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Review Article

Monitoring multivariate environments using artificial neural network approach: An overview

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Multivariate process;
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Change point.

Abstract. When a process shifts to an out-of-control condition, a search should be initiated to identify and eliminate the special cause(s) manifested to the technical specification(s) of the process. In the case of a process (or a product) involving several correlated technical specifications, analyzing the joint effects of the correlated specifications is more complicated compared to a process involving only one technical specification. Most real cases refer to processes involving more than one variable. The complexity of a solution to monitor the condition of these processes, estimate the change point and identify further knowledge leading to root-cause analysis motivated researchers to develop solutions based on Artificial Neural Networks (ANN). This paper provides, analytically, a comprehensive literature review on monitoring multivariate processes approaching artificial neural networks. Analysis of the strength and weakness of the proposed schemes, along with comparing their capabilities and properties,, are also considered. Some opportunities for new researches into monitoring multivariate environments are provided in this paper.

1. Introduction

The era of modern quality management refers to a new concept considered by Shewhart [1]. Shewhart [1] explained that common causes of variations of a process cannot be eliminated completely and then two products of a process are not produced exactly with the same specifications. A common cause in a process addresses a systemic problem. When a process works affecting a natural variation, i.e. common cause, the Shewhart's famous meaning of statistical control is addressed. Shewhart [1] also commented strongly that the unnatural variations of a process should be detected and the source responsible for the condition should be eliminated quickly. The elimination allows the process to work under a natural condition. The source(s) responsible for unnatural variation has been named assignable cause by Shewhart. Deming, however, called the source of an unnatural variation a special cause (Refer to Pyzdek [2]).

When a process affecting a unnatural variation(s) shifts to an out-of-control condition, a search should be started by practitioners to identify and eliminate the special cause(s). Although the control charts proposed by Shewhart [1] are recognized as a milestone in the area of quality management, the procedure is incapable of triggering on time when a small or moderate change affects a univariate process. Hence, Page [3] proposed cumulative sum (CUSUM) procedure to overcome this weakness of Shewhart's charts. Furthermore, Roberts [4] focused on overcoming the weakness of the Shewhart procedure and proposed Exponentially Weighted Moving Average (EWMA) procedure. CUSUM and EWMA allowed enhancement of the performance capability index of the control charts. Lucas and Saccucci [5] evaluated CUSUM and EWMA procedures and concluded that the performance properties of both procedures are the same.

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The importance of identifying special cause(s) in an out-of-control process motivated researchers to develop procedures leading to identification of the change point. A change point refers to the time when a process is really allowed to shift to an out-of-control condition. For details about the change point issue, the reader is directed to Atashgar [6]. The control charts introduced in literature are not capable of identifying the real time when the change first manifests itself into a process. In other words, the time of triggering an out-of-control condition by a control chart is not the same time as when a change has been allowed to start to take place in the process. Several authors, including Hinkley [7], Pettitt [8], Nishina [9], Samuel et al. [10], Pignatiello and Simpson [11], Perry and Pignatiello [12], Perry et al. [13], Noorossana and Shadman [14] and Habibi [15] focused on the change point when a special cause affects a univariate process. Although a univariate process is considered one of the case types that can be found in the real world, most cases refer to processes involving more than one variable. When a process includes multi correlated factors, it addresses a more complex case compared to a univariate process. The existence of different multivariate processes in real cases motivated researchers to investigate processes with several correlated quality specifications. The investigation led researchers to develop several different procedures to control multivariate processes statistically. T^2 Hotelling, multivariate cumulative sum (MCUSUM) and Multivariate Exponential Weighted Moving Average (MEWMA) are the most famous procedures introduced in the literature to control statistically processes involving several interrelated variables. MCUSUM and MEWMA were developed to overcome the performance weakness of the T^2 Hotelling procedure proposed by Hotelling [16]. The performance of the T^2 Hotelling procedure follows the same properties as in Shewhart's charts when a small or moderate change affects a multivariate process. The properties of MCUSUM have been investigated by several authors, such Woodall and Ncube [17], Healy [18], Crosier [19], Pignatiello and Runger [20], and Runger and Testik [21]. Moreover, several authors, including Lowry et al. [22], Rigdon [23], Runger and Prabhu [24], Kramer and Schmid [25], Runger et al. [26], Tseng et al. [27], Testik et al. [28] and Testik and Borror [29] contributed to the development of the MEWMA procedure.

In the case of a P-variate process, the root-cause analysis is more complicated compared to a process involving only one variable when the process affecting a special cause(s) departs to an out-of-control condition. In this case, when a p-variate process departs to an out-of-control condition, practitioners are only allowed to undertake an effective root-cause analysis when they are allowed to identify the change point, along with diagnosing the source(s) responsible for the out-of-control condition. The change point problem in multivariate literature has been approached statistically by several authors, such as Nedumaran et al. [30], Zamba and Hawkins [31], Li et al. [32], Noorossana et al. [33] and Arbabzadeh [34]. Diagnostic analysis, as one of the most attractive issues, was also approached statistically by several authors. Among the procedures introduced in literature, the reader is directed to the most famous one proposed by Mason et al. [35]. Mason et al. [35] approached, statistically, a solution by proposing the T^2 decomposition procedure. The reader is also directed to other references, including Jackson [36], Maravelakis et al. [37], and Kalagonda and Kulkarni [38] who focused on the diagnostic analysis problem in multivariate cases.

Although statistical procedures are considered a rational choice for monitoring a p-variate process, the high capabilities of soft computing methods, such as Artificial Neural Networks (ANN), motivated several researchers to use ANN to monitor multivariate environments. The ANN capabilities allowed the researchers to develop multi-task schemes to facilitate access to different knowledge simultaneously when an effective root cause analysis of an out-of-control process is considered. However, the statistical procedures introduced in the literature are incapable of providing the facility easily. Literature addresses the ANN models proposed to monitoring a process with more than one variable generally describes four issues:

1. Control charts, to detect an out-of-control condition;
2. Diagnostic analysis, to distinguish the variable(s) responsible to the out-of-control condition;
3. The change point, to identify the time when the process really shifts to an out-of-control condition;
4. Additional studies, such as the magnitude of the shift, shift direction and so on.

This paper provides literature on monitoring multivariate processes approached ANN. In this paper, significant reports focused on the problem of multivariate processes using ANN are discussed analytically. This investigation follows a classification of ANN models. Finally, the capabilities and properties of the schemes reported by authors are also categorized.

In the next section, the out-of-control condition and the required knowledge leading to an effective root cause analysis for a process involving more than one variable are described. Section 3 provides a briefing of the concepts of artificial neural networks. In Section 4, the models developed to monitor a multivariate process using ANN are discussed comprehensively. The concluding remarks are provided in the final section.

2. Considering an out-of-control condition in a multivariate process

Suppose $\mathbf{X}_1, \mathbf{X}_2, \cdots, \mathbf{X}_\tau, \mathbf{X}_{\tau+1}, \cdots, \mathbf{X}_T$ are independent vectors of the observations in a multivariate environment, where the vector $\mathbf{X}$ follows a known distribution with joint probability function $f(X, \Theta)$, where Θ denotes the parameters of the distribution. It is assumed that vector $\mathbf{X}$ includes p related random variables of a product or a process and then addresses the vector which has a $p \times 1$ dimension. So, the jth random variable is the jth quality specification of the product or the process. Suppose the process works in-control statistically up through time, τ, but, after time, τ, a special cause(s) affects the parameter(s) and the process shifts to an out-of-control condition. In this case, the process remains in the out-of-control condition until, at a later time T, the shift of the process is detected by a control chart. Time τ is considered the change point of the process. Identification of the change point is an essential phase in a root cause analysis. The knowledge of the time point helps practitioners to take a good start point to identify the cause(s) and then the knowledge allows practitioners to save the cost of error of incorrect identification of the source(s). When a special cause(s) takes place in a process, the parameter(s) of the process may drift due to different types of change. The different change types known in the literature include step shift, linear trend, isotonic, antitonic and monotonic. For details about change types, the reader is directed to Atashgar [6].

As stated before, when a process with several correlated quality specifications affecting a change type shifts to an out-of-control condition, identification of the change point by itself cannot lead to an effective root cause analysis. To undertake an effective effort to allow the process to work in-control statistically, a diagnostic analysis is also known as an essential step. Hence, in a multivariate process, when a control chart detects an out-of-control condition, to effectively perform a root cause analysis, at least two essential steps should be followed:

1. Identification of the change point;
2. Performing a diagnostic analysis to identify the source(s) responsible for the change.

Most solutions in literature focused on only one of the required pieces of knowledge. However, to save the cost of quality, practitioners should be allowed access to all the required knowledge at the same time. Moreover, most solutions proposed in literature assume the underlying process change type is known exactly a priori. However, in practice, the type of change and the directions corresponding to the drift(s) can rarely be predicted beforehand exactly for all variables of the process. Literature indicates that the capabilities of the ANN approach have allowed researchers to develop schemes to overcome this weakness.

3. Brief review of artificial neural network concepts

An artificial neural network is a mathematical model based on a biological network and basically owes its conception to the idea of neurons introduced by Cajal [39]. Cajal's pioneer work was the result of a struggle to understand the constituents of the structure of the brain. Hence, basically, ANN has been developed based on the structure of the brain and follows the brain's rules in the area of learning and storing knowledge. An ANN is designed to model the way the human brain performs a task of interest. Haykin [40] defined an ANN as follows:

"A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

1. Knowledge is acquired by the network through a learning process;
2. Interneuron connection strengths, known as synaptic weights, are used to store the knowledge."

Figure 1 shows biological and artificial neural networks graphically. Table 1 shows also the terms used for a biological neural network and the equivalent terms for ANN.

The growth of the automatic production line, along with the importance of the joint controlling of several correlated factors of a given process or product, where the factors, as random variables follow a joint probability function, led several different researchers to focus on ANNs to monitor the processes. The approach allowed them to use the capabilities of ANN to solve complex cases when conventional approaches are incapable of performing a solution simply.

There exist some important points in literature when designing an ANN based model is approached to monitor a process as follows:

Table 1. Equivalent terms used for biological and artificial neural networks.

Biological neural network	Artificial neural network
Neuron/Soma	Neuron
Dendrite	Input
Axon	Output
Synapse	Weight

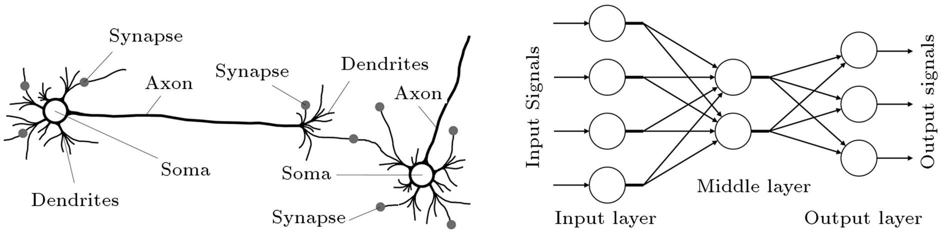

Figure 1. Natural and artificial neural networks.

Network type: Selection of the network type is an important issue in designing an ANN. The multilayer perceptron (MLP), the Radial Basis Function (RBF), Learning Vector Quantization (LVQ), Hopfield, and modular networks are types of neural network considered in the literature. Multilayer feed forward under a back propagation algorithm is used usually by researchers focused on process monitoring. Zorriasatine and Tannock [41] discussed the effectiveness of the multilayer feed forward with back propagation algorithm, and stated that it is most commonly applied successfully by authors focusing on univariate processes. Our survey research also leads to the consequence that MLP with back propagation algorithm has been used for Multivariate Statistical Process Control (MSPC) effectively by most authors. The main weakness of the back propagation algorithm refers to the length of the training phase. An ANN with MLP can perform nonlinear classification, which includes input, hidden and output layers. Figure 2 shows the algorithm of back propagation clearly.

MLP is usually used where the supervised paradigm is approached. Haykin [40] considers three types of learning rule or paradigm, including supervised, unsupervised and reinforcement learning. The special specification for the first paradigm, as its name implies, is the existence of supervision. Supervised learning uses a teacher to perform the training of the network. However, the reinforcement paradigm leads the training through a trial and error process. As shown in Table 2, the tasks usually fall within each of the paradigms.

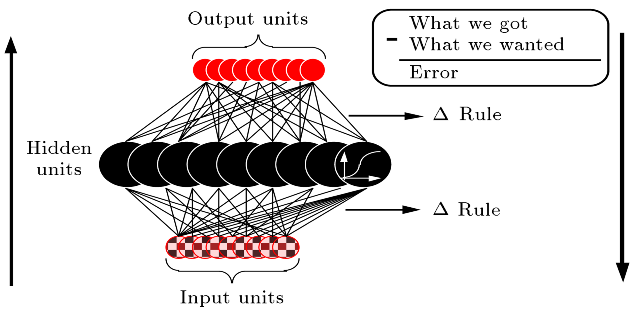

Figure 2. Back propagation algorithm.

Pham and Oztemel [42] stated that one cannot find a systematic procedure to select the best network type for the model of interest. The designer finds an applicable network type through a trial and error process. Moreover, to design an ANN, the first problem is to find a way how to change the input to the output of interest. The architecture of the network is one of the factors that describes how the transition will be performed. Architecture is the element that determines how a network transfers the inputs from the input layer to the output layer. Then the architecture affects the process of producing outputs directly. Architecture of a network describes the number of layers, the number of neurons for each layer, and the transfer function type for each layer, and determines the connection types of the layers. The type of case and the output of interest indicate the architecture type. The architecture of a network affects directly the training phase, and then, affects the process of learning. There exists, totally, two groups of architecture, including static and dynamic. However, Haykin [40] discussed four classes of network architecture, including single layer feed-forward network, multilayer feed-forward network, recurrent network, and lattice structures. Static architecture is the simplest situation without feedback or delay. However, the type of dynamic depends on the current input or the previous inputs, and also depends on the output or state of the network. In this case, the network is designed with feed forward connections regarding delay and feedback. Literature illustrates

Table 2. Tasks usually fall within each of the paradigm learning.

Supervised	Unsupervised	Reinforcement
• Regression	• Estimation	• Control
• Pattern recognition	• Clustering	• Games
	• Compression	• Sequential decision making
	• Filtering	

that the static class has been approached by most authors.

Transfer function: A transfer function, also called an activation function, is a descriptive channel to calculate the output of a layer from its set input, and has an important role in undertaking the behavior of an ANN. In other words, the output of a neuron depends on the inputs of the neuron and on its transfer function. Many useful transfer functions included in the literature show either linear or nonlinear shapes. Figure 3 shows a list of transfer functions.

Generalization: One of the problems that may occur during an ANN training is called 'over fitting', and is referred to as the generalization. Over fitting is referred to as large value errors appear in the performance results; however, errors appear reasonably small when the network is trained. It means that the network has not memorized the examples effectively and then the network is incapable of generalizing the new input. In this case, the network does not allow producing reasonable outputs when it is tested using examples not seen before. Haykin [40] stated that generalization is influenced by three factors, as follows:

1. The size and efficiency of the training set;
2. The architecture of the network;
3. The complexity of the problem.

The resources address two methods of generalization: 1) the modified performance function, referred to as regularization, and 2) early stopping. For further details about generalization and its methods, the reader is directed to Haykin [40] and Demouth and Beale [43].

Window size: The number of data in a sequence, i.e. an input vector, to induce the input layer of an ANN, is referred to as the window size. The data is considered as the observations measured in the process. In other words, the window plays the role of a mask for the observations. Here, the size of the window, which is referred to as the data set for the training phase, greatly influences the performance of the ANN and directly influences the capability of the network to recognize an unnatural pattern. As shown in Table 3, a small window size allows the model to detect the shift quickly, leading to high value of type I error. However, a large size for the window could reduce the efficiency of detecting the shift, leading to increase the

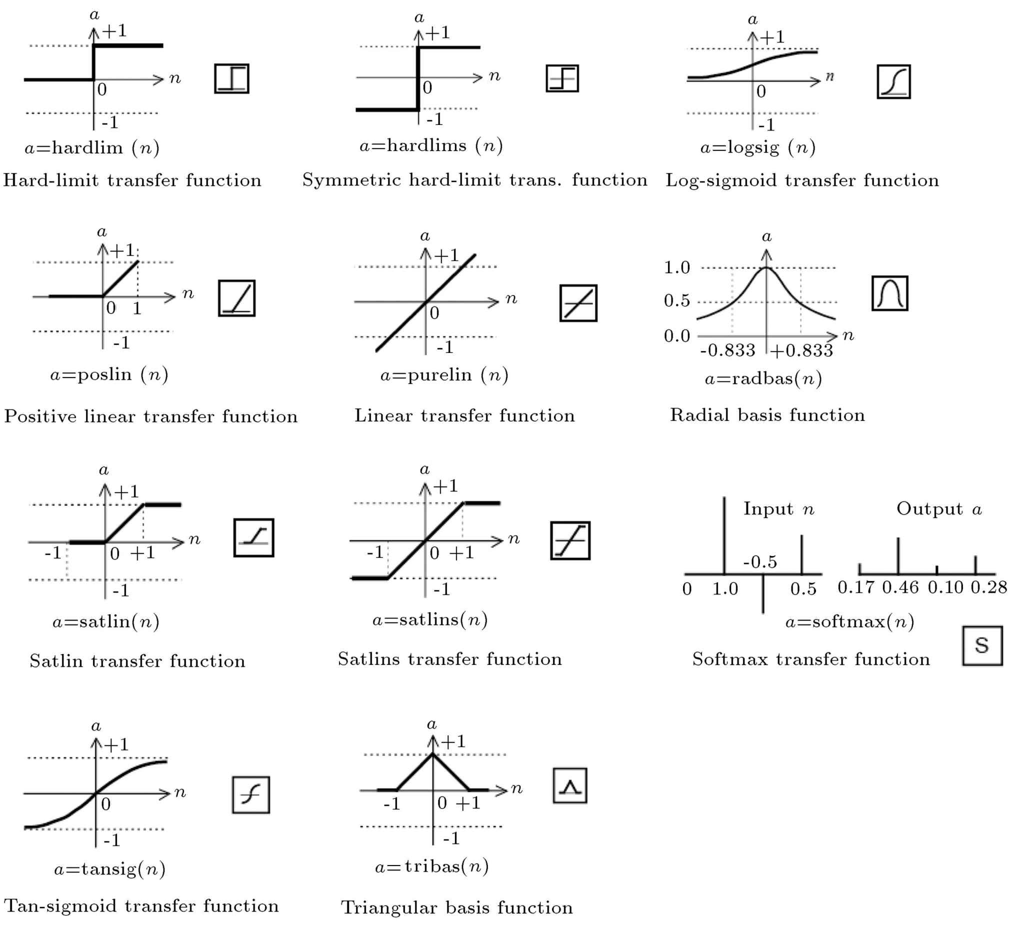

Figure 3. List of the transfer functions (Source: Demouth and Beal [43]).

Table 3. Neural network capabilities with small and big sizes for the window.

Factor	Small window size	Large window size
Type I error	Increases	
Type II error		Increases
Reaction (detect the shift)	Quicker	Slower
In-control ARL	Short	
Out-of-control ARL		Long
Result	More false alarm	Better discriminate
Computational time	Small	Long
Affects the ANN size		Grows quickly

out-of-control ARL criterion, i.e. a high value for type II error. Therefore, a suitable size for the window should be made of a balance between type I and type II errors. The bigger size of window, the bigger and more complex the network. Therefore, increasing the size of the window does not denote a consequence of increasing the efficiency of the network. The size of the window is determined through experiments. The literature shows one cannot conclude a systematic procedure to determine the size of the window. However, Zorriasatine and Tannock [41] commented that the size of the window should be increased only when the ANN does not allow an acceptable performance with a lower window size. It should be stated that no paper has reported usage of one variable window size. In the moving window approach, the process begins under an in-control condition. The size of the window used in the training phase must be equal to the size of the window used in the phase of the performance evaluation of an ANN. Clearly, to recognize a pattern, the window must include more than one data point. The survey reported by Zorriasatine and Tannock [41] for univariate processes states that the window size of the authors has been ranged between 5 and 60 points. However, our survey research indicates that the window size in multivariate literature ranges between 5 and 56 points. Several different authors, such as Guh [44], Cheng [45], Hwarng [46], Atashgar and Noorossana [47] and Noorossanaet al. [48], used the approach to train and evaluate their proposed model performance in a multivariate process.

Threshold: Threshold or cut off, as an important factor for a model based on ANN, is a value to categorize the output of a network. Defining a threshold allows the model to categorize the data greater than the threshold and the other values leading to identify the presence of an unnatural pattern in the process. The value of the threshold of a network is determined based on the value of in-control ARL. Atashgar and Noorossana [47] discussed how a cut off is determined where a multivariate process is considered. Zorriasatine and Tannock [41] discussed the importance of the threshold used to deal with the inexact nature of the outputs of the ANN.

As described in Section 2, there are three main arenas related to monitoring a process involving more than one random variable. In other words, when a multivariate process shifts to an out-of-control condition, to identify and eliminate, effectively, the special cause(s) affecting the parameter(s) of the process, practitioners should at least identify:

1. The out-of-control condition;
2. The change point;
3. The variable(s) responsible for the unnatural condition.

4. Monitoring schemes approaching ANN

4.1. Condition of monitoring schemes

Zorriasatine et al. [49] proposed a neural network based approach to detect an unnatural condition when a special cause, in the type of step change, affects the mean vector of a process. They introduced a method of classification called Novelty Detection (ND), and claimed that the novelty can be considered an effective alternative. They assumed that the mean vector affecting a sustained cause shifts to a new value, however, the covariance matrix remains constant. They evaluated the performance of the proposed model in terms of the percentage of correctly identifying the pattern using simulation data produced from the Mont Carlo simulation technique. In this research, reported by Zorriasatine et al. [49], the out-of-control Average Run Length (ARL), as the most important index to evaluate control charts performance, has not been considered, and then the lag of the change detection time has not been highlighted, i.e. the time when the proposed model signals an out-of-control condition compared with the change point. The report assumes that two random variables shift together at the same time. However, it potentially may occur, in practice, that only one of the variables affecting a special cause has shifted the process to an out-of-control condition. Furthermore, the report does not include evaluation of the performance of the proposed ANN for a case when the shifts of the two variables influencing a special cause follow converse directions, i.e. one of the variables shifts in a downward direction and the other shifts in an upward direction. Zorriasatine et al. [50] later proposed a model based on a semi-parametric density function to detect an out-of-control condition in multivariate processes. They discussed that the semi-parametric choice helps to manage the effect of the size of the process variables, along with achieving the desired accuracy when the dimension of the process variables is sufficiently large. The proposed model is the result of developing the Zorriasatine et al. [49] model. Although the conceptual model is discussed interestingly by Zorriasatine et al. [50], one can also find its drawbacks in [49]. Arkat et al. [51] also investigated detection of an out-of-control condition when a small step shift affects the mean vector of a multivariate process. Arkat et al. [51] assumed the process normally distributed in which the process provides a continuous production. They discussed that the sample observations of this case naturally have an autocorrelation, and then, by ignoring the issue, allows the chart to increase the false alarms through decreasing in-control ARL. In the case of the presence of autocorrelation, residual charts are provided in literature. The residual is referred to as the difference between the real values and the predicted values corresponding to the mean vector. The considerations led the authors to propose an ANN based model to forecast and construct residual CUSUM for multivariate Auto-Regressive of order one, AR(1), environments. They reported the results obtained using their proposed model and compared the results with the time series residual and CUSUM charts. Arkat et al. [51] did not address the detailed specifications of the proposed model. Moreover, they did not evaluate the robustness of the model for the different values of the factors, such as the correlation coefficient, that may influence the performance of the model.

The literature mostly focused on the mean vector when the deterioration issue is considered and authors have reported less the analysis of the variance parameter. In theory, the control of the variance parameter in a process cannot be considered independent of the mean parameter. Cheng and Cheng [52] considered the variance step shift in a bivariate process and proposed an ANN based model to detect the shift in the variance. They used a feed forward network with three layers following a supervised learning paradigm. They approached the window size to induce the data set to the network, and also the moving window approach, to evaluate the performance of the model in sizes 16 and 32. They compared different in-control ARL for the two window sizes, leading to the discovery of their effects. They concluded a window with a bigger size for the model provides better detection compared with the choice of a small size when the process affecting a change in the variance shifts to an out-of-control condition. The output of the proposed model can be analyzed using a log-sigmoid function to range the values from 0 to 1. The performance of the proposed model, due to the output results, are evaluated, based on in-control ARL 200. Although Cheng and Cheng [52] introduced the specifications of their proposed model in detail, they have not addressed the method used for generalization. To demonstrate the capability of the model, the authors evaluated the performance results of the model compared with a scheme approached statistically. Cheng and Cheng [52] reported interesting results corresponding to the performance of their proposed model. However, the authors have not considered different correlation coefficients for the variables. In other words, the authors did not demonstrate the robustness of the model, assuming the model may be used in different processes with different correlation coefficients.

The schemes proposed in the literature commonly assumed that observations follow a predefined density function. Typically, in literature, it is assumed the process is normally distributed. In the case when the joint probability density function of the process is unknown, Rafajlowicz [53] proposed a Radial Basis Function (RBF) neural network leading to detect the mean shift in the process. Rafajlowicz [53] discussed RBF and presented an algorithm to tune the RBF network. The proposed model has been evaluated in terms of ARL using three different data sets, i.e.:

1. A bivariate process, following normal standard distribution;
2. A mixture of mean vectors (2,0) and (0,0) with covariance matrix I;
3. A mixture of mean vectors (0,0), (2,0) and (0,-2) with covariance I, and compared the results of different shifts with the results obtained using the T^2 chart introduced by Hotelling [16].

Rafajtowicz [53] stated that the schemes existing in literature assumed a predefined distribution and claimed the proposed model is capable of detecting an out-of-control condition without assuming a predefined distribution. However, the report directs the reader to the data set following only normal distribution. Furthermore, although the author stated that the memorizing of a small section of the data allows the model to process the large stream of data, the text does not indicate how the approach affects the results. Rafajtowicz [53] has not reported the specifications of the proposed neural network in detail.

Many problems in quality engineering involve the relationship between two or more variables. In other words, sometimes, it is possible that the quality of a process or product is characterized by the relationship between a variable called the response variable and one or more explanatory variables, called independent variables. The relationship is referred to as the profile in literature when a profile is represented adequately by a straight line and the approach is referred to as the simplest case, called simple linear profile. Hosseinifard et al. [54] considered the linear profile using ANN to detect and classify the shifts which are allowed to appear in the profile of a process. They developed three artificial neural networks to monitor the linear profiles approaching MLP for phase II of the statistical control. The three networks introduced in the paper are used to detect shifts in the slope, intercept and residual variance of the linear profile. In the proposed model, the first network is used to detect a shift in slope, the second network is used to detect a shift in the intercept and, finally, the third network is used to detect a shift in the residual variance. The authors named their proposed model 3ANN. The report addresses input, hidden and output layers and the training data completely. Hosseinifard et al. [54] evaluated their proposed model performance by using the example described by Kang and Albin [55] and compared the results of the proposed model with EWMA and T^2 methods. The report shows a good performance for the proposed ANN compared with EWMA and T^2 methods. The report does not address the critical points leading one to simulate the proposed model. Hosseinifard et al. [54] have not described how the threshold is defined for the proposed model. As described before, generalization is an important issue in overcoming the over fitting in an ANN. Hosseinifard et al. [54] have not considered the method applied to overcome the over fitting problem. Robustness, as another important point, is also not discussed in the report.

Pacella and Semeraro [56] also approached an unsupervised ANN to monitor a profile for phase II of the statistical control. They focused on geometrical characteristics for profile monitoring. Pacella and Semeraro [56] represented an interesting report approaching ANN in order to model roundness profiles, where the parameters of this model are monitored by multivariate control charting and residual variance is monitored by univariate control charting. The ANN proposed by Pacella and Semeraro [56] considers the Adaptive Resonance Theory (ART). The proposed ANN model follows fuzzy ART to learn detection of the out-of-control condition. The authors examined the proposed model using simulated data and geometric specifications of measurement on machined items observed in a real case. Pacella and Semeraro [56] used the real case study presented by Colosimo et al. [57] to evaluate their proposed model. The report presents well a practical aspect for using the ANN approach, in which there exists a relationship between variables. The specification of the ANN has not been described in detail and the robustness of the model performance has not been discussed in the report.

4.2. Diagnostic analysis schemes

As discussed before, diagnostic analysis is known as an essential step in identifying the source(s) of an out-of-control condition in a multivariate process. When a control chart signals an out-of-control condition, considering the behavior of the variables of the process can help practitioners to find the source(s) responsible for the out-of-control condition. For this, Chen and Wang [58] considered the behavior of variables in an out-of-control condition and proposed an artificial neural network based model to supplement the χ^2 chart. The proposed model allows practitioners to interpret the unnatural condition of a multivariate environment affected by a sustained step change. The Chen and Wang [58] model provides:

1. Identification of the characteristic or a group of characteristics of an out-of-control process signaled by a χ^2 chart;
2. Classification of mean shift values after the out-of-control condition appears.

The interpretation could address a practitioner to an effective root cause analysis, leading to elimination of the cause contributing to the mean shift. The authors selected back propagation rule and used tangent sigmoid and log-sigmoid functions to canalyze the output of the hidden layer and the output layer, respectively. The authors described the process of the training phase of the model in detail and reported the evaluation of the model using a bivariate process following normal distribution with correlation coefficient 0.5 and type I error 0.0027. One of the problems of an ANN based model corresponds to robust performance. However, Chen and Wang [58] did not report the robustness of the model in which the correlation coefficient takes different values. To help practitioners to diagnose the source contributing to the out-of-control condition, Niaki and Abbasi [59] investigated the multivariate environment in phase II of the statistical control, when a step shift affects the mean vector and the process shifts to an out-of-control condition. Niaki and Abbasi [59] discussed the importance of identifying the source(s) of the fault in an unnatural multivariate process. They focused on diagnostic analysis and developed an artificial neural network based model. The model developed by Niaki and Abbasi [59] is incapable of performing as a built-in control chart. The proposed model will be activated after a control chart, like Hotelling T^2, signals an out-of-control condition for the process worked in-control, statistically, previously. Niaki and Abbasi [59] relied on the experiences using MLP and proposed a neural network model based on supervised learning paradigm. Niaki and Abbasi [59] evaluated the performance of the model under three illustrative examples, including:

1. The data measured stiffness and bending strength, the correlated specifications of a particular lumber production;
2. The example concerns testing of a ballistic missile discussed by Doganaksoy et al. [60], including four correlated random variables;
3. The real data corresponding to a detergent-making company with three related quality specifications, including color, free oil percentage, acidity percent and acidity number.

As described before, in practice, the proposed model must be used with another scheme, i.e. a control chart. Using different schemes naturally increases the complexity of analyzing the process and practitioners are not allowed to analyze a root cause simply. Niaki and Abbasi [59] examined their proposed model when a step shift, on the scale of medium and large shift, i.e. $2\sigma, 2.5\sigma$ and 3σ, affects the mean vector. The results in cases when the process experiences faults in the scale of small values have not been reported. Furthermore, Niaki and Abbasi [59] reported a significant level, $\alpha = 0.5$, leading to ARL=20, to design and perform the test of their proposed model. Later, Yu et al. [61] approached neural network ensemble to propose a model to identify the factor(s) leading to a multivariate process to an out-of-control condition. Figure 4 shows the structure of an ANN ensemble. The approach follows combining the output of several trained neural networks to achieve the output of interest. The era of neural network ensemble, as a new paradigm to train an ANN, refers to Hansen and Salamon [62]. They claimed

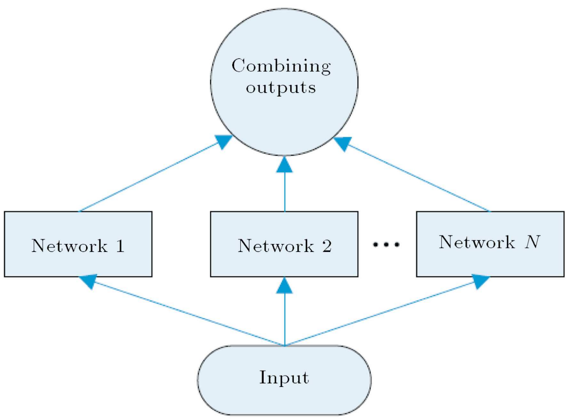

Figure 4. The structure of an ensemble approach (Source: Yu et al. [61]).

the approach could help to generalize the performance of an ANN effectively.

Yu et al. [61] focused on non-sequential data when a step shift appears in the mean vector of the process. They focused on cases including bivariate and three variables to illustrate the performance of their proposed model. Since the proposed model is incapable of detecting an out-of-control condition, they used the χ^2 chart to detect the unnatural condition before activating the proposed model leading to a diagnosis of the source of the fault of the process. The model developed by Yu et al. [61] is incapable of performing its task immediately after signaling an out-of-control condition. However, it should wait to receive more observations, i.e. half of the window size. Yu et al. [61] also considered the example, including data measured stiffness and bending strength, the correlated specifications of a particular lumber production used by Niaki and Abbasi [59], and reported the performance of their proposed model without comparing the performance with the results of the Niaki and Abbasi [59] model. In this case, Yu et al. [61] performed the test, considering $\alpha = 0.005$, leading to ARL=200. Later, Noorossana et al. [48] analyzed the results reported by Niaki and Abbasi [59], assuming the process follows ARL=200, i.e. $\alpha = 0.005$, and compared the results with the performance results of their proposed model. Noorossana et al. [48] considered the data related to the measured stiffness and bending strength, and the correlated specifications of a particular lumber production, reported by Niaki and Abbasi [59], and compared the capability of diagnostic analysis of their proposed model with the results reported by Niaki and Abbasi [59]. The report indicates that although the ARL assumed by Noorossana et al. [48] is significantly more acceptable compared to the ARL used by Niaki and Abbasi [59], the results of the test of the Noorossana et al. [48] model are highly superior compared to the results of the Niaki and Abbasi [59] model. Noorossana et al. [48], approaching supervised learning, developed an integrated model based on artificial neural network, which is not only capable of diagnosing the source responsible for the out-of-control condition when an assignable cause takes place in the mean vector of a process, but is also capable of identifying 1) the out-of-control condition, 2) the change point, and 3) the shift direction in the mean of the contributing variables, all simultaneously. As stated above, Yu et al. [61] also considered the production example and reported the results corresponding to the performance of their proposed model. Table 4 and Figure 5 compare the three proposed model performances with each other in terms of percentage of error rate. The ER tag of the vertical axis in Figure 5 addresses the percentage of error rate. The percentage of an error rate is calculated by the following equation:

Table 4. Comparing the model performances of Niaki & Abbasi [59], Yu et al. [61] and Noorossana et al. [48].

No.	Shift	Error rate %			Improving percentage	
		Niaki & Abbasi model [59]	Yu et al. model [61]	Noorossana et al. model [48]	Noorossana et al. [48] v.s. Niaki & Abbasi [59]	Noorossana et al. [48] v.s. Yu et al. [61]
1	$(2\sigma, 0)$	15.4	4.75	5.9296	159.7139	-19.8934
2	$(0, 2\sigma)$	12.6	5.28	2.5840	387.6161	104.3344
3	$(2\sigma, 2\sigma)$	13.8	10.2	0.2000	6800.0000	5000.0000
4	$(2.5\sigma, 0)$	9.8	4.03	3.7864	158.8210	6.4336
5	$(0, 2.5\sigma)$	11.6	5.39	2.7808	317.1461	93.8291
6	$(2.5\sigma, 2.5\sigma)$	10.8	9.61	0.2000	5300.0000	4720.0000
7	$(3\sigma, 0)$	7.0	4.15	4.1728	67.7531	-0.5464
8	$(0, 3\sigma)$	14.6	5.19	3.3792	332.0549	53.5866
9	$(3\sigma, 3\sigma)$	4.6	8.68	0.2000	2200.0000	4240.0000

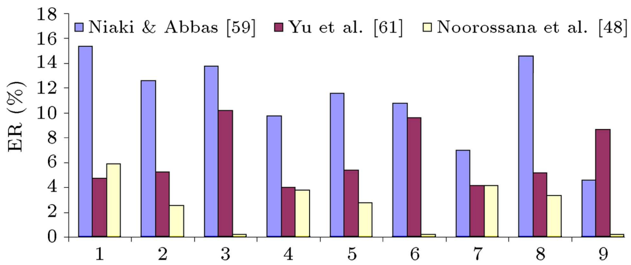

Figure 5. Comparative performance histogram for Noorossana et al. [48], Niaki & Abbasi [59], and Yu et al. [61] models.

$$\mathrm{ER}\% = \left(1 - \frac{cc}{n}\right) \times 100. \quad (1)$$

The two variables, cc and n, denote the correct classification number and the number of data corresponding to the measured quality specifications of the product induced into the network, respectively.

The ANN introduced by Noorossana et al. [48] is also capable of monitoring other required knowledge for an effective root cause analysis. Table 4 and Figure 5 also indicate that the Yu et al. [61] model is superior compared to the Niaki and Abbasi [59] model, assuming the fact that the significant level used by Niaki and Abbasi [59] is not evaluated as a good value. Noorossana et al. [48] approaching modularity designed their model based on MLP. They used subinterval logic introduced by Atashgar and Noorossana [63]. To improve the performance of the proposed model, they used four phases, including standardization, zoning, permutation, and scaling, as discussed by Atashgar and Noorossana [63]. They reported comprehensively the specifications of the interesting proposed model, along with the results of its performance under simulated data, and a case study data corresponding to a car manufacturing line. Noorossana et al. [48] claimed their proposed model is superior compared with the model proposed by Atashgar and Noorossana [64]. The Atashgar and Noorossana [64] model is capable of identifying the out-of-control condition, the change point, the source(s) of the shift, and the shift direction, all at the same time, when the mean vector affecting a step change type shifts the process to an out-of-control condition. Aparisi et al. [65] also considered the diagnostic analysis arena with considerable attention in MSPC and proposed an ANN based model. The proposed model, as the models developed by Niaki and Abbasi [59] and Yu et al. [61], is incapable of detecting an out-of-control condition inherently. To detect an out-of-control condition, they used the Hotelling T^2 procedure before using their proposed model. In other words, their proposed model will be activated after a chart signals the existence of an assignable cause in the multivariate process. They used back propagation network for the model and examined the model for phase II of statistical control. The report assumed that a sustained step change type takes place in the process and the covariance matrix is not affected by the source affecting the mean vector, i.e. the covariance matrix does not change. Aparisi et al. [65] focused on the positive correlation coefficients for the quality specifications. The report does not direct the reader to the performance results when all or some of the correlation coefficients take negative values. Aparisi et al. [65] investigated the model proposed by Mason et al. [35] and reported a comparative performance evaluation in the term of correct classification percentage. Mason et al. [35] proposed a T^2 decomposition procedure to perform diagnostic analysis statistically in multivariate processes. Aparisi et al. [65] used four different correlation coefficients, 0.2, 0.4, 0.6 and

0.8, to evaluate the performance of the model, and compared the results with the performance of the scheme proposed by Mason et al. [35]. For this, they considered the Mahalanobis distance for the case of two random variables, calculated as the following equation:

$$d = \sqrt{(\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0)' \boldsymbol{\Sigma}_0^{-1} (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0)}. \tag{2}$$

They obtained an ellipse, as shown in Figure 6, by fixing the value of the Mahalanobis distance to represent the distance, d, between points, $\boldsymbol{\mu}_1$, and the in-control mean vector, $\boldsymbol{\mu}_0$. Yu et al. [61] also considered this example to analyze the performance of their proposed model, but they did not report the performance of their model compared with the Aparisi at al. [65] model.

Later, Atashgar and Noorossana [66] developed a model based on ANN for a diagnostic analysis in multivariate environments. Atashgar and Noorossana [66] considered the eight different points corresponding to the ellipse considered by Aparisi et al. [65], and compared their proposed model performance results with the performance results corresponding to Aparisi et al. [65] and Mason et al. [35] models, in terms of

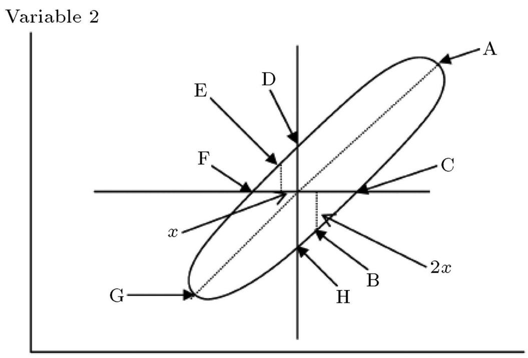

Figure 6. The ellipse considered by Aparisi et al. [65], Atashgar and Noorossana [66], and Yu et al. [61].

correct classification percentage. As discussed before, Yu et al. [61] considered also the same case discussed by Aparisi et al. [65] and evaluated their proposed model using the distances introduced in Figure 5. The results reported by Aparisi et al. [65], Mason et al. [35] and Atashgar and Noorossana [66] models, and the results reported by Yu et al. [61] are shown comparatively in Table 5. It should be stated that Atashgar and Noorossana [66] evaluated their proposed model shown in Table 5 for a significant level, $\alpha = 0.005$. However, Aparisi et al. [65] and Yu et al. [61] reported the results of performing the test for the same case, based on a significant level, $\alpha = 0.03$. It stated that the in-control ARLs assumed by the authors are 200 and 33, respectively. Although the ARL assumed by Atashgar and Noorossana [66] is significantly greater compared to the ARL assumed by Aparisi et al. [65] and Yu et al. [61], the results shown in Table 5 indicate that the model proposed by Atashgar and Noorossana [66], nevertheless, has a superior performance, on average.

Table 5 indicates that the capability of the diagnostic analysis of the model proposed by Atashgar and Noorossana [66] outperforms the models introduced by Mason et al. [35], Aparisi et al. [65] and Yu et al. [61], on average. It should be stated that the models introduced by Aparisi et al. [65], Mason et al. [35] and Yu et al. [61] assumed that only the step shift type appears in the mean vector of the process. However, Atashgar and Noorossana [66] discussed the different change types that might occur in the process and stated that the change type is rarely known beforehand by practitioners in real cases. The model based on MLP proposed by Atashgar and Noorossana [66] is capable of diagnosing the source contributing to the out-of-control condition without assuming the change type, i.e. the change belongs to the monotonic change. Furthermore, the model proposed by Atashgar and Noorossana [66] is capable of detecting the out-of-control condition

Table 5. Performance evaluation for Mason et al. [35], Aparisi et al. [65], Yu et al. [61] and Atashgar and Noorossana [66].

No.	Change group	Correct classification percentages			
		Mason et al. [35]	Aparisi et al. [65]	Yu et al. [61]	Atashgar and Noorossana [66]
1	A	86.02	85.36	80.05	98.6225
2	B	71.35	63.16	52.55	94.7112
3	C	39.06	55.73	62.56	34.0819
4	D	31.25	47.40	63.75	36.6131
5	H	32.08	50.26	65.08	38.5744
6	F	42.79	54.17	65.02	33.7006
7	E	74.02	65.41	57.55	93.9603
8	G	82.29	83.29	72.50	98.5444
Total average performance		57.3575	63.0975	64.88	66.1011

inherently. Thus, it could overcome the weakness of the models proposed by Aparisi et al. [65], Mason et al. [35], Niaki and Abbasi [59], and Yu et al. [61], and the other models focusing only on diagnostic analysis without considering the capability of detecting an out-of-control condition in a multivariate environment. The Atashgar and Noorossana [66] model is introduced based on supervised learning and on subinterval logic introduced by Atashgar and Noorossana [63]. As shown in Figure 7, the subinterval process leads the designer to divide the intervals of training to subintervals to improve the performance of the network. Atashgar and Noorossana [66] illustrated their introduced model using an example related to a chemical process. The paper directs the reader to an extended report corresponding to the model performance results. Atashgar and Noorossana [66] showed the robustness for different values of correlation coefficient in the interval [-0.9 0.9].

Atashgar and Noorossana [66] used the widow size approach to train the networks and used the moving window approach to test the model. The authors used logistic sigmoid and hyperbolic tangent sigmoid transfer functions for the output layer and the hidden layer, respectively

The attractive subject of diagnostic analysis in multivariate processes, the role of the results in performing an effective root cause analysis, and the high capabilities of artificial neural networks led the authors

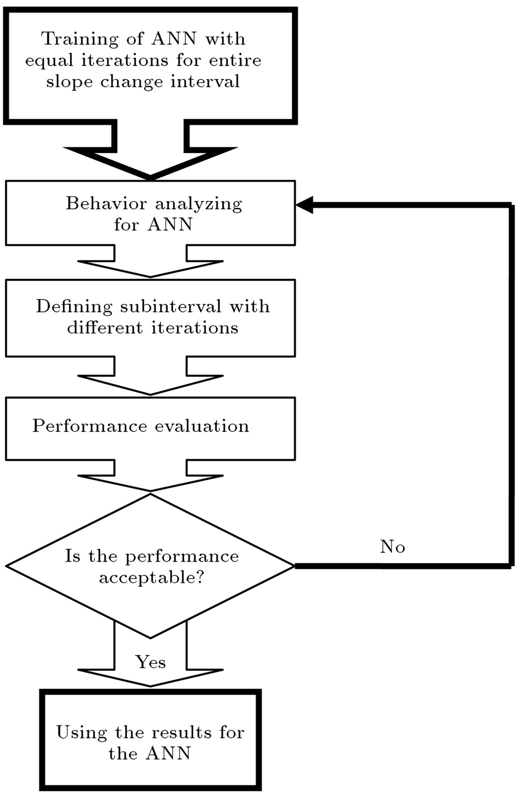

Figure 7. Flowchart for defining subintervals (Source: Atashgar and Noorossana [63]).

to develop models based on ANN. Guh [44] investigated diagnostic analysis for a process involving two correlated variables distributed normally. The ANN model developed by Guh [44] includes two main modules and is capable of performing multitasks when a sustained step change type affects the mean vector. Guh [44] illustrated the model using a numerical example simulated with the Mont Carlo technique and compared the results of out-control signals of the model with MCUSUM and MEWMA results, in terms of the out-of-control ARL. The model designed for use in phase II, assuming the covariance matrix does not change during the process, is in an out-of-control condition. The ANN based model includes two main modules, including five neural networks, which provide the out-of-control condition signal, diagnostic analysis for the variable(s), which contributes to the shift(s), the shift direction and the magnitude of the shift(s). Although the Guh's model is an interesting model conceptually, the report presented by the author does not address an assurance model. Guh [44] assumed the same value of threshold for all five networks introduced in the report, and since each of the networks is designed to recognize different patterns with different training, then, the same value of threshold does not allow the networks to perform their task precisely. This point automatically affects the accuracy of the model performance. In other words, the networks of the Guh [44] model have only a threshold value, but each of the networks follows different pattern recognition. Furthermore, Guh [44] has not described the method used to obtain the threshold value of the different networks. The first network of the Guh's model was designed to recognize several different patterns, i.e. the out-of-control condition, the variable(s) responsible and the shift(s) direction. Zorriasatine and Tannock [41] concluded that, commonly, only one type of pattern could be assumed or presented in a window. The first network of the Guh [44] model includes 36 neurons for the input layer; two hidden layers with 24 neurons for each one, and 9 neurons for the output layer. The number of neurons for the output layer is too large and, thus, practically, the expected values corresponding to the different pattern recognitions could not perform well, all simultaneously. Guh [44] used a hyperbolic tangent as the transfer function for both hidden and output layers. Hwarng [46], also using the ANN approach, proposed a model for phase II of a multivariate process. Hwarng [46] investigated the process in the out-of-control condition and addressed the architecture of the proposed model without using hidden layer. The proposed model is capable of detecting an out-of-control condition along with identifying the source(s) of the condition when the mean vector is affected by an especial cause in the type of step shift. Hwarng [46] used back propagation algorithm to develop the introduced model and tested the model under a normally distributed bivariate process. Hwarng [46] assumed that the covariance matrix is not changed during the process which experiences an out-of-control condition. Hwarng [46] reported the performance of the model is superior compared with the Hotelling T^2 and MEWMA schemes, in terms of out-of-control ARL. However, the extended report has not addressed the time when a downward step takes place in the process, i.e. a negative direction shift. Furthermore, in the case of a real case, one rarely knows the direction of each of the variables a priori, and then, the capability of the model when the variables follow converse directions needs to be known. However, the report does not allow one to find the important analysis. Cheng and Cheng [67] also considered the diagnostic analysis due to the shift in the variance(s) of the variables of a multivariate process and proposed an artificial neural network based model. The architecture of the model provides a classifier to diagnose the source(s) contributing to an out-of-control condition. They assumed an assignable cause affects the variance parameter of the p-variate process and the mean vector is not affected by the assignable cause during the time that the process works in an unnatural condition, i.e. the mean vector is constant. They demonstrated the model via a process including two and three related quality specifications, where the value of the sample size is equal to 5. They also analyzed the model under different positive correlation coefficients, but the report does not involve the performance of the model when each of the correlation coefficient is associated with negative values. The model used a log-sigmoid function to exchange the output values of the hidden and output layers from 0 to 1 values. Cheng and Cheng [67] discussed that three scenarios of shifts may occur in the covariance matrix introduced by Surtidahi et al. [68]. If only a known variance of a known variable shifts to a new value, since the variables are correlated, then only the row and the column of the covariance matrix, due to the variable, will be affected, and the other components do not change. When a variable parameter changes and the changed variable is unknown, then, the second scenario will be conducted. The third scenario will be conducted when all the variances change and then all the components of the covariance matrix will change to new values. Although Cheng and Cheng [67] discussed the three scenarios, they did not analyze the performance of their proposed model based on the scenarios. Yu and Xi [69] and concurrent Yu et al. [61] approached a selective ensemble to design an artificial neural network based model to detect a fault condition along with diagnosing the source(s) of the fault when a multivariate process departs to an out-of-control condition. The authors used the method of bagger introduced by Breiman [70] for the sake of selecting candidate networks. The authors reported the DPSO algorithm introduced by Kennedy and Eberhart [71] to select a subset of the candidates of the neural networks. Yu and Xi [69] also discussed window size and finally focused on a size equal to 12 points for the moving window. They evaluated the results produced by applying the model, and it is reported that the model is superior compared with the conventional models approached statistically. Yu and Xi [69] and Yu et al. [61] followed the same logic and structure, but the Yu and Xi [69] model is capable of detecting the out-of-control condition. However, the Yu et al. [61] model is incapable of detection. El-Midany et al. [72] developed a framework using artificial neural network approach to:

1. Recognize the set of subclasses of abnormal patterns;
2. Diagnose the source of the abnormal pattern;
3. Classify the parameters of the abnormal pattern, such as the magnitude of the shift in the mean vector.

They used a tangent hyperbolic and log sigmoid function as the transfer functions for the hidden and output layers of the networks in different modules. To normalize the input data, so that they fall in the interval [-1 +1], El-Midany et al. [72] used the following equation:

$$\text{Normalized variate} = 2\frac{x - \min}{\max - \min} - 1, \tag{3}$$

where x denotes the input value of a variate, min indicates the minimum value of the given set variate values, and max is the maximum of the given values. The model uses the χ^2 chart before inducing the data set to the input layer. They used 4 modules to construct their proposed model, and used the moving window approach, including 56 consecutive values. El-Midany et al. [72] analyzed the performance results of the model using different examples. The report indicates good results, but it does not address the robustness of the performance. Wang and Chen [73] proposed a model based on fuzzy logic to detect various shifts in the mean vector and classified the magnitudes of the shift. The proposed model consists of two modules. The first module was designed to detect the out-of-control condition when an assignable cause affects the mean vector of the multivariate process in various shift types. The second module was introduced to classify the magnitude of the shifts at various intervals based on the fuzzy logic. The authors used a bivariate example to illustrate the proposed model numerically. The results indicate that their proposed model has a better performance compared with the T^2 chart, in terms of out-of-control ARL. They also evaluated the model in terms of percentage of correct classification.

The importance of the diagnostic analysis caused Salehi et al. [79] to propose a model to monitor a process including several correlated random variables using a hybrid approach. The proposed model was designed not only to identify an out-of-control condition and the responsible variable(s) at the same time, but also to detect the magnitude of the change. This hybrid based model is defined with two modules, so that a support vector machine-classifier has been used for the first module to provide recognition of the type of unnatural pattern. The second module of this hybrid model includes three ANNs to recognize the magnitude of mean shift, slope of trend and cycle amplitude when a shift, trend and cycle type affects a mean vector, respectively. Since providing a rapid recognition of root cause analysis when a multivariate manufacturing shifts to an unnatural condition is evaluated as an important issue, this capability is very valuable for quality engineers. Salehi et al. [79] analyzed their proposed model comparing a similar model using moving window approach. The detailed specifications of the modules discussed by the authors address the reader to analyze the procedure effectively. A hybrid approach was also considered by Huda et al. [80] who proposed a hybrid wrapper-filter based model to perform diagnostic analysis of the shift in the mean vector of a multivariate process to relieve expert knowledge. The aim of the proposed hybrid approach is to overcome the drawbacks of wrapper and filter when diagnostic analysis of a fault is approached. In this paper, for the proposed hybrid model, a filter heuristic is introduced in the wrapper stage. The artificial neural network used in this approach, as the classification algorithm in the wrapper stage, follows MLP network type. Indeed, Huda et al. [80] used a MEWMA chart to detect an out-of-control condition. Huda et al. [80] examined their proposed approach using numerical cases corresponding to three sets of multivariate normal example produced by Minitab statistical package. These three sets include small, moderate and large shifts in mean. However, it is assumed that the covariance matrix does not change during the process which works in the unnatural condition. The authors compared results of the performance of the proposed model with MEWMA scheme.

Masood and Hassan [81] also focused on a process involving two or more correlated variables in cases when the mean vector of the process is affected by a step shift. The proposed artificial neural network proposed by Masood and Hassan [81] followed supervised learning algorithm. The proposed ANN has been evaluated using the criterion of ARL. The report indicates that the ANN is capable of only providing diagnostic analysis for variable(s) responsible for out-of-control conditions; the signal of the shift is also detected by MEWMA chart. This proposed model is similar to the model discussed by Ahmadzadeh [75] and Ahmadzadeh and Noorossana [74] to identify change point. Ahmadzadeh [75] and Ahmadzadeh and Noorossana [74] will be discussed in the next subsection. This proposed model, which is similar to Huda et al. [80], includes two modules; however, the out-of-control condition is also detected by MEWMA chart. Masood and Hassan [81] did not report the process of training and the specifications of the ANN in detail. In this paper, one can find comparison performance results to analyze the performance of the proposed model under correlation coefficients of 0.1, 0.5, and 0.9 compared with two other ANN models.

Yang [82] proposed an ANN model enabled by two distinct levels, optimization-based selective ensemble of learning vector quantization network. The proposed model has been designed to provide detection of the out-of-control condition, and identification of the variable(s) led the multivariate process to an unnatural condition. In this paper, a comparative analysis is available and the compared results allowed the author to claim that the proposed model can be evaluated as an effective model to monitor the mean vector of a process involving more than one correlated random variable. Yang [82] evaluated the proposed model when the correlated quality variables of a process follow different correlation coefficients.

As discussed before, profile monitoring as a new approach to monitor a process involving a functional relationship, is attended by researchers. Recently, Atashgar et al. [83], investigating the Allan variance issue as a complex function that addresses a nonlinear regression, proposed an ANN to monitor the profile of Allan variance. The Allan variance is used to measure the stability of tools, such as oscillators and amplifiers. The architecture of the model follows MLP type using a hidden layer. The flow of training of the network described in this paper followed a complex manner. The report indicates that the proposed ANN is capable of helping practitioners to monitor the condition of the process, i.e. the process works under a natural condition or an assignable cause has shifted the process to an out-of-control condition. The ANN model, designed by Atashgar et al. [83], addresses performing a diagnostic analysis to specify contributing variable(s) to the out-of-control condition at the same time as the model signals an out-of-control condition. Logistic sigmoid behavior is used as the transfer function in this introduced model. Furthermore, Levenberg-Marquardt and Early stopping have been approached in the training algorithm and generalization feature, respectively. Atashgar et al. [83], considering a numerical example, lead the readers to an effective performance for the proposed scheme using ARL and correct classification terms.

4.3. Change point schemes

As discussed before, change point detection is referred to as an essential phase of a root cause analysis when a process shifts to an out-of-control condition. Actually, the change point leads practitioners to the point when the change really has manifested itself to the process. Ahmadzadeh and Noorossana [74] proposed a model to identify mean change point. They investigated the process when a step shift affects the mean vector and MEWMA procedure used to detect the out-of-control condition. The model can only be activated after addressing an unnatural condition in a multivariate process by a control chart. Later, Ahmadzadeh (2009) published the same model in more detail. Her model follows a back propagation algorithm with three layers of input, hidden, and output. The author used tangent sigmoid as the transfer function for the hidden layer and a linear function for the output layer. The training phase of the proposed model approached the Levenberg Merquardt quasi network. The model has been analyzed using data simulated by the Mont Carlo simulation technique and it is provided in-control ARL 200. The model is the first ANN based model to address identification of the multivariate change point in the literature. The two reports contributing towards the change point issue by Ahmadzadeh [75] and Ahmadzadeh and Noorossana [74] do not address the analysis of the robustness of the model when the random variables follow different correlation coefficient values. However, the authors only considered the correlation coefficient, 0.5, for the variables belonging to the process. Moreover, the proposed model studied only the step change type and the report on the model is limited for use where the process experiences an unknown change type. Ahmadzadeh et al. [84] later developed the scheme reported by Ahmadzadeh and Noorossana [74] and Ahmadzadeh [75]. They reported the developed ANN model, which is not only capable of identifying the change point, but is also developed to diagnose the variable(s) responsible for the out-of-control condition when the mean vector of a multivariate process is affected by a sudden change. In this report, they assumed the mean vector includes four variables, and its covariance matrix is known when the process is monitored. The report states that the assumed process follows multivariate normal distribution. Indeed, Ahmadzadeh et al. [84] increased a network to the work reported by Ahmadzadeh and Noorossana [74] and Ahmadzadeh [75] to provide the capability of diagnosing the variable(s) responsible. In this developed model, one is required to use a control chart such as MEWMA to detect an out-of-control condition, i.e. the developed model is not yet capable of presenting a comprehensive report simultaneously when a multivariate process is monitored. Ahmadzadeh et al. [84] reported that their proposed model trained under unit variance and a correlation coefficient of 0.5 by assuming a significant level of 0.005. The ANN model presented by Ahmadzadeh et al. [84] excludes the report corresponding to the case when more than one parameter of the multivariate process is affected by an especial cause.

The discussion clears most schemes proposed in the literature were analyzed assuming a step change takes place in the process. However, different types of deterioration may affect the parameter(s) of a process, leading to an out-of-control condition. Step change is only one of the change types that may appear in the process. It is potentially possible, in practice, that a change follows a gradient shape, and then the process may drift, influencing a change type gradually. In this case, the trend of the process is affected linearly, and then the change type is referred to as linear change type. Tool wear, corrosion in a gearbox, and corrosion in a pipe, leading to increased leakage, gradually, are due to the change type following the linear trend. Atashgar and Noorossana [63] addressed an artificial neural network based model to help practitioners to detect an out-of-control condition in a bivariate environment, and simultaneously help to identify the change point and diagnostic analysis when the mean vector is allowed to change linearly. They used a novel procedure called subinterval, as introduced previously, to manage the behavior of networks when the iteration of intervals by itself cannot lead the networks to an effective learning. The new approach allows a researcher to manage the type of training in more detail. By identifying the weakness of the learning phase, the subinterval approach, based on the results of the performance analysis for each of the intervals, allows the designer to define subintervals to overcome the weakness of each of the intervals. The subinterval was approached first by Atashgar [76] when he undertook his PhD dissertation. The effectiveness of the procedure is examined by Atashgar and Noorossana [47,63,64,66,77] and Noorossana et al. [48] for several models. The subinterval approach is commented upon, especially when a multivariate process with correlation random variables is studied. Atashgar and Noorossana [63] introduced their proposed model in detail. They discussed a procedure to standardize the input set, leading to the robustness performance for an ANN model when different correlation coefficients are evaluated.

In practice, rarely are the change types that may affect the parameter(s) of a multivariate process known a priori. Therefore, a scheme developed assuming a predefined change type does not allow the practitioners to use the scheme when the change type is unknown. Assuming a predefined change type in the process addresses the existence of the restriction on using the model. In other words, in a real case, it is not always practical to assume the same change type for all variables of a multivariate process a priori. Hence, a scheme, regardless of predefined change type, is desirable for practitioners in practical cases. For cases when the change type of the source(s) affecting the process is unknown, Atashgar and Noorossana [47], without assuming a change type, proposed a comprehensive model to provide all the required knowledge, leading to an effective root cause analysis. The interesting results corresponding to the analyzed performance of the introduced model indicate that the model performs effectively, regardless of how change type and change direction may affect the variables of a multivariate process. Although the report addresses a very interesting model, the authors have not considered the process, including more than two random variables. Atashgar [78] evaluated a scheme to provide monitoring a process involving more than two variables. The proposed scheme following ANN approach addressed an effectiveness model, where the case of a multivariate environment is considered.

To summarize, effectively, the discussion leading to future studies based on the models introduced in literature, Table 6 was designed to show all the information. Table 6 shows the capabilities and specifications of the different ANN based models discussed in literature. The summarized information allows the researchers to find a total image of the ANN models of multivariate environments in literature. Table 6 directs the reader to find the main specifications considered by the researchers to design their proposed model; however, it might be a model for various conditions when performing the test. The column entitled by “SHIFT SIZE” is addressed. Although an author(s) designed an ANN considering standard deviation for the shift, the test for the model has been also evaluated considering non centrality.

In this paper, investigations of different technical specifications corresponding to different models proposed in literature address the level of effectiveness of the performance of the models, and tries to compare the ANN schemes. Naturally, this review is cannot be more in depth, however, some schemes have been designed, focusing on only a specified condition. For instance, some models trained assuming the correlation coefficient value is equal to 0.5, and also the reported test of the model addressing this value is based on the evaluation of the performance. Naturally, in this case, the applicability is in doubt.

In the literature, Psarakis [85] attempted to consider literature addressing an ANN based model to use in statistical process control approach. This paper focuses on presenting sources considering the ANN approach, but one is not led to an effective and comprehensive technical analysis by this report. Psarakis [85] only allocated a section of the paper to discuss multivariate process issues and did not provide a detailed discussion corresponding to artificial neural networks proposed in literature to monitor a multivariate process. Although this paper briefly reviewed a few sources contributing to monitoring a multivariate process, it can be used by researchers interested in developing ANN schemes to monitor a process statistically.

5. Conclusions

Control charts commonly relative to the size of a change, signals after real time when a change takes place in a process. A control chart only helps to detect an out-of-control condition, and hence, when a disturbance manifests itself in a multivariate process, it cannot perform an effective root cause analysis. Quality engineers can experience a root cause analysis effectively when there exists the opportunity of identifying the change point and conducting a diagnostic analysis, along with detecting the out-of-control condition at the same time. The three required pieces of knowledge (i.e. out-of-control signal, identification of change point, and diagnostic analysis), which lead practitioners to an effective root-cause analysis, are referred to as crucial knowledge.

When a change of a process is investigated, the change type(s) is also known as a principal point. In practice, rarely is the change type(s) known a priori, and then, when the real change type deviates from the predefined change type approached by a scheme, the performance of the scheme deteriorates considerably. The comprehensive consideration in this paper showed that the literature does not address a comprehensive scheme to provide all crucial knowledge simultaneously without assuming a predefined change type using the statistical method. This complicated case type led several researchers to approach soft computing, such as artificial neural network, to monitor multivariate processes. However, literature addresses only a few of them which effectively provide all the crucial knowledge at the same time without requiring a predefined assumption regarding the type of change.

This paper attempted to comprehensively and analytically survey the scientific reports focusing on monitoring a multivariate environment. The survey and the interesting reports corresponding to multivariate processes indicate that the schemes that approach ANN have more capabilities compared with schemes that are approached statistically. The literature shows that the ANN approach is also used to identify the direction of the change and its magnitude which allow the process to depart to an out-of-control condition.

Work is needed to develop the performance of the existing models, as well as to understand the capa-

Table 6. Comparative capabilities and properties of the models proposed in literature.

		Chance type			Shift size		Capabilities							Properties					
												Covariance type		Followed logic		Model architecture			
Reference	Affected parameter	Step	Linear	Combination (Unknown)	Standard deviation	Non centrality	Detection of out-of control condition	Identify change point	Diagnose	Shift magnitude	Shift direction	Equal	Non equal	Crisp	Fuzzy	Number of module	Number of NN	Window size	Network type
[49]	Mean	*			*		*					*		*		1	1		ND
[50]	Mean	*			*		*					*		*		1	1		ND
[51]	Mean	*			*		*					*		*		1	1		MLP
[52]	Variance	*			*		*					*		*		1	1	16 & 32	MLP
[53]	Mean	*			*		*					*		*		1	1		RBF
[58]	Mean	*			*				*	*		*		*		1	1	5	MLP
[59]	Mean	*			*				*			*		*		1	1		MLP
[61]	Mean	*			*	Evaluated			*			*		*		2		12	Ensemble
[48]	Mean	*			*		*	*	*		*	*		*		3	6	12	MLP
[63]	Mean		*		*	Evaluated	*	*	*			*		*		2	3	12	MLP
[65]	Mean	*				*			*			*		*		1	1		MLP
[66]	Mean	*	*	*	*	Evaluated	*		*			*		*		1	1	12	MLP
[44]	Mean	*				*	*		*	*	*	*		*		2	5	12	MLP
[46]	Mean	*			*		*		*			*		*		1	1	30	MLP
[67]	Variance	*			*				*				*	*		1	1		MLP
[69]	Mean	*			*		*		*			*		*		2		12	Ensemble
[72]	Mean	*	*		*				*	*		*		*		4	12	56	MLP
[73]	Mean	*				*	*			*		*			*	2	2		MLP
[74]	Mean	*			*			*				*		*		1	1		MLP
[75]	Mean	*				*		*				*		*		1	1		MLP
[64]	Mean	*				*	*	*	*		*		*	*		3	7	12	MLP
[47]	Mean	*	*	*	*		*	*	*		*		*	*		3	7	12	MLP
[77]	Mean	*	*	*	*		*		*				*	*		2	3	12	MLP
[78]	Mean	*			+++		++++	*	*			*		*		2	2	12	MLP
[80]	Mean	*			*				*				*	*		2	1		MLP
[81]	Mean	*			*				*				*	*		2	1	24	
[82]	Mean	*			*	Evaluated	*		*					*		2		12	LVQ
[79]	Mean	*	*		*		*		*	*		*		*		2	3	12	MLP

bilities of ANN architecture. Some opportunities of research in monitoring multivariate parameters include the following:

1. The study to design a model to monitor, simultaneously, the crucial knowledge of a process involving high correlated variables without assuming a predefined change type;
2. Detection of spread or the shape of a distribution of a multivariate process when the change affects the spread or shape or both;
3. Some monitoring of ideas in health care and industrial areas focusing on small change detection;
4. There are many topics related to profile monitoring that deserve attention by authors.

As the use of ANN increases, there will be an increasing number of practical applications where the concept of the root cause analysis or statistical process control plays an essential role.

References

1. Shewhart, W.A., *Economic Control of Quality of Manufactured Product*, Milwaukee, WI: ASQ Quality Press (1931,1980).

2. Pyzdek, T., *Quality Engineering Handbook*, 2nd Edn., Marcel Dekker Inc. New York, Basel (2003).
3. Page, E.S. "Continuous inspection schemes", *Biometrika*, **41**, pp. 100-114 (1954).
4. Roberts, S.W. "Control chart tests based on geometric moving averages". *Technometrics*, **1**, pp. 239-250 (1959).
5. Lucas, J.M., and Saccucci M.S. "Exponentially weighted moving average control schemes: properties and enhancements", *Technometrics*, **32**, pp. 1-12 (1990).
6. Atashgar, K. "Identification of the change point: An overview", *International Journal of Advanced Manufacturing Technology*, **64**(9-12), pp. 1663-1683 (2013).
7. Hinkley, D.V. "Inferences about the change-point in a sequence of random variables", *Biometrika*, **57**, pp. 1-17 (1970).
8. Pettitt, A.N. "A simple cumulative sum type statistic for the change-point problem with zero-one observations", *Biometrika*, **67**(1), pp. 79-84 (1979).
9. Nishina, K. "A comparison of control charts from the viewpoint of change-point estimator", *Quality and Reliability Engineering International*, **8**(6), pp. 537-541 (1992).
10. Samuel, T.R., Pignatiello, J.J. Jr., and Calvin, J.A. "Identifying the time of a step change with X bar control charts", *Quality Engineering*, **10**(3), pp. 521-527 (1998).
11. Pignatiello, J.J. Jr. and Simpson, J.R. "A magnitude-robust control chart for monitoring and estimating step change for normal process means", *Quality and Reliability Engineering International*, **18**(6), pp. 429-441 (2002).
12. Perry, M.B. and Pignatiello, J.J. Jr. "Estimation of the change point of a normal process mean with a linear trend distribution in SPC", *Quality Technology and Quality Management*, **3**(3), pp. 325-334 (2006).
13. Perry, M.B., Pignatiello, J.J. Jr. and Simpson, J.R. "Estimating the change point of the process fraction non-conforming with monotonic change disturbance in SPC", *Quality and Reliability Engineering International*, **23**(3), pp. 327-339 (2007).
14. Noorossana, R. and Shadman, A. "Estimating the change point of a normal process mean with a monotonic change", *Quality and Reliability Engineering International*, **25**(1), pp. 79-90 (2009).
15. Habibi, R. "Change point detection using bootstrap methods", *Advanced Modeling and Optimizing*, **13**(3), pp. 341-347 (2010).
16. Hotelling, H. "Multivariate quality control-illustrated by the air testing of sample bombsights", In *Techniques of Statistical Analysis*, Eisenhart, C., Hastay, M.W. and Wallis, W.A., Eds., McGraw-Hill, New York (1947).
17. Woodall, W.H. and Ncube, M.M. "Multivariate CUSUM quality-control procedures", *Technometrics*, **27**(3), pp. 285-292 (1985).
18. Healy, J.D. "A note on multivariate CUSUM procedures", *Technometrics*, **29**(4), pp. 409-412 (1987).
19. Crosier, R.B. "Multivariate generalization of cumulative sum quality control schemes", *Technometrics*, **30**(3), pp. 291-302 (1988).
20. Pignatiello, J.J. Jr. and Runger, G.C. "Comparisons of multivariate CUSUM charts", *Journal of Quality Technology*, **22**(3), pp. 173-186 (1990).
21. Runger, G.C. and Testik, M.C. "Multivariate extensions to cumulative sum control charts", *Quality and Reliability Engineering International*, **20**(6), pp. 587-606 (2004).
22. Lowry, C.A., Woodall, W.H., Champ, C.W. and Rigdon, S.E. "A multivariate exponential weighted moving average control chart", *Technometrics*, **34**(1), pp. 46-53 (1992).
23. Rigdon, S.E. "An integral equation for the in-control average run length of a multivariate exponentially weighted moving average control char", *Journal of Statistical Computations and Simulation*, **52**(4), pp. 351-365 (1995).
24. Runger, G.C. and Prabhu, S.S. "A Markov chain model for the multivariate exponentially weighted moving average control chart", *Journal of the American Statistical Association*, **91**(436), pp. 1701-1706 (1996).
25. Kramer, H.G. and Schmid, W. "EWMA charts for multivariate time series", *Sequential Analysis*, **16**(2), pp. 131-154 (1997).
26. Runger, G.C., Keats, J.B., Montgomery, D.C. and Scranton, R.D. "Improving the performance of a multivariate exponentially weighted moving average control chart", *Quality and Reliability Engineering International*, **15**(3), pp. 161-166 (1999).
27. Tseng, S., Chou, R. and Lee, S. "A study on a multivariate EWMA controller", *IIE Transactions*, **34**(6), pp. 541-549 (2002).
28. Testik, M.C., Runger, G.C. and Borror, C.M. "Robustness properties of multivariate EWMA control charts", *Quality and Reliability Engineering International*, **19**(1), pp. 31-38 (2003).
29. Testik, M.C. and Borror, C.M. "Design strategies for the multivariate exponentially weighted moving average control chart", *Quality and Reliability Engineering International*, **20**(6), pp. 571-577 (2004).
30. Nedumaran, G., Pignatiello, J.J. Jr and Calvin, J.A. "Estimation of the time of a step-change with control chart", *Quality Engineering*, **13**(2), pp. 765-778 (1998).
31. Zamba, K.D. and Hawkins, D.M. "A multivariate change-point model for statistical process control", *Technometrics*, **48**(4), pp. 539-549 (2006).

32. Li, F., Runger, G.C. and Tuv, E. "Supervised learning for change point detection", *International Journal of Production Research*, **44**(14), pp. 2853-2868 (2006).

33. Noorossana, R., Arbabzadeh, N., Saghaie, A. and Painabar, K. "Development of procedure of detection change point in multi environment", *6th International Conference on Industrial Engineering*, Iran-Tehran (Written in Persian language) (2008).

34. Arbabzadeh, N. "Estimating of the change point of a multivariate normal process", Thesis of Degree of Master of Science in Industrial Engineering, Iran University of Science and Technology, Industrial Engineering Faculty (2008).

35. Mason, R.L., Tracy, N.D. and Young, J.C. "A practical approach for interpreting multivariate control chart signals", *Journal of Quality Technology*, **29**(4), pp. 396-406 (1997).

36. Jackson, J.E., *A User's Guide to Principle Components*, New York, NY: John Weily & Sons, Inc (1991).

37. Maravelakis, P.E., Bersimis, S., Panaretos, J. and Psarakis, S. "Identifying the out of control variable in a multivariate control char", *Communication in Statistics*, **31**(12), pp. 2391-2408 (2002).

38. Kalagonda, A.A. and Kulkarni, S.R. "Diagnosis of multivariate control chart signal based on dummy variable regression technique", *Communications in Statistics - Theory and Methods*, **32**(8), pp. 1665-1684 (2003).

39. Cajal, R.Y. "Histology of the nervous system of man and vertebras" [Histologie du systeme nerveux de l'homme et des vertebras], *Madrid, Consjo Sperior de Investigationes Cientificas* (1955).

40. Haykin, S., *Neural Networks a Comprehensive Foundation*, Printed by Prentice-Hall, Inc. New Jersey, USA (1994).

41. Zorriassatine, F. and Tannock, J.D.T. "A review of neural networks for statistical process control", *Journal of Intelligent Manufacturing*, **9**, pp. 209-224 (1998).

42. Pham, D.T. and Oztemel, E. "Combining multi-layer perceptrons with heuristics for reliable control chart pattern classification", *Applications of Artificial Intelligence in Engineering Conference Proceedings*, pp. 801-810 (1993).

43. Demouth, H. and Beal, M. "Neural network toolbox for use with MATLAB", *User's Guide Ver. 4*, Math Works Inc (2000).

44. Guh, R.S. "On-line identification and quantification of mean shifts in bivariate processes using a neural network-based approach", *Quality and Reliability Engineering International*, **23**(3), pp. 367-385 (2007).

45. Cheng, C.S. "A multi-layer neural network model for detecting changes in the process mean", *Computer and Industrial Engineering Journal*, **28**(1), pp. 51-61 (1995).

46. Hwarng, H.B. "Toward identifying the source of mean shifts in multivariate SPC: a neural network approach", *International Journal of Production Research*, **46**(20), pp. 5531-5559 (2008).

47. Atashgar, K. and Noorossan, R. "Identifying change point in a bivariate normal process mean vector with monotonic changes", *International Journal of Industrial Engineering and Production Management*, **21**(1), pp. 1-13 (2010).

48. Noorossana, R., Atashgar, K. and Saghaie, A. "An integrated solution for monitoring process mean vector", *International Journal of Advanced Manufacturing Technology*, **56**(5), pp. 755-765 (2011).

49. Zorriasatine, F., Tannock, J.D.T. and Brien, C. "Using novelty detection to identify abnormalities caused by mean shifts in bivariate process", *Computer and Industrial Engineering*, **44**, pp. 385-408 (2003).

50. Zorriasatine, F., Al-Habaibeh, A., Parkin, R.M., Jakson, M.R. and Coy, J. "Novelty detection for practical pattern recognition in condition monitoring of multivariate processes: a case study", *International Journal of Advanced Manufacturing Technology*, **25**, pp. 945-963 (2005).

51. Arkat, J., Niaki, S.T.A. and Abbasi, B. "Artificial neural networks in applying MCUSUM residual charts for AR(1) processes", *Applied Mathematics and Computation*, **189**, pp. 1889-1901 (2007).

52. Cheng, C.S. and Cheng, H.P. "Using neural networks to detect the bivariate process variance shift pattern", *Computers and Industrial Engineering*, **60**, pp. 269-278 (2011).

53. Rafajtowicz, E.S. "RBF neural network for probability density function estimation and detecting changes in multivariate processes", *Artificial Intelligence and Soft Computing, Lecture Notes in Computer Science*, **40**(29), pp. 133-141 (2006).

54. Hosseinifard, S.Z., Abdollahian, M. and Zeephongsekul, P. "Application of artificial neural networks in linear profile monitoring", *Expert Systems with Applications*, **38**, pp. 920-4928 (2011).

55. Kang, L. and Albin, S.L. "On-line monitoring when the process yields a linear profile", *Journal of Quality Technology*, **32**, pp. 418-426 (2000).

56. Pacella, M. and Semeraro, Q. "Monitoring roundness profiles based on an unsupervised neural network algorithm", *Computers & Industrial Engineering*, **60**(4), pp. 677-689 (2011).

57. Colosimo, B.M., Pacella, M. and Semeraro, Q. "Statistical process control for geometric specifications: On the monitoring of roundness profiles", *Journal of Quality Technology*, **40**(1), pp. 1-8 (2008).

58. Chen, L.H. and Wang, T.Y. "Artificial neural networks to classify mean shifts from multivariate chart signals", *Computers and Industrial Engineering*, **47**, pp. 195-205 (2004).

59. Niaki, S.T.A. and Abbasi, B. "Fault diagnosis in multivariate control charts using artificial neural network", *Quality and reliability Engineering International*, **218**, pp. 825-840 (2005).

60. Doganaksoy, N., Faltin, F.W. and Tucker, W.T. "Identification of out of control quality characteristics in a multivariate manufacturing environment", *Communications in Statistics-Theory and Methods*, **20**, pp. 2775-2790 (1991).

61. Yu, J.B., Xi, L.F. and Zhou, X. "Identifying source(s) of out-of-controlling signal in multivariate manufacturing process using selective neural network ensemble", *Engineering Applications of Artificial Intelligence*, **22**, pp. 141-152 (2009).

62. Hansen, L.K. and Salamon, P. "Neural network ensembles", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **12**, pp. 993-1001 (1990).

63. Atashgar, K. and Noorossana, R. "An integrating approach to root-cause analysis of a bivariate mean vector with a linear trend disturbance", *International Journal of Advanced Manufacturing Technology*, **52**(1), pp. 407-420 (2011).

64. Atashgar, K. and Noorossana, R. "A comprehensive scheme to monitor simultaneously all required knowledge for an effective root cause analysis", *The 2nd International Conference on Industrial Engineering and Operations Management (IEOM)*, Koulalanpour, Malazia (2011).

65. Aparisi, F., Avendano, G. and Sanz, J. "Tchniques to interpret control chart signal", *IIE Transactions*, **38**, pp. 647-657 (2006).

66. Atashgar, K. and Noorossana, R. "Diagnosing the source(s) of a monotonic change in the process mean vector", *International Journal of Advanced Manufacturing Technology*, **60**(9), pp. 1175-1183 (2012).

67. Cheng, C.S. and Cheng, H.P. "Identifying the source of variance shifts in the multivariate process using neural networks and support vector machines", *Expert Systems with Applications*, **35**, pp. 198-206 (2008).

68. Surtihadi, J., Raghavachari, M. and Runger, G.C. "Multivariate control charts for process dispersion", *International Journal of Production Research*, **42**, pp. 2993-3009 (2004).

69. Yu, J.B. and Xi L.F. "A neural network ensemble-based model for on-line monitoring and diagnose out-of-control signals in multivariate manufacturing processes", *Expert Systems with Applications*, **36**, pp. 909-921 (2009).

70. Breiman, L. "Bagging predictors", *Machine Learning*, **24**(2), pp. 123-140 (1996).

71. Kennedy, J. and Eberhart, R. "A discrete binary version of the particle swarm optimization", *In Proceedings IEEE International Conference on Computational Cybernetics and Simulation*, Piscataway, NJ, IEEE, pp. 4104-4108 (1997).

72. El-Midany, T.T., El-Baz, M.A. and Abd-Elwahed, M.S. "A proposed framework for control chart pattern recognition in multivariate process using artificial neural networks", *Expert Systems with Applications*, **37**, pp. 1035-1042 (2010).

73. Wang, T.Y. and Chen, L.H. "Mean shifts detection and classification in multivariate process: A neural-fuzzy approach", *Journal of Intelligent Manufacturing*, **13**(3), pp. 211-221 (2002).

74. Ahmadzadeh, F. and Noorossana, R. "Identifying the time of a step change with MEWMA control charts by artificial neural network", *The 8th International Industrial Engineering and Engineering Management Conference*, Singapore (2008).

75. Ahmadzadeh, F. "Change point detection with multivariate control charts by artificial neural network", *International Journal of Advanced Manufacturing Technology*, DOI 10.1007/s00170-009-2193-6 (2009).

76. Atashgar, K. "Estimating the change point of a multivariate normal process with a monotonic change using artificial neural network", Thesis for degree of doctor of philosophy in Industrial Engineering, Iran University of Science and Technology, Industrial Engineering Faculty (2010).

77. Atashgar, K. and Noorossana, R. "Identifying root causing monotonic change in the mean vector using artificial neural network", *The 8th International Conference on Management*, Tehran, Iran (2010).

78. Atashgar, K. "A multi task scheme to monitor multivariate environments using artificial neural network", *International Conference on Industrial Engineering (ICIE)*, Paris, France (2013).

79. Salehi, M., Bahreininejad, A. and Nakhai, I. "On-line analysis of out-of-control signals in multivariate manufacturing process using a hybrid learning-based model", *Neurocomputing*, **74**, pp. 2083-2095 (2011).

80. Huda, S., Abdollahian, M., Mammadov, M., Yearwood, J., Ahmed, S. and Sultan, I. "A hybrid wrapper-filter approach to detect the source(s) of out-of-control signals in multivariate manufacturing process", *European Journal of Operational Research*, **237**, pp. 857-870 (2014).

81. Masood, I. and Hassan, A. "A frame work for multivariate process monitoring and diagnosis", *Applied Mechanics and Materials*, **315**, pp. 374- 379 (2013).

82. Yang, W.A. "Monitoring and diagnosing of mean shifts in multivariate manufacturing process using two-level selective ensemble of learning vector quantization neural network", *Journal of Intelligent Manufacturing*, **26**(4), pp. 769-783 (2015). DOI 10. 1007/s10845-013-0833-z (2013).

83. Atashgar, K., Amiri, A. and Keramati Nejad, M. "Monitoring Allan variance nonlinear profile using artificial neural network approach", *International Journal of Quality Engineering and Technology*, **5**(2), pp. 162-177 (2015).

84. Ahmadzade, F., Lundberg, J. and Stromberg, T. "Multivariate process parameter change identification by neural network", *International Journal of Advanced Manufacturing Technology*, **68**, pp. 2261-2268 (2013).

85. Psarakis, S. "The use of neural networks in statistical process control charts", *Quality and Reliability Engineering International*, **22**(5), pp. 641-650 (2011).

Biography

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