



Process Variation Identification Using Small Recognition Window Size

Ibrahim Masood^{1*}, Azray Idiz Azizi¹

¹Faculty of Mechanical and Manufacturing Engineering,
Universiti Tun Hussein Onn, 86400 Parit Raja, Batu Pahat, Johor, Malaysia

*Corresponding Author Designation

DOI: <https://doi.org/10.30880/rpmme.2021.02.01.006>

Received 05 March 2021; Accepted 25 March 2021; Available online 15 April 2021

Abstract: Identification of unnatural mean shifts variation is challenging when involve with two or more correlated variables (bivariate). Statistical process control (SPC) is applied for improving product quality through statistical. The number of samples used is small window of size. Just-in-time (JIT) is applied because it required a small batch of sample to ensure the production is keep on running once have a demand. The scheme that used for identified the out-of-control variation is Statistical Features-Multilayer Perceptron (SF-MLP). Recognition accuracy (RA) was used as the performance measures. The best statistical features obtain from this study are Maximum and minimum values of each variable (Minmax), mean, slope, sinus, vector, and last value of exponentially weighted moving average (LEWMA) with recognition accuracy average in between (RA = 85 ~ 96 %).

Keywords: Statistical Process Control, Multilayer Perceptron, Recognition Accuracy, Statistical Features.

1. Introduction

Statistical Process Control (SPC) has been a major process industry solution or technique until today. SPC is a sufficiency way to enhance processes through the widespread use of statistical and process analysis tools and techniques to improve product quality. By reducing the cost of high-quality production of defective products to achieve the main objective of SPC. Dr. Walter A. Shewhart was developed a statistical process control chart that commonly used for previous researchers [1]. In general, a chart plot is a diagram of a mechanism with statistically determined limits generally over time. It allows the consumer to decide the correct type of process when used for controlling process variation process action to take.

In fact, manufacturing process were used two or sometimes more dependent variables. Therefore, appropriate planning is needed to monitor and detect these variables simultaneously. In this case, the number of samples is needed to be in the small size of window. The small size of sample is usually related to the Just-in-Time (JIT) process. JIT is required a small batch of production in a manufacturing because to ensure that the production is keep on running when it is required without it being delayed in inventory [2].

1.1 Problem statement

The problem is when faced with two associated variables in quality control, it is difficult to consider the unnatural mean shifts variance (bivariate). The traditional multivariate statistical process control (MSPC) charting schemes such as Chi-square (T^2), multivariate cumulative sum (MCUSUM) and multivariate exponentially weighted moving average (MEWMA) control charts have been developed and widely implemented [3]. These schemes are useful and effective for monitoring, for example, statistically identifying the status of processes running in-control or out-of-control. Unfortunately, there is no diagnostic feature in this scheme that can identify the cause that is out of control. The existing SPC pattern recognition scheme was mainly developed based on large recognition window size (WS). For example, Guh and Shieu [3] and Chen et. al [4] are 24 WS, Hassan and Nabi Baksh [5], Hassan et. al. [6] is 20 WS, and Gauri and Chakraborty [7] is 32 WS. However, this approach will not be suited for Just-in-Time (JIT) because it required in a small batch production. Theoretically, a smaller window size may produce inconsistent and lower accuracy of point recognition performance.

1.2 Purpose of study

The purpose of this research is to design, develop SPC pattern scheme and test runs a scheme for enabling accurate diagnosis of bivariate process mean shifts using small window size. The scheme's characteristics correspond to bivariate processes (correlated data streams) and on-line condition (dynamic data streams). The diagnosis recognition capability shall be improved by applying or performing design of experiment technique during the selection of feature base (FB) input representation.

2. Materials and Methods

In this section, the emphasis is on the development of the SPC ANN pattern recognition scheme for bivariate in order to classify variance sources in small window sizes. It is also discussing about the raw data for input representation and the optimization method of ANN to be used to recognized the shift pattern. Design of experiment (DOE) was design to determined the performance of recognition accuracy.

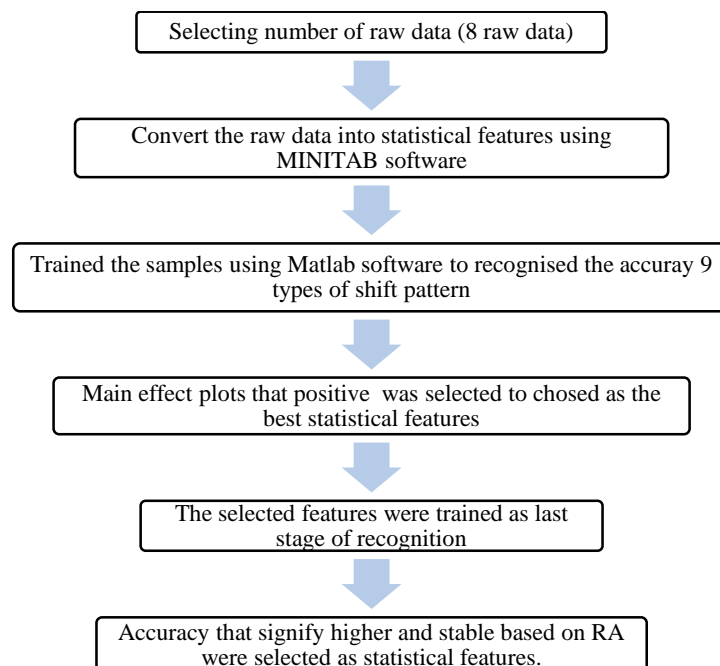


Figure 1: Design of Experiment (DOE)

2.1 Materials

Number of raw data is 8. Then, raw data is converted into statistical features using minitab software. The number of statistical features were used as input representation for diagnosed the recognition accuracy. The selected suitable input representation for an ANN recognizer is Lewma, minmax, mean, standard deviation, slope, sinus, and vector.

2.2 Methods

The input representation can be selected by using the design of experiment (DOE) method. The figures show the design on the pattern recognition to diagnosed the statistical features by using computational software that is Matlab software, measure the shift pattern based on the recognition accuracy (RA) and if there have any error on training data, there have a corrective action on it. Artificial neural network (ANN) that perform to detect the lowest false alarm is Multilayer Perceptron (MLP). Bivariate process variation is limited to nine categories (US10, US01, US11, DS10, DS01, DS11, USDS, DSUS and N00). In a statistically out-of-control process state, predictable bivariate patterns are limited to sudden shifts (upward shift and downward shift) in component variables. Figure 2 show the SPC pattern recognition scheme.

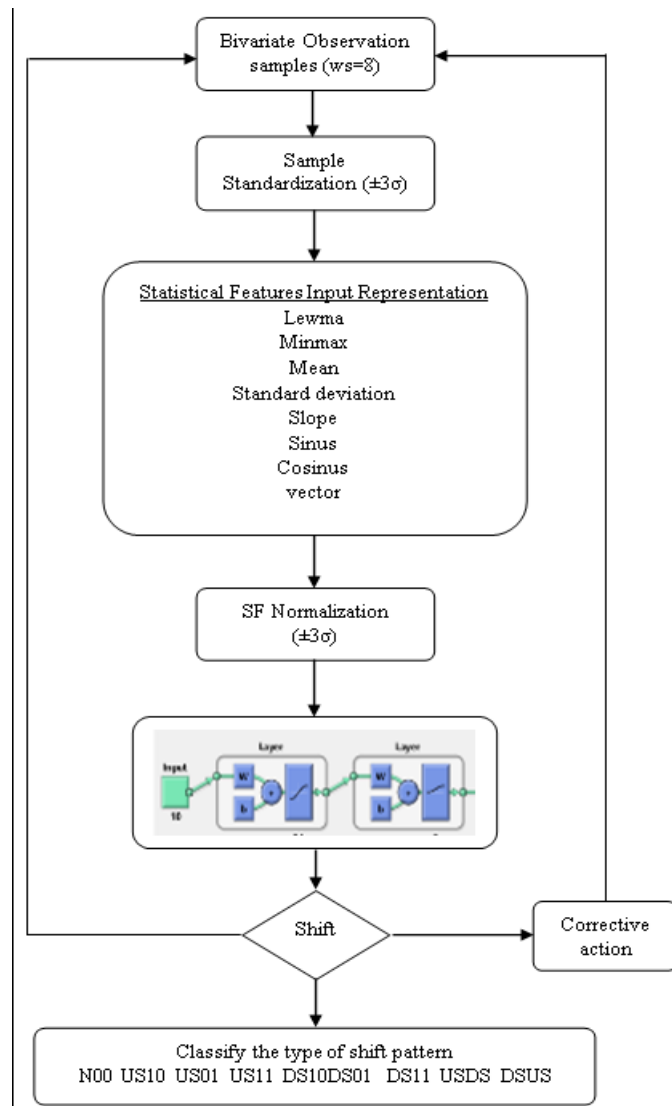


Figure 2: Statistical Features of MLP Recognition Scheme

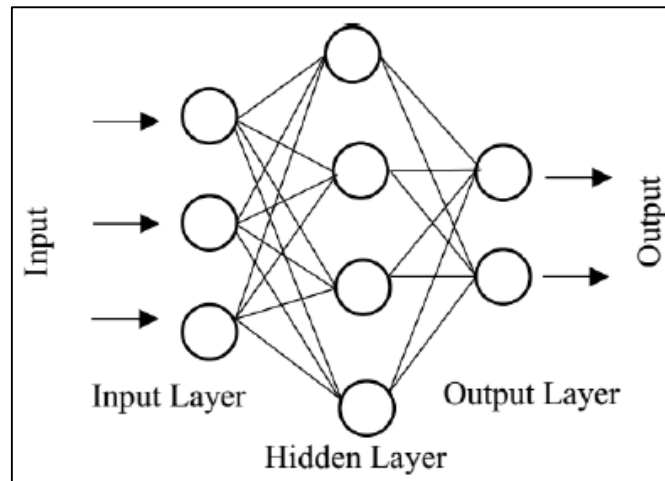


Figure 3: Multilayer Perceptron (MLP)

3. Results and Discussion

The procedure to obtain the result in this study are analyze based on design of experiment (DOE) that has designed. The results are obtain started from selecting number of raw data, converting raw data into statistical features, and lastly diagnose the samples based of accuracy of RA.

3.1 Results

After simulation stage, there have result for 16 of data at first phase. Each of data diagnosed according to the positive number of input representation. Based on table, 13th run and 14th run are the highest accuracy for TOT with 92.5%. The impact of LEWMA on each run is make the accuracy high because LEWMA can reacts more quickly Based on this observation, it can be inferred that the candidate characteristics can contain effective and ineffective pattens. This means that in relation to the efforts to enhance recognition accuracy, any feature may have a positive, negative or null effect. All of the result tabulates on the Table 1 shows that the results of statistical features of MLP scheme at first phase.

Table 1: Result of Statistical Features of MLP Scheme at First Phase

Run	N00	US10	US01	US11	DS10	DS01	DS11	USDS	DSUS	TOT	MSE	TIME	EPOCH
1	75.7	91	90.6	94.1	89.6	91.4	94.4	93.3	92.8	89.8	0.0113	0:01:56	37
2	87.7	93.2	92	95.7	93.6	0	0	96	95.8	73.2	0.0286	0:00:33	5
3	86.4	91	91.2	95.4	90.5	90.5	95	94.4	93.9	91.7	0.00853	0:00:32	5
4	83.2	91.5	91.5	94	89.9	91.8	93.2	92.9	92.4	90.8	0.0101	0:01:14	5
5	86.9	92.4	93.4	94.6	92.7	91.5	94.4	93.4	94.8	92.4	0.00875	0:00:42	8
6	0	0	0	0	0	0	0	0	0	0	0	0	0
7	70.6	91.3	91.6	95.6	91.8	91.1	93.6	92.3	92.4	89.4	0.0118	0:01:45	32
8	87.1	90.7	91.5	94.2	92	93.5	94.6	94.7	94.4	92.2	0.00846	0:00:34	5
9	80.6	91.3	90.6	93.8	0	91.1	95	93.6	94.8	79.1	0.0221	0:14:12	320
10	86.3	91.5	92.4	95.3	92.6	91.3	93.9	95	94.8	92.2	0.00822	0:00:33	5
11	92.7	95.3	0	0	94.5	0	0	0	0	36.5	0.0655	0:00:41	8
12	0	0	0	99.8	96	96	0	97.1	96.9	50.6	0.0515	0:00:32	5
13	86.6	91.3	91.9	94.6	92.4	94.1	94.7	94.9	95.1	92.5	0.00813	0:00:33	5
14	86.4	92.2	92.4	96.1	91	91.9	95.6	95.9	94.7	92.5	0.00858	0:01:29	25
15	85.6	91.7	91.5	94.3	90.4	92.3	94.4	94.2	94.4	91.7	0.00864	0:00:32	5
16	88.2	93.1	92.1	95.5	91.8	0	95.7	95.6	96	81.6	0.0197	0:00:33	5

However, some of the statistical features are not perform well on diagnosed the data. The statistical features are selected again to get the best accuracy among the all the statistical features. Based on the main effect plots in Figure 4 the features are selected if it performs positive effect. The features are minimum and maximum, last value of exponentially weighted moving average, mean, slope, sinus, and vector. However, the statistical features were categorised by set. Then, the set of statistical features are diagnosed at second phase.

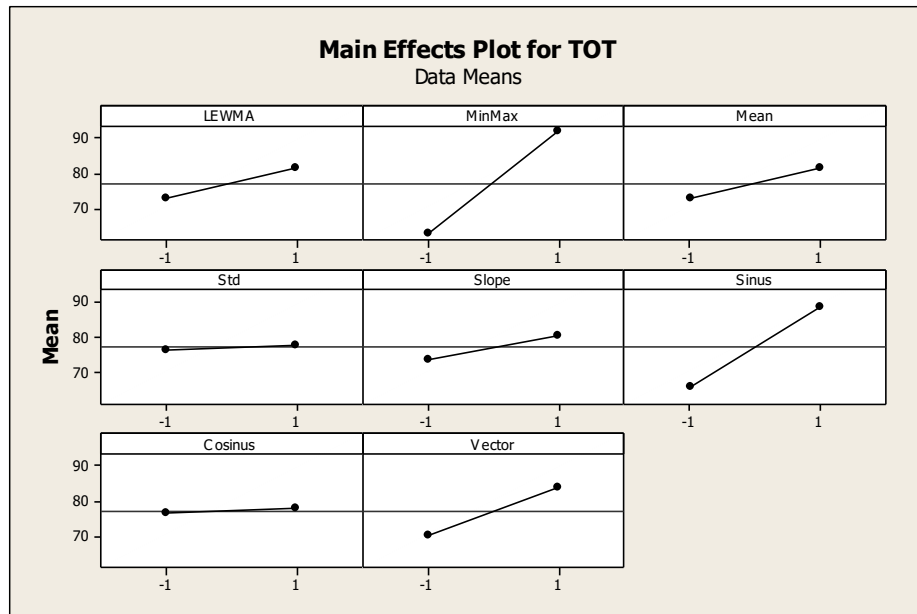


Figure 4: Main Effects Plot

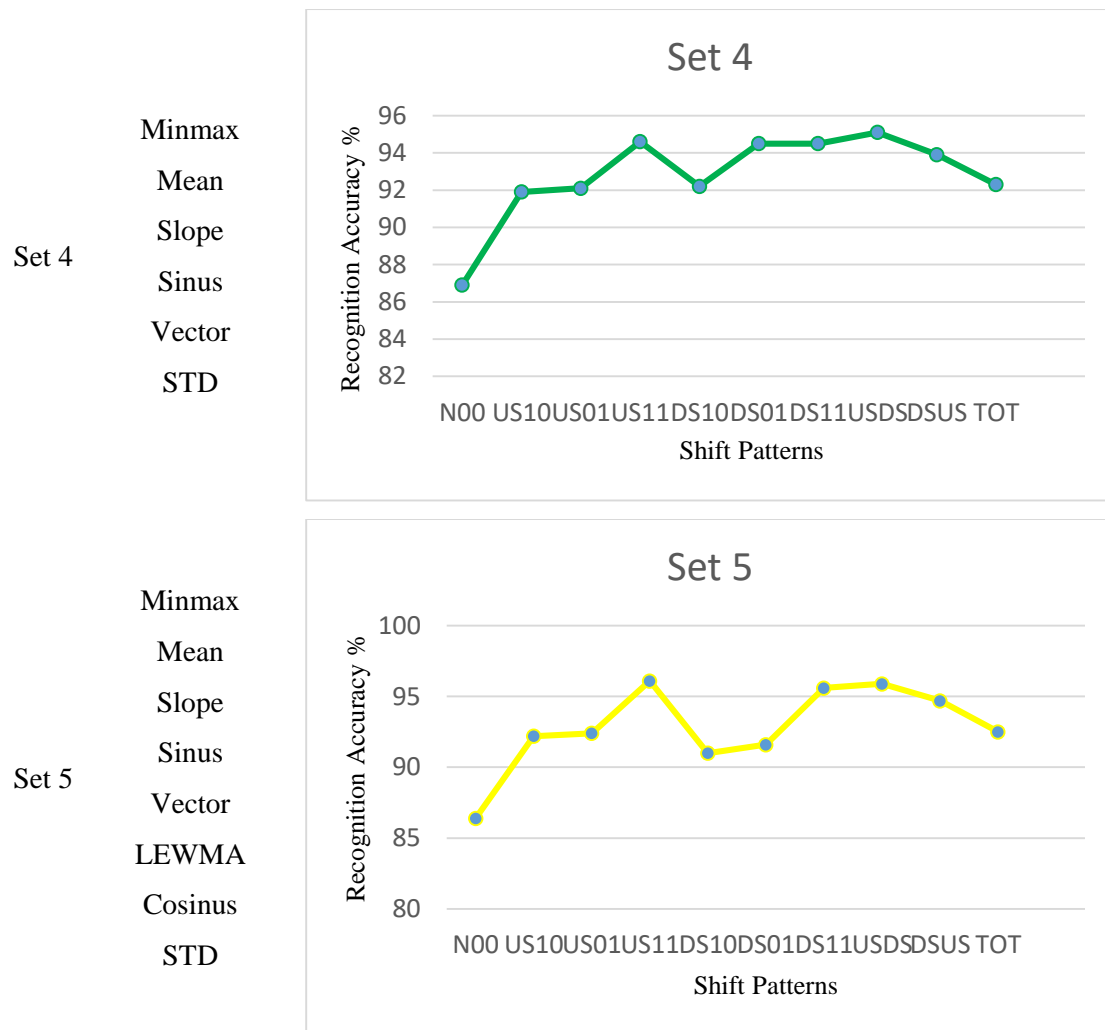
After selecting five statistical features based on the main effect plots, the input representation was utilized on the last stage to recognize the pattern and results. Based on Table 2 set 2 was chosen as the best result of bivariate statistical pattern recognition scheme. This is because, the data result is more stable compared to the other set. The range of percentage between bivariate percentage are not far. The performance of recognition accuracy is in between (RA = 85.4 ~ 95.6 %). Fluctuated of the graph in Table 3 for all data set can be seen similar but when compared clearly through the graph it can be seen that other than set 2 are not stable. Even though there has certain higher accuracy on a few SF, but for overall it fluctuates highly.

Table 2: Result of Statistical Features of MLP Scheme at Second Phase

	N00	US10	US01	US11	DS10	DS01	DS11	USDS	DSUS	TOT
Set 1	86	90.7	92.4	94	92.4	91.6	92.8	95.3	94.3	91.9
Set 2	85.4	90.4	92.9	95.6	91.4	92	94.4	95.6	94.4	92
Set 3	85.6	91.4	91.7	95.7	92.4	91.6	93.4	94.9	94.6	92
Set 4	86.9	91.9	92.1	94.6	92.2	94.5	94.5	95.1	93.9	92.3
Set 5	86.4	92.2	92.4	96.1	91	91.6	95.6	95.9	94.7	92.5

Table 3: Interpreting Results to Graph

Set	SF	Graph																						
Set 1	Minmax Mean Slope Sinus Vector	<p style="text-align: center;">Set 1</p> <table border="1"> <caption>Set 1 Data</caption> <thead> <tr> <th>Shift pattern</th> <th>Recognition Accuracy %</th> </tr> </thead> <tbody> <tr><td>N00</td><td>86</td></tr> <tr><td>US10</td><td>91</td></tr> <tr><td>US01</td><td>93</td></tr> <tr><td>US11</td><td>94</td></tr> <tr><td>DS10</td><td>92</td></tr> <tr><td>DS01</td><td>91</td></tr> <tr><td>DS11</td><td>93</td></tr> <tr><td>USDS</td><td>95</td></tr> <tr><td>DSUS</td><td>94</td></tr> <tr><td>TOT</td><td>92</td></tr> </tbody> </table>	Shift pattern	Recognition Accuracy %	N00	86	US10	91	US01	93	US11	94	DS10	92	DS01	91	DS11	93	USDS	95	DSUS	94	TOT	92
Shift pattern	Recognition Accuracy %																							
N00	86																							
US10	91																							
US01	93																							
US11	94																							
DS10	92																							
DS01	91																							
DS11	93																							
USDS	95																							
DSUS	94																							
TOT	92																							
Set 2	Minmax Mean Slope Sinus Vector LEWMA	<p style="text-align: center;">Set 2</p> <table border="1"> <caption>Set 2 Data</caption> <thead> <tr> <th>Shift Patterns</th> <th>Recognition Accuracy %</th> </tr> </thead> <tbody> <tr><td>N00</td><td>85</td></tr> <tr><td>US10</td><td>90</td></tr> <tr><td>US01</td><td>93</td></tr> <tr><td>US11</td><td>95</td></tr> <tr><td>DS10</td><td>91</td></tr> <tr><td>DS01</td><td>92</td></tr> <tr><td>DS11</td><td>94</td></tr> <tr><td>USDS</td><td>95</td></tr> <tr><td>DSUS</td><td>94</td></tr> <tr><td>TOT</td><td>92</td></tr> </tbody> </table>	Shift Patterns	Recognition Accuracy %	N00	85	US10	90	US01	93	US11	95	DS10	91	DS01	92	DS11	94	USDS	95	DSUS	94	TOT	92
Shift Patterns	Recognition Accuracy %																							
N00	85																							
US10	90																							
US01	93																							
US11	95																							
DS10	91																							
DS01	92																							
DS11	94																							
USDS	95																							
DSUS	94																							
TOT	92																							
Set 3	Minmax Mean Slope Sinus Vector Cosinus	<p style="text-align: center;">Set 3</p> <table border="1"> <caption>Set 3 Data</caption> <thead> <tr> <th>Shift Patterns</th> <th>Recognition Accuracy %</th> </tr> </thead> <tbody> <tr><td>N00</td><td>85</td></tr> <tr><td>US10</td><td>91</td></tr> <tr><td>US01</td><td>91</td></tr> <tr><td>US11</td><td>95</td></tr> <tr><td>DS10</td><td>92</td></tr> <tr><td>DS01</td><td>91</td></tr> <tr><td>DS11</td><td>93</td></tr> <tr><td>USDS</td><td>94</td></tr> <tr><td>DSUS</td><td>94</td></tr> <tr><td>TOT</td><td>92</td></tr> </tbody> </table>	Shift Patterns	Recognition Accuracy %	N00	85	US10	91	US01	91	US11	95	DS10	92	DS01	91	DS11	93	USDS	94	DSUS	94	TOT	92
Shift Patterns	Recognition Accuracy %																							
N00	85																							
US10	91																							
US01	91																							
US11	95																							
DS10	92																							
DS01	91																							
DS11	93																							
USDS	94																							
DSUS	94																							
TOT	92																							



4. Conclusion

In conclusion, this study is mainly focus to design SPC pattern recognition scheme for identifying shift variation in bivariate process using small recognition window size and improve the recognition performance using statistical features input representation. However, developing the SPC pattern recognition scheme is achieved using multilayer perceptron (MLP). The SF that resulted in high and stable performance condition on 9 types of shift patterns are last value of exponentially weighted moving average (LEWMA), maximum and minimum values of each variable (Minmax), mean, slope, sinus, and cosinus with recognition accuracy average in between (RA = 85 ~ 96 %).

Acknowledgement

This research was made possible this study as a requirement for graduate by the Ministry of Higher Education, Malaysia. The authors would also like to thank the Faculty of Mechanical and Manufacturing Engineering, Universiti Tun Hussein Onn Malaysia for its support.

References

- [1] M. Best and D. Neuhauser, "Walter A Shewhart, 1924, and the Hawthorne factory," *Qual. Saf. Heal. Care*, vol. 15, no. 2, pp. 142–143, 2006, doi: 10.1136/qshc.2006.018093.
- [2] V. Kumar, "JIT Based Quality Management: Concepts and Implications in Indian Context," *Int. J. Eng. Sci. Technol.*, vol. 2, no. 1, pp. 40–50, 2010.
- [3] R. S. Guh and Y. R. Shiue, "On-line identification of control chart patterns using self-organizing approaches," *Int. J. Prod. Res.*, vol. 43, no. 6, pp. 1225–1254, 2005, doi: 10.1080/0020754042000268884.
- [4] C. Cheng, "International Journal of A neural network approach for the analysis of control chart patterns," no. June 2013, pp. 37–41, 2010.
- [5] A. Hassan, M. Shariff Nabi Baksh, A. M. Shaharoun, and H. Jamaluddin, "Improved SPC chart pattern recognition using statistical features," *Int. J. Prod. Res.*, vol. 41, no. 7, pp. 1587–1603, 2003, doi: 10.1080/0020754021000049844.
- [6] I. Masood and A. Hassan, "Statistical features-ANN recognizer for bivariate process mean shift pattern recognition," 2010 *Int. Conf. Intell. Adv. Syst. ICIAS 2010*, no. January 2014, 2010, doi: 10.1109/ICIAS.2010.5716155.
- [7] M. Bag, S. K. Gauri, and S. Chakraborty, "An expert system for control chart pattern recognition," *Int. J. Adv. Manuf. Technol.*, vol. 62, no. 1–4, pp. 291–301, 2012, doi: 10.1007/s00170-011-3799-z.
- [8] S. Boran and D. D. Diren, "Analysis of out of control signals in multivariate processes with multilayer neural network," *Acta Phys. Pol. A*, vol. 132, no. 3, pp. 1054–1057, 2017, doi: 10.12693/APhysPolA.132.1054.