A comprehensive scheme to monitor simultaneously all required knowledge for an effective root cause analysis

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Abstract

When a control chart indicates that a sustained disturbance has manifested itself to the process, practitioners begin a root cause analysis to find and eliminate the disturbance source. In the case of multivariate process, practitioners could experience an effective root cause analysis when a model leads them to identify four main knowledge including the out-of-control condition, the change point, the contributing source leading to the out-of-control condition and direction of the shift, all simultaneously. Although simultaneous identification of the main knowledge is a serious necessity, the existing methods in the literature fail to response the need when a multivariate process shifts to an out-of-control state. In this paper with an integrated monitoring approach a supervised learning based on a combination of artificial neural networks is proposed which helps practitioners to monitor all the required knowledge simultaneously, when a change(s) takes place in the bivariate process mean vector. Two case studies are used to verify and compare the performance of the proposed integrated approach under a step change assumption.

Key words: Change point, Artificial neural network, Statistical process control, Diagnostic analysis, Root cause analysis

1. Introduction

When a process shifts to an out-of-control state and the monitoring tool detects the out-of-control condition a search should be begun to find and eliminate the special cause. Several methods exist in the literature to monitor and detect any departure of the underlying process from in-control state to an out-of-control state for univariate and multivariate processes. Hotelling's T^2 , multivariate CUSUM (MCUSUM) and multivariate EWMA (MEWMA) are known as the common monitoring procedures in the multivariate processes. Hotelling [1] who introduced his proposed model using an applied example in a military sight uses only recent sample and relatively is insensitive when a small or a moderate shift induces itself to the process. In the sake of overcoming the weakness, MCUSUM and MEWMA methods have been investigated by several researchers. Several authors including Woodall and Ncube [2], Healy [3], Crosier [4], Pignatiello and Runger [5], Ngai and Zhang [6], Chan and Zhang [7], Qiu and Hawkins [8, 9], Runger and Testik [10] have investigated MCUSUM scheme for detecting an out-of-control condition in p-variate processes. For the issues related to MEWMA domain one can refer to the works done by Lowry et al. [11], Rigdon [12], Yumin [13], Runger and Prabhu [14], Kramer and Schmid [15], Prabhu and Runger [16], Fasso [17], Borror et al. [18], Runger et al. [19], Tseng et al. [20], Yeh et al. [21], Testik et al. [22, 23] and Chen et al. [24].

The time that an out-of-control signal appears on a control chart usually is not the first time when the change has manifested itself to the process. The time when the change first takes place in the process is referred to as the change point. Identification of the change point is known as an essential step for a root cause analysis. Although the proposed control charts are capable of detecting the out-of-control condition in a multivariate environment, they fail to identify the change point directly. To identify the step change point in a multivariate process Nedumaran et al. [25] proposed an estimator using maximum likelihood estimator (MLE). Moreover, Sullivan and Woodall [26] proposed a method to identify change point. Li et al. [27] also considered p-variate process with multiple mean change points using a supervised learning. All the stated proposed procedures must be used after detecting an out-of-control condition using another scheme like Hotelling's T^2 .

Although identification of the change point is an essential step in a root cause analysis, without diagnostic analysis of the parameter(s) contributing to the out-of-control condition, practitioners could not be led to an effective root cause analysis and corrective action when a multivariate process shifts to an out-of-control state. Neither proposed control charts nor proposed change point estimators are capable of diagnosing the parameter(s) responsible to the out-of-control condition directly. Several authors including Blazek et al. [28], Jackson [29], Funchs and Benjamin [30], Subramanyam and Houshmand [31], Mason et al. [32, 33], Atienza et al. [34], Maravelakis et al. [35] Niaki and abbasi [36] and Aparisi et al. [37] have considered interpretation of the variable(s) responsible when a multivariate process shifts to an out-of-control condition.

Each of the diagnostic analytical models itself is not able to provide all required knowledge without using other schemes.

Therefore, the existing methods in the literature are incapable to allow practitioners identifying an out-of-control condition, the change point, the variable contributing to the out-of-control condition and the shift direction simultaneously. Hence, practitioners could not be led to a comprehensive and proper root cause analysis when a multivariate process shifts to an out-of-control condition. In addition, the lack of an integrated monitoring solution (IMS) makes limiting in desired level of success of practitioners and allows increasing, 1) waste time, 2) stopping time of the production line when an out-of-control signal appears, 3) human intervention and 4) production cost.

In this paper a combination of artificial neural networks (ANN) is considered based on IMS which helps to address a comprehensive and effective root cause analysis in a bivariate environment. The proposed ANN could help practitioners to monitor all the required knowledge simultaneously, when a step change allows manifesting itself into the mean vector. This unique capability of the proposed model helps practitioners to effectively find and eliminate the source(s) of the assignable cause.

In the next section briefing of the proposed model is introduced. Section three provides the process of training to store the experiential knowledge. Two case studies and compared performance of the proposed model are presented in section four. In the final section concluding remarks are provided.

2. Briefing of the proposed ANNs

An artificial neural network (ANN) is a systematic tool which is designed to model the way in which the brain performs a function of interest through a process of learning. The structure of ANN allows storing experiential knowledge and making it available where the experienced knowledge could be used. The experiential knowledge is acquired through a learning process and the used synaptic weights make it to store the knowledge. Synapses mediate the interactions between neurons. The unique capability of ANN allows researchers to use it for complex problems of interest. So that ANN could help to solve problems that are difficult for conventional methods.

The proposed model consists of three modules. As shown in Figure 1, module I consists of an ANN (Network A) that after training will be able to detect the out-of-control condition and could also determine the new condition is due to one of the variables or both variables. Module II consists of two ANNs (Network B and Network C) that could help practitioners to distinguish the positive or negative direction of the shift of variable(s) responsible. Further, module II helps to identify the disturbance source when the condition is due to one of the variables. If Network A indicates the out-of-control condition is due to both variables, then Network B will distinguish the direction of each of the shifts. However, if Network A indicates that the out-of-control condition is due to one the variables, Network B will not be used and Network C will be activated to diagnose the variable responsible and its shift direction. Module III is designed to estimate change point in the process. Each one of the ANNs corresponding to module III (Networks D, E, F and G) based on a signal from module II will activate and estimate change point in the process mean vector. If a positive or negative shift in the mean of the first variable occurs then ANNs D or E will activate to identify the change point, respectively. If the out-of-control condition is due to the positive or negative shift in the mean of the second variable then ANNs F or G will be used to identify the change point, respectively. If the out-of-control condition is due to both variables, for the first variable one of the networks D and E and for the second variable one of the networks F and G associated with positive or negative mean shift will be used, respectively. In this case minimum output of the networks identifies the change point. This modularity approach helps the result of each ANN be traceable and allows managing performance of the model.

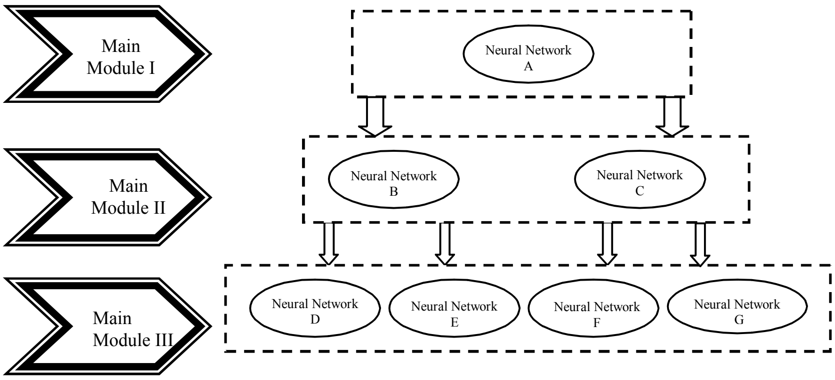

Figure 1: Main modules and secondary modules

In this research, since pattern recognition, off-line condition, and good capability in input-output mapping are sought then supervised learning is considered. Moreover, Multi layer perceptron (MLP) with back propagation algorithm is used in designing the desired model. Zorriassatine and Tannock [38], Guh [39] and Hwarng [40] have discussed the effectiveness of the algorithm in detecting process shifts.

The input layer of each designed ANN contains 24 neurons but the number of neurons in their hidden layers is not equal. The number of hidden layer neurons for each ANN along with the other detail information is represented in Table 1. Furthermore, the number of output layer neurons for each ANN is shown in Table 2. All the outputs are scaled within [0, 1]. As shown in Table 2, the output layer of Network A contains two neurons, where "one" indicates a mean shift in the process. If the first neuron indicates to "one" we will conclude that both elements of the mean vector have shifted. If the first neuron and the second neuron indicate to zero and "one", respectively, we will conclude that one of the variables has contributed to the out-of-control condition. The output layer of Network B, as shown in Table 2, contains four neurons to distinguish shift direction when the shift is due to both variables. The output layer of Network C contains four neurons to identify the variable responsible and the shift direction when one of the variables leads to the out-of-control condition. The output layer of each ANN of module III contains one neuron to allow detecting the change point in the process, where "one" indicates the time when the variable first has changed. For all the networks two transfer functions, hyperbolic tangent sigmoid and logistic sigmoid are used for the hidden layer and the output layer, respectively. Furthermore, for the proposed model “Early stopping” method is used to improve generalization.

Table 1: Detail specifications for the ANNs

Network	No. of Hidden Layer	No. of Hidden Layer Neurons	Training Algorithm
A	2	14	Trainlm
B	2	30	Trainbfg
C	2	30	Trainlm
D	2	19	trainbfg
E	2	19	Trainbfg
F	2	19	Trainbfg
G	2	19	Trainbfg

Table2: Output category for the Networks

Network A		Network B		Network C		Network D,E,F,G		Output			
$x_{i,1}$	$x_{i,2}$	$x_{i,1}$	$x_{i,2}$	$x_{i,1}$	$x_{i,2}$	$x_{i,1}$	$x_{i,2}$	1	2	3	4
S	S	P	P	P	NS	P/N	P/N	1	0	0	0
S/NS	NS/S	P	N	NS	P	-	-	0	1	0	0
-	-	N	P	NS	N	-	-	0	0	1	0
-	-	N	N	N	NS	-	-	0	0	0	1

S=shift, NS=No Shift, P=Positive mean shift, N=Negative mean shift

3. Training of the proposed model

Assume a sequence of independent output quality of a process be as $\boldsymbol{X}_1, \boldsymbol{X}_2, ..., \boldsymbol{X}_\tau, \boldsymbol{X}_{\tau+1}, ..., \boldsymbol{X}_T$, where $\boldsymbol{X}_i = (\mathrm{X}_{i1}, \mathrm{X}_{i2}, ..., \mathrm{X}_{ip})^T$ represents a $p \times 1$ random vector of related quality specifications and $\mathbf{X}_i$ with mean $\boldsymbol{\mu}_0 = (\mu_{01}, \mu_{02}, ..., \mu_{0p})$ and covariance matrix Σ, follows a p-variate normal distribution. If after the unknown time of τ a step change takes place in the process affecting the mean vector of $\boldsymbol{X}_\tau$ and it changes from μ_0 to μ_1 then τ be considered as the change point. In another word, through time τ the process is in-control state but after time τ a sustained disturbance affects mean vector in phase II and the process departures to an out-of–control state and a control chart generates a signal of out-of-control condition at a later time T. For the purpose of detecting the new condition one might compute the χ^2 statistic as:

$$\chi^2 = n(\overline{\boldsymbol{X}} - \mu_0)'\Sigma^{-1}(\overline{\boldsymbol{X}} - \mu_0) \qquad (1)$$

For the sake of simplicity, here a vector of observations consisting of two quality characteristics is considered, i.e. $N_2(\mu_0, \boldsymbol{\Sigma})$. It is assumed that based on phase I analysis the values for $\boldsymbol{\mu}_0$ and $\boldsymbol{\Sigma}$ are known and the proposed model is designed to monitor all the required knowledge assuming a mean step change.

In this paper Mont Carlo simulation is used to generate required data sets for training and test phases. Equation 2 is used for the purpose:

$$\boldsymbol{X}_t = \boldsymbol{\mu} + \boldsymbol{n}_t + \boldsymbol{k\sigma} \qquad (2)$$

where t indicates the sampling time and $\boldsymbol{X}_t$ is an independent random vector corresponding to the two quality characteristics measured at time t. When the process is in control, X_t follows $N(\mu_0, \Sigma)$, where the mean vector is $\boldsymbol{\mu}_0$ and Σ is the covariance matrix, as follow:

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix} \qquad (3)$$

Moreover, $\boldsymbol{n}_t$ follows $N(0, \Sigma)$ and represents the inherent cause variation at time t. Vector $\boldsymbol{k}$ represents the shift magnitude and defined as (k_1, k_2). Vector $\boldsymbol{k}$ with zero value indicates no shift in the mean vector.

To provide supervised learning, equation 2 is used to simulate the training data. The data sets are generated first from a bivariate normal distribution with unit variances and $\boldsymbol{\mu} = (0,0)'$ when the process is in the condition of in-control. Furthermore, shift magnitudes in each quality variable are allowed to take place from -3.25 to 3.25 with increments of 0.25. Based on the experience gained during the training phase of the network, we concluded to separate shift combinations in which the source of shift was due to one of the variables from the other combinations. Here sub-section method is used for effectiveness of the training. This is the same concept used by Atashgar and Noorossana [41]. Analysis showed that 676*16 and 52*685 out-of-control combinations in addition to 1000 in-control observations could be an optimal number of data sets for training the network. Where 676 is the combination cases due to the shifts in the mean of both variables and 52 is the combinations correspond to the shifts in the mean of only one of the variables. Further, 16 and 685 are the iterations for the first sub-section and the second sub-section, respectively. Therefore, 47436 different combinations of data sets were simulated to train network A.

Network B is trained using 100 iterations of combinations are associated with both variable being out of control. In addition, 2000 examples from in-control condition are used for this purpose. Two sub-sections with the exception of using 5200 out-of-control and 2000 in-control examples holds here for training network C.

To train networks D, E, F and G, shift magnitudes for each quality variable are allowed to take place in the intervals [-3.25 -1] and [1 3.25] with increments of 0.25, and in the intervals [-1 0] and [0 1] with increments of 0.05 leading to 1711 different shift combinations for each variable with positive mean shift or negative mean shift. Each shift combination in the variables is used suitably for training networks D through G.

The supervised learning process begins by specifying the change points in the training data. According the logic of the moving window which is discussed in next section, since the window is moving and data are entering to the window from the right side then any shift would correspond to the last observation in the window. Hence, the logic of moving window is considered here for defining correct output for the training data and the time of mean shift is equal to window size, i.e. 12.

To produce training data for ANNs D through G, Table 2 is used as a guiding rule. Table 3 provides the number of examples in each group for different networks of module III. For example, in network D there are 300 iterations and 413 shift combinations in group one, in group two there are 54 iterations and 1298 shift combinations, and 85,000 vectors of in-control observations leading to 278992 total examples. In this research MATLAB software has been used to develop the networks and perform the analyses.

Table 3: Number of examples for networks D-G

Group	**Network**			
	D	**E**	**F**	**G**
1	300*413	300*413	300*413	300*413
2	54*1298	54*1298	50*1298	54*1298
In Control	85000	85000	85000	90000
Total	**278992**	**278992**	**273800**	**283992**

4. Case study and comparison

4.1 Lumber production case study

Niaki and abbasi [36] have considered the production of a particular grade of lumber to demonstrate the diagnostic capability of their proposed bivariate model. The mean vector and the covariance matrix parameters corresponding to the measured stiffness and bending strength in unit of 1 b/sq inch which corresponds to in-control condition are as follow:

$$\boldsymbol{\mu}_L = \begin{bmatrix} 265 \\ 470 \end{bmatrix} \qquad \Sigma_L = \begin{bmatrix} 100 & 66 \\ 66 & 121 \end{bmatrix} \qquad R = \begin{bmatrix} 1 & 0.6 \\ 0.6 & 1 \end{bmatrix} \qquad (4)$$

They assumed due to an assignable cause the process shifts to an out-of-control state. Then they generated required data sets from a bivariate normal distribution when Σ_L was held constant and a magnitude of a step mean shift in each quality characteristic was allowed to take place from set A:

$$\boldsymbol{A} = \{(2\sigma,0),(0,2\sigma),(2\sigma,2\sigma),(2.5\sigma,0),(0,2.5\sigma),(2.5\sigma,2.5\sigma),(3\sigma,0),(0,3\sigma),(3\sigma,3\sigma)\} \quad (5)$$

They considered 500 detected out-of-control data sets for each scenario of set A when each mean shift scenario influences the lumber production line. The probability of the false alarm has been assumed equal to $\alpha = 0.005$.

In this research to evaluate the proposed model, suppose the process is under an in-control condition for the first 100 productions, but at time 101 an assignable cause affects mean vector and without any change to the covariance matrix the process shifts to an out-of-control state. In another words, at time 101 a sustained step mean shift, i.e. each of the scenarios of set A, is introduced to the process. Hence, the first 100 data sets are generated from an in-control bivariate normal distribution with mean vector $\boldsymbol{\mu_L}$ and covariance matrix $\boldsymbol{\Sigma_L}$. Since observations are generated from an in-control condition, any out-of-control observation vector whose χ^2 statistic exceeds UCL is considered as a false alarm (using equation 2) and it is treated the same way as one would treat it in a real case.

Moving window approach which has been considered by Hwarng and Hubele [42], Hwarng [40], Chang and Aw [43] and Cheng [39] for evaluating the performance of their proposed models is used in this research. In this approach, when the process is under an in-control condition the window first moves. As the window moves, measured characteristics under the shift enter the window from the right side. This concept is considered to evaluate the performance of the proposed model.

Table 4 shows the results obtained from the proposed model and the results obtained from Niaki and abbasi [36] model in term of error rate percentage. Error rate percentage is calculated as:

ER%=1-correct classification percentage (6)

As shown in Table 4, the diagnostic analysis capability of Niaki and abbasi [36] model which they reported on table I of their paper is very weaker than the capability of the proposed model. Also, Niaki and abbasi [36] model is not a comprehensive model, because it is incapable of detecting the out-of-control condition, identifying the change point and distinguishing shift direction for an out-of-control process.

Table 4: Comparing Niaki [36] model and proposed model

No.	**Shift**	**Error Rate %**		**Improving Percentage**
		Niaki (2005) Model	**Proposed Model**	
1	$(2\sigma,0)$	**15.4**	**5.9296**	**259.7139**
2	$(0,2\sigma)$	**12.6**	**2.5840**	**487.6161**
3	$(2\sigma,2\sigma)$	**13.8**	**0.2000**	**6900.0000**
4	$(2.5\sigma,0)$	**9.8**	**3.7864**	**258.8210**
5	$(0,2.5\sigma)$	**11.6**	**2.7808**	**417.1461**
6	$(2.5\sigma,2.5\sigma)$	**10.8**	**0.2000**	**5400.0000**
7	$(3\sigma,0)$	**7.0**	**4.1728**	**167.7531**
8	$(0,3\sigma)$	**14.6**	**3.3792**	**432.0549**
9	$(3\sigma,3\sigma)$	**4.6**	**0.2000**	**2300.0000**

4.2 Chemical industry case study

The case study related to a chemical industry that Mason et al. [33] has considered is used here to evaluate the performance of the proposed model. They have considered two by-products NaOH and NaCL of a chemical industry. The measured parameters corresponding to the by-products which have been measured under an in-control condition are as follow:

$$\overline{\boldsymbol{X}} = \begin{bmatrix} 143.94 \\ 200.83 \end{bmatrix} \quad \boldsymbol{S} = \begin{bmatrix} 225.80 & 91.81 \\ 91.81 & 116.37 \end{bmatrix} \quad \boldsymbol{R} = \begin{bmatrix} 1 & 0.57 \\ 0.57 & 1 \end{bmatrix} \quad (7)$$

Assume at the time 101 a step shift affects mean vector and the process shifts to an out-of-control state. The 120 scenarios available in Table 5 are simulated for 10,000 iterations. The simulated results are represented in Table 5. The first row of Table 5 indicates to the out-of-control average run length. The second row represents the error rate percentage. The third row shows the error rate percentage related to distinguish the shift direction when each shift scenario allows taking a place in the process. The two last rows represent the average of estimated change point and standard error, respectively. Table 5 shows the performance of the proposed model improves along with the magnitude of shifts gets larger.

Table5. Performance of proposed model for the case study 2

Shift combination	**-3,-3**	**-3,-2.5**	**-3,-2**	**-3,-1.5**	**-3,-1**	**-3,0**	**-3,1**	**-3,1.5**	**-3,2**	**-3,2.5**	**-3,3**
ARL	3.0503	3.2666	3.7272	4.6745	7.0321	10.4472	13.4702	6.0429	3.9656	3.2552	2.8455
Error Rate(Dia.) %	0.90	0.75	0.55	0.65	7.15	9.63	20.69	1.03	1.24	1.3	1.52
Error Rate(Dir.) %	0.41	0.31	0.34	0.35	0.53	0.59	1.57	1.04	0.71	0.72	1.18
Change Point	100.2762	100.3294	100.4174	100.4883	100.5555	100.5455	100.4026	100.3117	100.2431	100.1777	100.0943
Standard Error	0.0043	0.0055	0.0076	0.0098	0.0117	0.0111	0.0073	0.0052	0.0038	0.0025	0.0013
Shift combination	**-2.5,-3**	**-2.5,-2.5**	**-2.5,-2**	**-2.5,-1.5**	**-2.5,-1**	**-2.5,0**	**-2.5,1**	**-2.5,1.5**	**-2.5,2**	**-2.5,2.5**	**-2.5,3**
ARL	3.5330	3.6651	4.0780	4.9911	7.4939	11.0492	13.3132	6.0469	4.2913	3.6861	3.3300
Error Rate(Dia.) %	0.94	0.83	0.54	0.45	5.32	9.10	18.56	1.34	1.54	1.78	1.83
Error Rate(Dir.) %	0.41	0.40	0.39	0.38	0.49	0.59	2.09	1.39	1.27	1.18	1.27
Change Point	100.538	100.6748	100.8092	100.9782	101.134	101.2812	100.9978	100.7799	100.6094	100.4581	100.1942
Standard Error	0.0109	0.0155	0.0204	0.0287	30.058	0.0443	0.0295	0.0195	0.0138	0.0088	0.0028
Shift combination	**-2,-3**	**-2,-2.5**	**-2,-2**	**-2,-1.5**	**-2,-1**	**-2,0**	**-2,1**	**-2,1.5**	**-2,2**	**-2,2.5**	**-2,3**
ARL	4.2056	4.3200	4.6480	5.5682	8.4521	12.3517	15.8102	6.7977	4.9256	4.3793	4.0697
Error Rate(Dia.) %	1.86	1.20	0.71	0.58	2.55	8.18	18.62	1.99	2.48	2.65	3.11
Error Rate(Dir.) %	0.23	0.40	0.35	0.33	0.32	0.92	2.28	1.46	1.47	1.76	1.69
Change Point	100.4964	100.9635	101.5512	101.8637	102.2456	102.6596	102.351	101.9057	101.4805	100.7513	100.3201
Standard Error	0.0102	0.0289	0.0604	0.0839	0.1143	0.1667	0.1320	0.0890	0.0568	0.0176	0.0053
Shift combination	**-1.5,-3**	**-1.5,-2.5**	**-1.5,-2**	**-1.5,-1.5**	**-1.5,-1**	**-1.5,0**	**-1.5,1**	**-1.5,1.5**	**-1.5,2**	**-1.5,2.5**	**-1.5,3**
ARL	5.4963	5.4915	5.8118	6.8433	10.6540	16.2456	27.5288	10.6859	6.8966	6.0174	5.6725
Error Rate(Dia.) %	4.58	3.46	2.24	1.24	1.17	8.92	30.92	4.37	5.31	5.67	6.28
Error Rate(Dir.) %	0.73	0.57	0.38	0.49	0.38	1.41	2.53	1.74	1.97	2.24	2.49
Change Point	100.5605	101.1586	102.2954	103.6665	104.5140	106.3077	105.8435	104.6024	102.2958	101.0385	100.4632
Standard Error	0.0122	0.0390	0.1281	0.2928	0.4246	0.8498	0.7470	0.4371	0.1168	0.0297	0.0088
Shift combination	**-1,-3**	**-1,-2.5**	**-1,-2**	**-1,-1.5**	**-1,-1**	**-1,0**	**-1,1**	**-1,1.5**	**-1,2**	**-1,2.5**	**-1,3**
ARL	9.3559	9.4071	9.4342	10.5697	17.2176	42.2547	50.3134	28.0936	14.8841	11.5901	10.5758
Error Rate(Dia.) %	29.1	20.39	15.07	10.03	4.33	12.8	77.76	31.83	23.93	21.54	19.51
Error Rate(Dir.) %	2.74	1.93	1.20	0.61	0.58	2.42	3.24	3.15	3.92	4.27	5.50
Change Point	100.5878	101.2663	102.6652	105.4974	109.8048	115.6736	115.6978	106.3158	102.6959	101.2071	100.5532
Standard Error	0.0130	0.0455	0.1672	0.6453	1.9691	5.0289	5.0748	0.8383	0.1653	0.0394	0.0118
Shift combination	**0,-3**	**0,-2.5**	**0,-2**	**0,-1.5**	**0,-1**		**0,1**	**0,1.5**	**0,2**	**0,2.5**	**0,3**
ARL	9.7013	13.4409	16.1984	15.6229	20.6921		17.5131	10.8156	9.1447	8.7019	9.0685
Error Rate(Dia.) %	2.20	3.33	3.64	3.38	5.19		4.88	2.24	1.62	1.46	2.04
Error Rate(Dir.) %	0.69	0.78	0.85	1.15	2.66		3.96	1.57	1.04	0.71	0.72
Change Point	100.5557	101.2274	102.7709	106.8583	118.3377		112.0782	105.1033	102.4197	101.1996	100.5742
Standard Error	0.0114	0.0413	0.1832	1.0252	7.0183		3.0018	0.5527	0.1355	0.0401	0.0125
Shift combination	**1,-3**	**1,-2.5**	**1,-2**	**1,-1.5**	**1,-1**	**1,0**	**1,1**	**1,1.5**	**1,2**	**1,2.5**	**1,3**
ARL	14.1810	11.5347	11.0371	14.4653	42.764	65.3198	25.9778	17.2166	15.5818	16.8389	20.6122
Error Rate(Dia.) %	33.23	26.81	20.95	15.36	25.94	11.76	4.33	12.78	23.91	36.65	50.80
Error Rate(Dir.) %	4.37	4.34	3.55	3.38	2.68	2.68	0.80	0.73	0.98	1.68	2.72
Change Point	100.4217	100.9892	102.1122	105.3208	111.7586	116.0496	107.6364	103.6196	101.8313	100.9314	100.4837
Standard Error	0.0073	0.0260	0.1022	0.6200	2.3972	4.9483	1.2765	0.2970	0.0827	0.0259	0.0093
Shift combination	**1.5,-3**	**1.5,-2.5**	**1.5,-2**	**1.5,-1.5**	**1.5,-1**	**1.5,0**	**1.5,1**	**1.5,1.5**	**1.5,2**	**1.5,2.5**	**1.5,3**
ARL	7.5693	6.7190	6.7428	8.1868	15.5073	23.5895	12.9315	7.8576	6.6713	6.5887	7.3432
Error Rate(Dia.) %	13.73	11.16	8.34	6.36	11.91	6.41	1.75	0.58	1.52	2.34	3.72
Error Rate(Dir.) %	2.81	2.42	2.62	2.33	1.87	1.06	0.97	0.70	0.56	0.80	1.03
Change Point	100.3412	100.7761	101.7526	103.4868	104.8325	106.8785	104.7246	102.9088	101.4728	100.7802	100.4012
Standard Error	0.0055	0.0176	0.0703	0.2332	0.4410	0.9214	0.4484	0.1914	0.0550	0.0197	0.0074
Shift combination	**2,-3**	**2,-2.5**	**2,-2**	**2,-1.5**	**2,-1**	**2,0**	**2,1**	**2,1.5**	**2,2**	**2,2.5**	**2,3**
ARL	5.1303	4.8797	5.2562	6.6919	11.2452	14.7785	10.4365	6.0800	4.6539	4.0881	3.9062
Error Rate(Dia.) %	6.42	5.25	3.94	2.99	10.93	4.84	3.73	0.38	0.38	0.48	0.76
Error Rate(Dir.) %	2.27	1.94	1.95	1.68	1.62	0.99	1.84	0.66	0.53	0.52	0.51
Change Point	100.2356	100.5979	101.1418	101.5346	102.0807	103.0105	102.6000	101.9764	101.2256	100.6465	100.3191
Standard Error	0.0035	0.0121	0.0321	0.0549	0.0994	0.1983	0.1463	0.0890	0.0408	0.0146	0.0053
Shift combination	**2.5,-3**	**2.5,-2.5**	**2.5,-2**	**2.5,-1.5**	**2.5,-1**	**2.5,0**	**2.5,1**	**2.5,1.5**	**2.5,2**	**2.5,2.5**	**2.5,3**
ARL	3.7574	3.9328	4.5184	6.0413	10.3361	11.9134	9.9708	5.7014	4.0683	3.3490	2.9913
Error Rate(Dia.) %	3.90	3.23	2.52	2.79	11.27	4.23	6.48	0.33	0.27	0.32	0.38
Error Rate(Dir.) %	1.92	1.62	1.46	1.55	1.59	0.81	4.04	0.74	0.44	0.52	0.59
Change Point	100.1438	100.4084	100.5239	100.6896	100.9045	101.3742	101.3322	101.1229	100.9022	100.5226	100.2746
Standard Error	0.0020	0.0070	0.0096	0.0152	0.0246	0.0508	0.0465	0.0336	0.0231	0.0104	0.0043
Shift combination	**3,-3**	**3,-2.5**	**3,-2**	**3,-1.5**	**3,-1**	**3,0**	**3,1**	**3,1.5**	**3,2**	**3,2.5**	**3,3**
ARL	3.0326	3.3267	4.0552	5.7533	10.0788	10.6338	10.4252	5.6571	3.8677	2.9930	2.5983
Error Rate(Dia.) %	2.40	2.24	1.62	2.28	12.3	3.68	8.19	0.79	0.17	0.29	0.27
Error Rate(Dir.) %	1.54	1.33	1.40	1.21	1.59	0.75	7.43	1.24	0.57	0.47	0.45
Change Point	100.0942	100.1799	100.2238	100.2809	100.3672	100.5999	100.6963	100.6018	100.5185	100.3958	100.2108
Standard Error	0.0011	0.0023	0.0031	0.0042	0.0062	0.0133	0.0159	0.0127	0.0100	0.0070	0.0031

Dia. =Diagnostic Analysis Dir. = Shift Direction

5. Conclusion

The methods exist in the literature could not lead to an appropriate root cause analysis when a change(s) takes place in a multivariate process. When a multivariate process shifts from in-control state to an out-of-control state, an appropriate root cause analysis requires four main knowledge including detection of an out-of-control condition, identification of the change point, diagnosis of the variable(s) contributing to the out-of-control condition and distinguishing of the shift direction. Hence, an applied scheme could lead practitioners to a proper root cause analysis and an effective corrective action if only the scheme identifies the main knowledge, all simultaneously.

In this paper, an integrated monitoring solution (IMS) based on artificial neural network is proposed which allows practitioners to access all the required knowledge simultaneously. The proposed model was evaluated via two case studies. The reported results indicate that, in practice, the proposed model could help practitioners effectively.

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