value respectively. The mathematical expressions of mean and standard deviation are widely available in textbook on SPC. The mean square value feature can be derived as in Hassan et al. (2003). Further discussion on selection of statistical features can be found in Masood and Hassan (2013).

3.4. Recognizer training and testing

Partially developed shift patterns and dynamic patterns were applied into the ANN training and testing respectively since these approaches have been proven effective to suit for on-line process situation (Guh, 2007). Detail parameters for the training patterns are summarized in Tables 1 and 2.

In order to achieve the best training result for overall pattern categories, the amount of training patterns were set as follows: (i) bivariate normal patterns = [1500 × (total combination of data correlation)] and (ii) bivariate shift patterns = [100 × (total combination of mean shifts) × (total combinations of data correlation)]. In order to improve discrimination capability between normal and shift patterns, a huge amount of N (0,0) patterns was applied into ANN training. The US (1,1) and DS (1,1) pattern categories also require a huge amount of training patterns since it contain a more complex combination of mean shifts compared to the other bivariate shifts pattern categories.

Guh (2007) reported that the utilization of partially developed shift patterns in ANN training could provide the shorter ARL_1 results. In order to achieve the best ARL_1 results for this scheme, different percentage of partially developed shift patterns were utilized for different range of mean shifts as shown in Table 2. The starting points of sudden shifts (SS) were determined empirically. The actual value of data correlation is dependent to the variability in the bivariate samples. The simulated values ($\rho = 0.1, 0.3, 0.5, 0.7, 0.9$) as shown in Table 1 could only be achieved when the process data streams are in fully normal pattern or in fully developed shift pattern. Input representations were normalized to a compact range between [−1,+1]. The maximum and the minimum values for normalization were taken from the overall data of training patterns.

Based on BPN algorithm, 'gradient decent with momentum and adaptive learning rate' (traingdx) was used for training the MLP model. The other training parameters setting were learning rate (0.05), learning rate increment (1.05), maximum number of epochs (500) and error goal (0.001), whereas the network performance was based on mean square error (MSE). Hyperbolic tangent function was used for hidden layer, while sigmoid function was used for an output layer. The training session was stopped either when the number of training epochs was met or the required MSE has been reached.

4. Performance results and discussion

The monitoring and diagnosis performances of 2S-IMS were evaluated based on average run lengths (ARL_0, ARL_1) and recognition accuracy (RA) as summarized in Table 4. The ARLs results were also compared to the traditional multivariate statistical process control (MSPC) charting schemes such as χ^2 (Hotelling, 1947), MCUSUM (Pignatiello & Runger, 1990), and MEWMA (Lowry et al., 1992), as reported in the literature.

In order to achieve balanced monitoring and accurate diagnosis, the proposed 2S-IMS should be able to achieve the target performances as follows:

Table 1
Parameters for the training patterns.

Pattern category	Mean shift (in standard deviations)	Data correlation (ρ)	Amount of training patterns
N (0,0)	X1: 0.00 X2: 0.00	0.1, 0.3, 0.5, 0.7, 0.9	1500 × 5 = 7500
US (1,0)	X1: 1.00, 1.25,…,3.00 X2: 0.00, 0.00,…,0.00		100 × 9 × 5 = 4500
US (0,1)	X2: 0.00, 0.00,…,0.00 X1: 1.00, 1.25,…,3.00		100 x 9 x 5 = 4500
US (1,1)	X1: 1.00, 1.00, 1.25, 1.25,…,3.00 X2: 1.00, 1.25, 1.00, 1.25,…,3.00		100 × 25 × 5 = 12,500
DS (1,0)	X1: −1.00, −1.25,…, −3.00 X2: 0.00, 0.00,…,0.00		100 × 9 × 5 = 4500
DS (0,1)	X2: 0.00, 0.00,…,0.00 X1: −1.00, −1.25,…,−3.00		100 × 9 × 5 = 4500
DS (1,1)	X1: −1.00, −1.00, −1.25, −1.25,…,−3.00 X2: −1.00, −1.25, −1.00, −1.25,…,−3.00		100 × 25 × 5 = 12,500

Table 2
Parameters for the partially developed shift patterns.

Range of mean shifts (in standard deviations)	Amount of partially developed shift patterns	Starting point of sudden shift (SS)
±[1.00, 1.50]	2/3 (66.7%)	Sample 9th
±[1.75, 2.25]	1/2 (50.0%)	Sample 13th
±[2.50, 3.00]	1/3 (33.3%)	Sample 17th

Table 3
Summary of monitoring-diagnosis capabilities.

Traditional MSPC	2S-IMS
Effective in monitoring (to identify out-of-control signal)	Comparable to the traditional MSPC in monitoring aspect
Limited to avoid false alarm ($ARL_0 \cong 200$)	Capable to maintain smaller false alarm ($ARL_0 \gg 200$)
Unable to identify the sources of variation (mean shifts)	High accuracy in identifying the sources of variation (mean shifts)

(i) $ARL_0 \gg 200$ to maintain small false alarm in monitoring bivariate in-control process.
(ii) Short ARL_1 (average $ARL_1 \leqslant 7.5$ for shifts range ±0.75–3.00 standard deviations) to rapidly detect bivariate process mean shifts.
(iii) High RA (average RA ⩾ 95% for shifts range ±0.75–3.00 standard deviations) to accurately identify the sources of mean shifts.

4.1. Monitoring performance

In monitoring aspect, the ARL_0 represents the average number of natural observation samples of in-control process before the first out-of-control process signal exist as a false alarm. In other word, the ARL_0 measures how long a SPC scheme could maintain an in-control process running without any false alarm. On the other hand, the ARL_1 represents the average number of unnatural observation samples before it is truly identified as out-of-control process signal. In other word, the ARL_1 measures how fast a SPC scheme could detect process mean shifts. Further discussion on this measure can be referred to Montgomery (2009).

Ideally, a SPC scheme should provide ARL_0 as long as possible in order to minimize cost for investigating the discrepancy and troubleshooting while the process still within control. Meanwhile, it should provide ARL_1 as short as possible in order to minimize cost for reworks or waste materials. Since the false alarm cannot be eliminated, the $ARL_0 \gg 200$ is considered as the *de facto* level for balanced monitoring.

In this research, the ARLs results of 2S-IMS were simulated based on correctly classified patterns. Generally, it can be observed that the smaller the mean shifts, the longer the ARL_1 values. This trend support the conclusion that process mean shifts with smaller magnitudes would be more difficult to detect. Specifically, the 2S-IMS indicated rapid detection capability for large shifts (shifts = 3σ, ARL_1 = 3.18–3.19) and moderate shifts (shifts = 2σ, ARL_1 = 4.76–4.78) with short ranges of ARL_1. It was also capable to deal with smaller shifts (shifts = $[1\sigma, 0.75\sigma]$, ARL_1 = [10.33–10.60, 15.69–16.75]).

In comparison to the χ^2 charting scheme, detection capability as shown by 2S-IMS was faster for small and moderate shifts (shifts = 0.75–2σ). In comparison to the MCUSUM and the MEWMA, it was slightly comparable in rapid detection for large shifts (shifts = 2.5σ, ARL_1: 2S-IMS = 3.80–3.81, MCUSUM = 2.91, MEWMA = 3.51) and moderate shifts (shifts = 1.5σ, ARL_1: 2S-IMS = 6.41–6.52, MCUSUM = 5.23; MEWMA = 6.12). Similar trend can also be found when dealing with smaller shifts (shifts = 1σ, ARL_1: 2S-IMS = 10.33–10.60, MCUSUM = 9.28; MEWMA = 10.20).

Meanwhile, based on the range of ARL_0 results (ρ = 0.1, 0.5, 0.9; ARL_0 = 335.01, 543.93, 477.45), the 2S-IMS was observed to be more effective in maintaining smaller false alarm compared to the traditional MSPC ($ARL_0 \cong 200$). It should be noted that the results for medium and high correlation processes have exceeded 370 as shown in the Shewhart control chart (Nelson, 1985; Shewhart, 1931). Overall, it can be concluded that the proposed scheme indicated balanced monitoring performance.

4.2. Diagnosis performance

In diagnosis aspect, the RA measures how accurate is a SPC scheme could identify the sources of mean shifts towards diagnosing the root cause error and conducting troubleshooting. Generally, it can be observed that the smaller the mean shifts, the lower the RA results. This trend supports the conclusion that diagnosis information for small process mean shifts (⩽1.0 standard deviations)

Table 4
Performance comparison between the 2S-IMS and the traditional MSPC.

Pattern category	Mean shifts		Average run lengths				Recognition accuracy
			2S-IMS	χ^2 UCL = 10.6	MCUSUM k = 0.50 h = 4.75	MEWMA λ = 0.10 H = 8.66	2S-IMS
	X1	X2	ARL_0 for ρ = 0.1, 0.5, 0.9	ARL_0 for ρ = 0.0			RA for ρ = 0.1, 0.5, 0.9
N (0,0)	0.00	0.00	335.01, 543.93, 477.45	200 (0.005)	203 (0.0049)	200 (0.005)	NA
			ARL_1 for ρ = 0.1, 0.5, 0.9				
US (1,0)	0.75	0.00	17.60, 18.34, 20.00				92.7, 90.4, 89.5
US (0,1)	0.00	0.75	16.20, 15.99, 16.21				92.9, 89.3, 90.6
US (1,1)	0.75	0.75	13.64, 13.28, 14.17				82.4, 94.8, 99.9
DS (1,0)	−0.75	0.00	16.31, 16.43, 17.35				92.3, 89.2, 89.4
DS (0,1)	0.00	−0.75	16.94, 17.44, 18.75				92.3, 87.8, 88.5
DS (1,1)	−0.75	−0.75	13.46, 13.37, 14.03				84.1, 96.1, 99.9
Average			15.69, 15.81, 16.75				89.5, 91.3, 93.0
US (1,0)	1.00	0.00	11.52, 11.57, 11.70	42–0.976	9.28–0.892	10.2–0.902	95.3, 93.1, 94.4
US (0,1)	0.00	1.00	10.50, 10.22, 10.20				95.8, 93.5, 94.4
US (1,1)	1.00	1.00	9.16, 9.09, 9.66				90.0, 96.5, 100
DS (1,0)	−1.00	0.00	10.99, 10.86, 11.06				95.3, 93.2, 92.3
DS (0,1)	0.00	−1.00	11.08, 11.12, 11.36				93.8, 92.1, 92.6
DS (1,1)	−1.00	−1.00	9.15, 9.12, 9.63				89.5, 98.0, 100
Average			10.40, 10.33, 10.60				93.3, 94.4, 95.6
US (1,0)	1.50	0.00	7.02, 7.07, 7.03	15.8–0.937	5.23–0.809	6.12–0.837	97.4, 96.5, 97.1
US (0,1)	0.00	1.50	6.54, 6.33, 6.40				97.1, 96.5, 96.2
US (1,1)	1.50	1.50	5.82, 5.73, 5.94				91.7, 97.9, 100
DS (1,0)	−1.50	0.00	6.81, 6.81, 6.92				97.4, 96.3, 95.5
DS (0,1)	0.00	−1.50	6.82, 6.80, 6.85				96.2, 95.8, 95.6
DS (1,1)	−1.50	−1.50	5.81, 5.69, 5.98				93.2, 99.0, 100
Average			6.47, 6.41, 6.52				95.5, 97.0, 97.4
US (1,0)	2.00	0.00	5.23, 5.15, 5.19	6.9–0.855	3.69–0.729	4.41–0.773	97.8, 97.1, 97.6
US (0,1)	0.00	2.00	4.80, 4.72, 4.70				97.7, 97.8, 97.1
US (1,1)	2.00	2.00	4.36, 4.32, 4.39				91.6, 98.4, 100
DS (1,0)	−2.00	0.00	5.04, 5.04, 5.02				96.8, 96.7, 96.6
DS (0,1)	0.00	−2.00	4.97, 5.03, 4.98				96.5, 96.5, 95.6
DS (1,1)	−2.00	−2.00	4.29, 4.27, 4.33				93.7, 98.9, 100
Average			4.78, 4.76, 4.77				95.7, 97.6, 97.8
US (1,0)	2.50	0.00	4.10, 4.14, 4.12	3.5–0.714	2.91–0.656	3.51–0.715	98.0, 98.4, 98.0
US (0,1)	0.00	2.50	3.83, 3.81, 3.81				97.3, 97.4, 97.0
US (1,1)	2.50	2.50	3.54, 3.49, 3.53				93.2, 98.4, 100
DS (1,0)	−2.50	0.00	3.99, 3.96, 3.95				97.3, 97.3, 97.0
DS (0,1)	0.00	−2.50	3.97, 4.02, 3.98				96.5, 96.6, 97.0
DS (1,1)	−2.50	−2.50	3.41, 3.40, 3.46				94.9, 98.8, 100
Average			3.81, 3.80, 3.81				96.2, 97.8, 98.2
US (1,0)	3.00	0.00	3.47, 3.46, 3.46	2.2–0.545	2.4–0.583	2.92–0.658	98.6, 98.3, 98.2
US (0,1)	0.00	3.00	3.20, 3.20, 3.21				97.8, 97.8, 98.0
US (1,1)	3.00	3.00	2.98, 2.93, 2.98				93.8, 98.4, 100
DS (1,0)	−3.00	0.00	3.31, 3.30, 3.27				98.0, 97.1, 97.6
DS (0,1)	0.00	−3.00	3.33, 3.32, 3.32				96.7, 97.1, 97.1
DS (1,1)	−3.00	−3.00	2.84, 2.85, 2.90				94.6, 99.1, 100
Average			3.19, 3.18, 3.19				96.6, 98.0, 98.5
Grand average	±(0.75–3.00)		7.39, 7.38, 7.61				94.5, 96.0, 96.8

Note: Design parameters for MEWMA control chart in 2S-IMS (λ = 0.1, H = 8.64).

would be more difficult to identify. Specifically, the 2S-IMS indicated accurate diagnosis capability for large shifts (shifts = 3σ, RA = 96.6–98.5%) and moderate shifts (shifts = 2σ, RA = 95.7–97.8%) with high ranges of RA. Although the results were slightly degraded, it is still effective to deal with smaller shifts (shifts = [1σ, 0.75σ], RA = [93.3–95.6%, 89.5–93.0%]). It should be noted that the RA results for medium and highly correlated processes were higher compared to low correlation process, which is effective for practical case. Since the traditional MSPC charting schemes were unable to provide diagnosis information, diagnosis capability as shown by 2S-IMS was absolutely capable in solving such issue. Overall, it can be concluded that the proposed scheme indicated accurate diagnosis performance. Table 3 summarizes the comparison of monitoring–diagnosis capabilities between the 2S-IMS and the traditional MSPC.

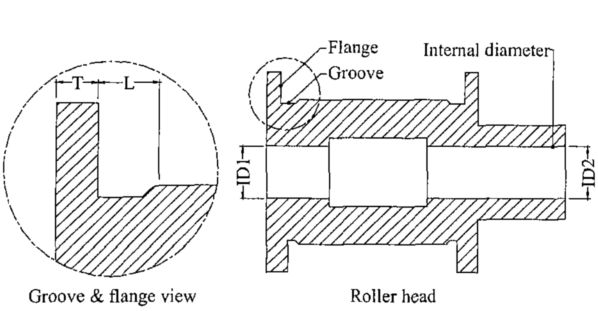


Fig. 8. Functional features of roller head.

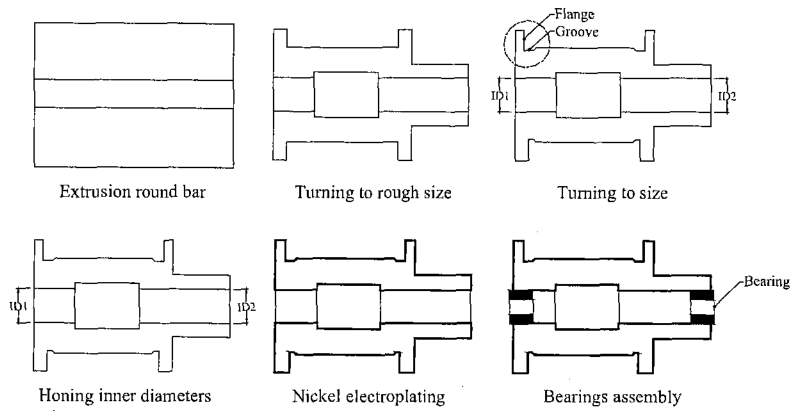


Fig. 9. Process plan for the manufacture of roller head.

5. Industrial case study

Broadly, the need for BQC could be found in manufacturing industries involved in the production of mating, rotational or moving parts. Investigation for this study was focused on the manufacturing of audio video device (AVD) component, namely, roller head. This investigation was based on the author's working experience in manufacturing industry in Johor, Malaysia. In an AVD, the roller head functions to guide and control the movement path of a film tape. Inner diameters of roller head (ID1 and ID2) as shown in Fig. 8 are two dependent quality characteristics (bivariate) that need for joint monitoring-diagnosis. In current practice, such functional features are still widely monitored independently using Shewhart control charts. It is unsure why the MSPC was not implemented. Based on the author's point of view, it could be due to lack of motivation, knowledge and skills to adapt new technology.

The process plan for the manufacture of roller head can be illustrated in Fig. 9. Initially, an aluminium extrusion round bar was turned to rough size (rough cut machining). Then, it was turned to size (finish cut machining) to form functional features such as inner diameters, and groove and flange, among others. The machining of inner diameters was then extended into honing process to achieve tight tolerance for bearing assembly. Hard coated surface was also necessary. As such, the machined work-piece was electroplated using nickel alloy before assembly.

Bivariate process variation can be found in turning to size operation due to tool bluntness and loading error as illustrated in Fig. 10. These disturbances will cause unnatural changes in the process data streams as shown in Table 5. The work piece is automatically loaded into pneumatic chuck using a robotic system. Bluntness in the cutting tool will cause gradual decrement in both inner diameters (ID1, ID2) with positive cross correlation ($\rho > 0$). In another situation, such inner diameters could be suddenly increased simultaneously and yields positive cross correlation ($\rho > 0$) due to loading error.

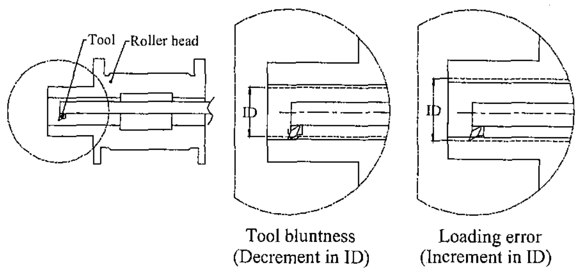


Fig. 10. Process variation occurred in turning-to-size operation.

Based on two examples of bivariate process variation, industrial process samples were simulated into the 2S-IMS for validating its applicability in real world. The first case study involves tool bluntness. The mean (μ) and standard deviation (σ) of bivariate in-control process were determined based on the first 24 samples (observations 1st–24th). Tool bluntness begins between observation samples 41st–50th. Validation results are summarized in Table 6, whereby the determination of process status (monitoring)

Table 5
Sources of variation in machining inner diameters.

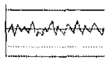
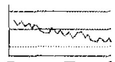
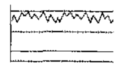
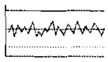
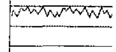
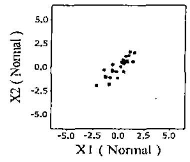
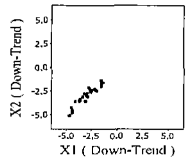
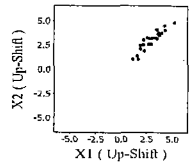
	Stable process **Process noise N (0,0)**	Tool bluntness **DS (1,1)**	Loading error **US (1,1)**
$X_{1\text{-}i}$ (ID1)	 Normal	 Down-Trend	 Up-Shift
$X_{2\text{-}i}$ (ID2)	 Normal	 Down-Trend	 Up-Shift
Scatter diagram			

Table 6
Inspection results based on tool bluntness case.

i	Original samples		Standardized samples		Window range	Monitoring–diagnosis decision
	X_{i_1} (ID1)	X_{i_2} (ID2)	Z_{i_1} (ID1)	Z_{i_1} (ID2)		
1	7.9420	7.9428	0.3393	1.0790		
2	7.9412	7.9420	−1.1414	−0.5917		
3	7.9412	7.9416	−1.1414	−1.4271		
4	7.9420	7.9428	0.3393	1.0790		
5	7.9412	7.9420	−1.1414	−0.5917		
6	7.9412	7.9416	−1.1414	−1.4271		
7	7.9420	7.9428	0.3393	1.0790		
8	7.9424	7.9420	1.0797	−0.5917		
9	7.9416	7.9420	−0.4010	−0.5917		
10	7.9412	7.9416	−1.1414	−1.4271		
11	7.9416	7.9424	−0.4010	0.2437		
12	7.9428	7.9432	1.8201	1.9144		
13	7.9420	7.9424	0.3393	0.2437		
14	7.9416	7.9424	−0.4010	0.2437		
15	7.9424	7.9428	1.0797	1.0790		
16	7.9412	7.942	−1.1414	−0.5917		
17	7.9412	7.9416	−1.1414	−1.4271		
18	7.9420	7.9424	0.3393	0.2437		
19	7.9428	7.9428	1.8201	1.0790		
20	7.9420	7.9424	0.3393	0.2437		
21	7.9412	7.9416	−1.1414	−1.4271		
22	7.9424	7.9428	1.0797	1.0790		
23	7.9424	7.9424	1.0797	0.2437		
24	7.9420	7.9424	0.3393	0.2437	1–24	N
25	7.9412	7.9416	−1.1414	−1.4271	2–25	N
26	7.9424	7.9420	1.0797	−0.5917	3–26	N
27	7.9424	7.9428	1.0797	1.0790	4–27	N
28	7.9412	7.9420	−1.1414	−0.5917	5–28	N
29	7.9420	7.9428	0.3393	1.0790	6–29	N
30	7.9420	7.9424	0.3393	0.2437	7–30	N
31	7.9412	7.9420	−1.1414	−0.5917	8–31	N
32	7.9420	7.9428	0.3393	1.0790	9–32	N
33	7.9428	7.9424	1.8201	0.2437	10–33	N
34	7.9416	7.9424	−0.4010	0.2437	11–34	N
35	7.9424	7.9432	1.0797	1.9144	12–35	N
36	7.9428	7.9424	1.8201	0.2437	13–36	N
37	7.9416	7.9420	−0.4010	−0.5917	14–37	N
38	7.9420	7.9424	0.3393	0.2437	15–38	N
39	7.9424	7.9420	1.0797	−0.5917	16–39	N
40	7.9416	7.9420	−0.4010	−0.5917	17–40	N
41	7.9408	7.9412	−1.8818	−2.2625	18–41	N
42	7.9408	7.9408	−1.8818	−3.0978	19–42	N
43	7.9404	7.9408	−2.6222	−3.0978	20–43	N
44	7.9404	7.9408	−2.6222	−3.0978	21–44	DS (1 1)
45	7.9404	7.9404	−2.6222	−3.9332	22–45	DS (1 1)
46	7.9400	7.9404	−3.3626	−3.9332	23–46	DS (1 1)
47	7.9400	7.9400	−3.3626	−4.7686	24–47	DS (1 1)
48	7.9396	7.9400	−4.1029	−4.7686	25–48	DS (1 1)
49	7.9396	7.9396	−4.1029	−5.6040	26–49	DS (1 1)
50	7.9396	7.9396	−4.1029	−5.6040	27–50	DS (1 1)

$(\mu_1, \mu_2) = (7.9417, 7.9422)$; $(\sigma_1, \sigma_2) = (4.6687 \times 10^{-4}, 4.2495 \times 10^{-4})$.
Note: Observation samples highlighted in bold (41st–50th) represent out-of-control process.

Table 7
Outputs of the scheme for tool bluntness case.

Recognition window (RW)	1–24	2–25	3–26	4–27	5–28	6–29	7–30	8–31	9–32
ρ	0.8280	0.8449	0.8007	0.7962	0.8062	0.7962	0.7792	0.7927	0.8336
Decision based on MEWMA control chart	N	N	N	N	N	N	N	N	N
RW	10–33	11–34	12–35	13–36	14–37	15–38	16–39	17–40	18–41
ρ	0.7944	0.7671	0.7721	0.7083	0.7144	0.7245	0.6695	0.6683	0.7088
Decision based on MEWMA control chart	N	N	N	N	N	N	N	N	N
RW	19–42	20–43	21–44	22–45	23–46	24–47	25–48	26–49	27–50
ρ	0.7591	0.8002	0.8325	0.8530	0.8731	0.8911	0.9069	0.9199	0.9372
N	**1.5200**	**1.1136**	0.7150	0.3311	0.1207	0.0603	0.0307	0.0251	0.0156
US (1 0)	0.2578	0.1864	0.1696	0.1573	0.2009	0.2195	0.2576	0.2872	0.3176
US (0 1)	0.1618	0.1330	0.1175	0.1344	0.1543	0.1851	0.2120	0.2664	0.3710
US (1 1)	0.1186	0.1163	0.1329	0.1918	0.1753	0.1515	0.1708	0.1700	0.1626
DS (1 0)	0.1363	0.1007	0.1063	0.0890	0.0823	0.0788	0.0842	0.0791	0.0576
DS (0 1)	0.4044	0.5004	0.4905	0.6189	0.3953	0.3682	0.3018	0.2669	0.3030
DS (1 1)	0.2582	0.6196	**0.9434**	**1.1542**	**1.5168**	**1.5218**	**1.5927**	**1.5403**	**1.5065**

Note: **Bold value** represents the maximum output of ANN that determines pattern category.

and sources of variation (diagnosis) are based on output of the scheme as shown in Table 7.

In the first 40 samples, this scheme was able to correctly recognize the bivariate process data streams as in-control patterns (N). In this case, it was effective to identify bivariate in-control process without triggering any false alarm. Bluntness of the cutting tool begins at sample 41st, whereby this scheme was able to correctly recognize bivariate process data streams as Down-Shift patterns (DS (1,1)) starting from sample 44th (at window range 21st–44th). In overall diagnosis aspect, this scheme was observed to be effective to identify the sources of variation in mean shifts without mistake.

The second case study involves loading error. Similar as in the first case study, the mean (μ) and the standard deviation (σ) of bivariate in-control process were computed based on the first 24 observation samples. Loading error exist between samples 40th–50th. Validation results and related output of the scheme are summarized in Tables 8 and 9 respectively.

Based on the first 39 samples, this scheme is effective to correctly recognize the bivariate process data streams as in-control patterns (N). In this situation, the process was running smoothly without false alarm. Improper condition of pneumatic chuck and robotic arm causes loading error between samples 40th–50th. In this situation, this scheme was able to correctly recognize the bivariate process data streams as Up-Shift patterns (US (1,1)) starting from sample 40th (at window range: 17th–40th). In overall diagnosis aspect, this scheme is capable to correctly identify the sources of variation in mean shifts without mistake.

Table 8
Inspection results based on loading error case.

i	Original samples		Standardized samples		Window range	Monitoring–diagnosis decision
	X_{i_1} (ID1)	X_{i_2} (ID2)	Z_{i_1} (ID1)	Z_{i_1} (ID2)		
1	7.9416	7.9420	−0.2856	−0.5099		
2	7.9412	7.9428	−1.1424	1.3727		
3	7.9420	7.9424	0.5712	0.4314		
4	7.9412	7.9416	−1.1424	−1.4512		
5	7.9420	7.9428	0.5712	1.3727		
6	7.9412	7.9420	−1.1424	−0.5099		
7	7.9412	7.9416	−1.1424	−1.4512		
8	7.9416	7.9424	−0.2856	0.4314		
9	7.9424	7.9420	1.4279	−0.5099		
10	7.9416	7.9420	−0.2856	−0.5099		
11	7.9412	7.9416	−1.1424	−1.4512		
12	7.9424	7.9428	1.4279	1.3727		
13	7.9420	7.9424	0.5712	0.4314		
14	7.9416	7.9424	−0.2856	0.4314		
15	7.9412	7.9416	−1.1424	−1.4512		
16	7.9424	7.9428	1.4279	1.3727		
17	7.9416	7.9420	−0.2856	−0.5099		
18	7.9420	7.9424	0.5712	0.4314		
19	7.9412	7.9420	−1.1424	−0.5099		
20	7.9424	7.9424	1.4279	0.4314		
21	7.9420	7.9424	0.5712	0.4314		
22	7.9420	7.9424	0.5712	0.4314		
23	7.9412	7.9416	−1.1424	−1.4512		
24	7.9424	7.9428	1.4279	1.3727	1–24	N
25	7.9420	7.9424	0.5712	0.4314	2–25	N
26	7.9412	7.9416	−1.1424	−1.4512	3–26	N
27	7.9424	7.9420	1.4279	−0.5099	4–27	N
28	7.9424	7.9428	1.4279	1.3727	5–28	N
29	7.9412	7.9420	−1.1424	−0.5099	6–29	N
30	7.9420	7.9428	0.5712	1.3727	7–30	N
31	7.9428	7.9424	2.2847	0.4314	8–31	N
32	7.9420	7.9424	0.5712	0.4314	9–32	N
33	7.9412	7.9420	−1.1424	−0.5099	10–33	N
34	7.9420	7.9428	0.5712	1.3727	11–34	N
35	7.9428	7.9424	2.2847	0.4314	12–35	N
36	7.9416	7.9424	−0.2856	0.4314	13–36	N
37	7.9424	7.9428	1.4279	1.3727	14–37	N
38	7.9416	7.9420	−0.2856	−0.5099	15–38	N
39	7.9428	7.9424	2.2847	0.4314	16–39	N
40	7.9428	7.9432	2.2847	2.3140	17–40	US (1 1)
41	7.9432	7.9428	3.1415	1.3727	18–41	US (1 1)
42	7.9436	7.9432	3.9982	2.3140	19–42	US (1 1)
43	7.9428	7.9432	2.2847	2.3140	20–43	US (1 1)
44	7.9432	7.9428	3.1415	1.3727	21–44	US (1 1)
45	7.9436	7.9432	3.9982	2.3140	22–45	US (1 1)
46	7.9428	7.9432	2.2847	2.3140	23–46	US (1 1)
47	7.9432	7.9428	3.1415	1.3727	24–47	US (1 1)
48	7.9428	7.9436	2.2847	3.2553	25–48	US (1 1)
49	7.9428	7.9432	2.2847	2.3140	26–49	US (1 1)
50	7.9436	7.9432	3.9982	2.3140	27–50	US (1 1)

$(\mu_1,\mu_2) = (7.9417, 7.9422)$; $(\sigma_1,\sigma_2) = (4.6687 \times 10^{-4}, 4.2495 \times 10^{-4})$.
Note: Observation samples highlighted in bold (40th–50th) represent out-of-control process.

Table 9
Outputs of the scheme for loading error case.

Window range (RW)	1–24	2–25	3–26	4–27	5–28	6–29	7–30	8–31	9–32
ρ	0.6896	0.6910	0.8333	0.7723	0.7733	0.7822	0.7733	0.7234	0.7407
Decision based on MEWMA control chart	N	N	N	N	N	N	N	N	N
RW	10–33	11–34	12–35	13–36	14–37	15–38	16–39	17–40	18–41
ρ	0.7924	0.7753	0.7202	0.6941	0.7075	0.7254	0.6693	0.6973	0.7040
N	N	N	N	N	N	N	N	0.8220	0.4510
US (1 0)								0.5067	0.6528
US (0 1)								0.1665	0.1370
US (1 1)								**0.9479**	**1.1855**
DS (1 0)								0.0985	0.0719
DS (0 1)								0.1533	0.1453
DS (1 1)								0.1257	0.1129
RW	19–42	20–43	21–44	22–45	23–46	24–47	25–48	26–49	27–50
ρ	0.7546	0.7504	0.7561	0.7815	0.7806	0.7486	0.7258	0.7228	0.6886
N	0.1775	0.1609	0.1053	0.0434	0.0403	0.0376	0.0313	0.0318	0.0200
US (1 0)	0.7116	0.4926	0.5886	0.6606	0.4464	0.5521	0.3923	0.2824	0.3099
US (0 1)	0.1184	0.1124	0.1317	0.1724	0.1631	0.1540	0.1762	0.1711	0.2213
US (1 1)	**1.4012**	**1.6147**	**1.5717**	**1.5235**	**1.6681**	**1.5983**	**1.7006**	**1.7666**	**1.7163**
DS (1 0)	0.0632	0.0852	0.0817	0.0766	0.0802	0.0970	0.1002	0.1142	0.1221
DS (0 1)	0.1537	0.1508	0.1350	0.1830	0.2023	0.1735	0.1754	0.2060	0.2468
DS (1 1)	0.1304	0.1144	0.0875	0.0636	0.0597	0.0384	0.0434	0.0493	0.0283

Note: **Bold value** represents the maximum output of ANN that determines pattern category.

6. Conclusions

This paper proposed two-stage monitoring approach in monitoring and diagnosis of bivariate process variation in mean shifts. Based on the framework of 2S-IMS that integrates the powerful of MEWMA control chart and Synergistic-ANN recognizer, it has resulted in a smaller false alarm (ARL_0 = 335.01–543.93), rapid shifts detection (ARL_1 = 3.18–16.75), and accurate diagnosis capability (RA = 89.5–98.5%) compared to the traditional SPC charting schemes for BQC. Since the monitoring and diagnosis performances were evaluated using modeling data, real industrial data were used for the purpose of validation. The case studies involved tool bluntness and loading error in machining operations, whereby the proposed scheme has shown an effective monitoring capability in identifying the bivariate in-control process without any false alarm. The scheme also effective in diagnosis aspect, that is, in correctly identifying the sources of mean shifts when process becomes out-of-control. Based on the promising results, the 2S-IMS could be a reference in realizing balanced monitoring and accurate diagnosis of bivariate process variation. In the future work, further investigation will be extended to other causable patterns such as trends and cyclic.

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