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Research Article

Orca-RBFNN: A New Machine Learning Method for Control Chart Pattern Recognition

Abdoljalil Addeh[1*], Noorbakhsh Amiri Golilarz[2], Tayyebeh Asgari Gashteroodkhani[3], Aref Moradkhani Roshandeh[4]

[1] *University of Calgary, Calgary, Canada*
[2] *School of Electrical, Computer, and Biomedical Engineering, Southern Illinois University Carbondale, Carbondale, Illinois, USA*
[3] *Department of Electrical and Computer Engineering, University at Albany SUNY, NY, USA*
[4] *University of Illinois at Urbana-Champaign, Illinois, USA*

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Abstract

Supervising the production process in different factories and industries is one of the important and basic measures for the production of high quality goods and is of special importance. This is accomplished by monitoring the behavior of a system. Control chart is one of the most widely used and accurate statistical quality control tools that has been used in recent years in various industries to monitor the production process. In this study, a new method for detecting control chart patterns (CCPs) with the aim of online monitoring of the production process is proposed. In the proposed method, the radial basis function neural network (RBFNN) is used as a classifier of CCPs and a combination of shape and statistical features is used as input. In the proposed method, unlike the conventional methods in the literature, which use a set of shape or statistical features as input, the features are used intelligently and at different steps. In the RBFNN, center of clusters, number of clusters and their spread has a high impact on the network performance. Therefore, their optimal value must be determined correctly. In the proposed method, Orca optimization algorithm (OOA) is used to determine the value of these parameters. The proposed method was tested on a data set containing 800 samples and the simulation results showed that the proposed method is able to identify eight CCPs with 99.41% accuracy.

1. Introduction

In recent years, controlling the production process and producing the best quality goods has become one of the most important parameters for many factories and products. Factories can attract more customers by improving the quality of manufactured goods and constant control over the production process. Given the competitive market in which competitors strive to produce

* **Corresponding Author:** Abdoljalil Addeh
E-mail address: abdoljalil.addeh@ucalgary.ca

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the best quality goods, it is essential that quality control tools and methods be developed and new methods used [1]. The main task of production process control and monitoring systems is to detect any disruption in the production process in the shortest possible time and to take corrective measures in order to solve the problem. Given these issues, automatic quality control systems are an important part of a modern factory. The following factors have led to the use of automatic control systems [2]:

- Human operators detect a small percentage of unreliable products during inspections.
- As the volume of data increases, the analysis of this data by human operators becomes more difficult and the possibility of error increases. Analyzing product quality data requires trained and experienced analysts to monitor the production process continuously and around the clock.
- Training of human experts and their presence will increase costs. By using intelligent methods to control the production process, the costs of control and supervision can be significantly reduced.

During the production process, the quality of the product may change for a variety of reasons. This must be reported to the production planning system. The most important reasons for quality change are lack of raw materials or semi-manufactured parts, quality problem of parts, machine breakdown, and absence of machine worker. The control chart is one of the most widely used and accurate statistical quality control tools introduced by Walter Schwartz.

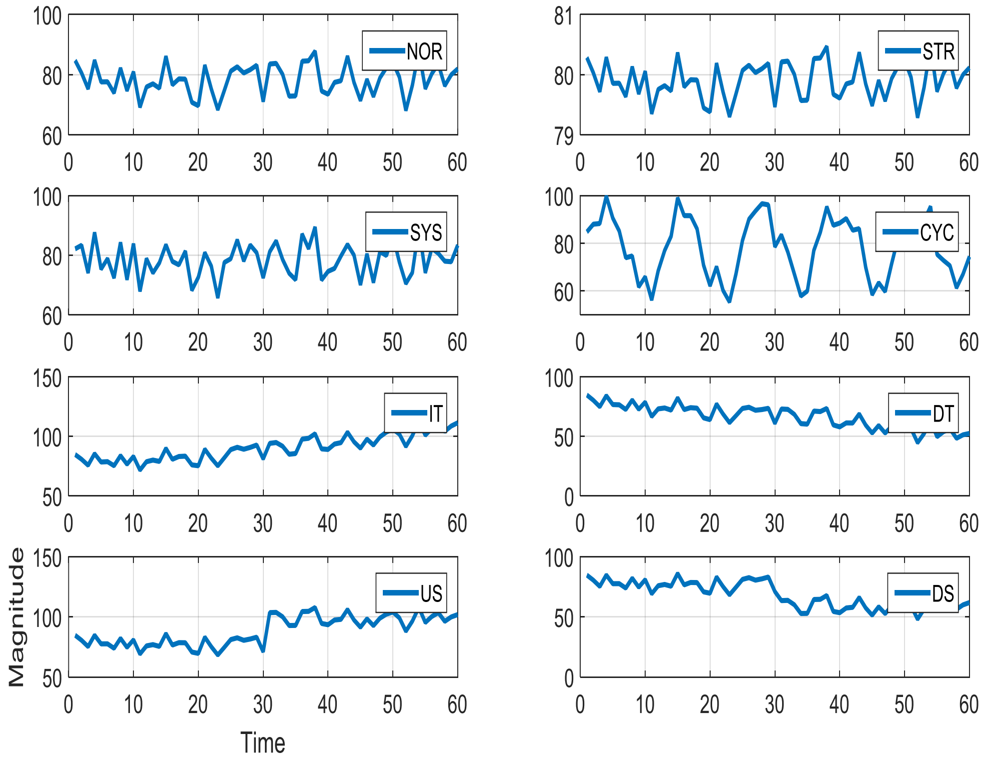

Figure 1. The eight CCPs [5]

Schwartz first used the control chart to control the quality of Bell products in New Jersey, USA, and since then this method has been one of the most widely used methods of quality control. Control chart is a useful tool for implementing statistical quality control system. The control diagram provides a graphical representation of process behavior that is used to monitor the production process and to identify abnormal conditions. Understanding control chart patterns (CCPs) is essential to quickly identify problems in the production process. In recent years, different types of production quality control table templates have been introduced in accordance with different quality properties and control objectives. The control table has eight main patterns called Normal (NOR), Systematic (SYS), Stratification (STR), Cyclic (CYC), Increasing Trend (IT), Decreasing Trend (DT), Upward Shift (US) and Downward Shift (DS). Figure 1 shows the different CCPs [3- 5].

The reasons for the emergence of each of the patterns are [5]:

- Systematic pattern: incorrect sampling and overlapping.
- Stratification pattern: If the system has noise.
- Cyclic patterns: Cyclic behavior with a peak and depression is observed in the process. The reasons for this are the periodic rotation of the operators and the environmental changes of the system or fluctuations in the equipment.
- Trend patterns: A trend pattern is defined as a continuous path, both positive and negative. The reason for this is the corrosion and wear of the tools and the fatigue of the operators and the loss of equipment and vice versa.
- Shift Patterns: A shift occurs suddenly, below or above the average (normal) process. This is because the raw materials have been replaced periodically, or a small defect has occurred in the machine parts located in the factory, or a new workforce has arrived and so on.

During the production process, the factory may have problems and one of the above patterns may be created. To quickly fix a problem, you must first identify where the problem occurred. For this reason, correct diagnosis of the type of pattern is very important. Due to the importance of the issue, in recent years, extensive studies have been conducted in this regard and various methods have been proposed to control the production process. Most of the introduced methods have used machine learning (ML) algorithms such as multi-layer Perceptron neural network (MLPNN), support vector machine, adaptive neuro-fuzzy system (ANFIS), probabilistic neural network (PNN) [6- 22].

By studying the developed methods on detection of CCPs, it can be seen that four main issues including type of classifier, its learning algorithm, type of input, and number of inputs to classifier have must be considered carefully. If it is possible to design a system in which these issues are properly considered, one can expect the diagnosis to be made with high accuracy. In most ML-based methods to recognize CCPs, the type and structure of the classifier is not seriously studied and their simplest form is used to recognize the patterns. In most of these studies, the back propagation (BP) algorithm or its modified versions have been used for training. In addition, in order to increase the accuracy of diagnosis in previous studies, only a series of shape, statistics, frequency, etc. features have been extracted and all of them have been used as classifier input. Previous studies have shown that the use of new features has increased relative accuracy, but the simultaneous use of all features as the input can also lead to a decrease in accuracy, because:

- Some of the newly extracted features contain duplicate and redundant information that, when used as a classifier input, complicates the issue and reduces accuracy.
- Some new features can provide information to the classifier that bias the classifier in a certain direction and ultimately reduce the accuracy of the diagnosis.

Therefore, these features should be used intelligently. Given the importance of controlling the production process and the existence of fundamental shortcomings in previous methods, it seems necessary to introduce a new method that has high accuracy and robust performance in this field. In this study, a new method based on RBFNN and effective shape and statistical features is proposed. Orca optimization algorithm (OOA) has also been used to train the network and determine its optimal structure. The OOA is a new meta-heuristic algorithm that is inspired from hunting strategy of Orca in nature. More details about the proposed method and its performance are given in sections three and four.

2. Basic Concepts

2.1. RBFNN

The RBFNN, along with its structural simplicity and training efficiency, is a suitable tool for performing a nonlinear mapping between input and output vector spaces. The network is a fully connected forward structure and consists of three layers, an input layer, a single layer of nonlinear processing units and an output layer. The network structure is shown in Figure 2.

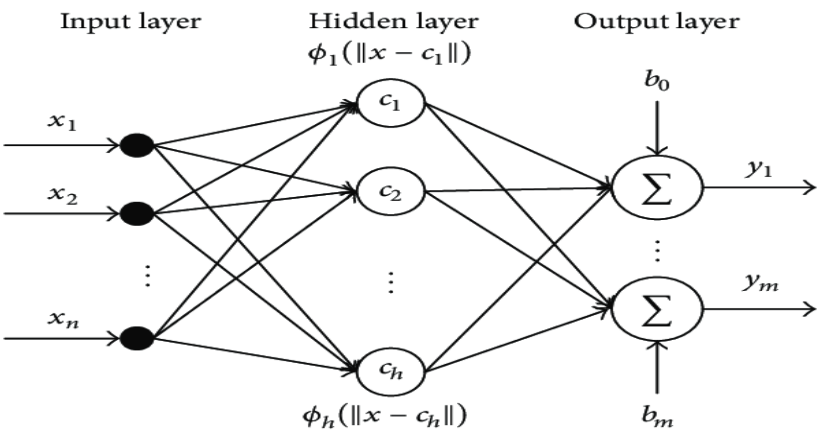

Figure 2. Structure of RBFNN

Let $h_j(.)$ be the jth radial function. The output of each radial function can be computed using Eq. (1) [23]:

$$H_j = h(x,c,\sigma) = \exp(\|x - c_j\| / \sigma_j^2) \quad , \quad j = 1,\ 2,\ ....,\ m \tag{1}$$

In Eq. (1), $\mathrm{x} = (\mathrm{x}_1, x_2, ..., x_d)^T$ is the input vector to the network with dimension d, $\|.\|$ is Euclidean norm, $\mathrm{c}_j = (c_{1j}, c_{2j}, ..., c_{dj})^T$ is the j-th cluster's center and σ is its width or spread. The network's output, is the linear sum of RBFs, which can be computed using Eq. (2):

$$y = w_i^T H = \sum_{j=1}^{m} w_{ij} H_j \quad , \quad i = 1,\ 2,\ ....,o \tag{2}$$

In this equation, y and o show the network's output and number of outputs, $w_i = [w_{i1}, w_{i2}, \dots, w_{im}]^T$, $i = 1, 2, \dots, o$ are the weight vectors, $H = [H_1, H_2, \dots, H_m]^T$ is the vector of basis functions [23]. The standard RBFNN, uses K-means clustering algorithm for clustering the input data and the number of RBFs usually is equal to number of samples in the training dataset.

2.2. Orca Optimization Algorithm

Orcas living in Antarctic region utilize the cunning tactic of repeatedly hunting in a crowd and forming strong waves for washing the seals off drifting ice block. The population produce strong waves in different directions and then they continuously repeat this treat until the target falls from the ice into the ocean. The optimization model of OOA is briefly discussed in [24]. In this optimizer, each orca is considered as the unknown variable of the problem.

3. Proposed Method

In Figure 4, the eight CCPs are shown simultaneously. In this figure, the horizontal axis represents the time and the vertical axis represents the signal value. It can be seen that these patterns are very similar and it is very difficult to separate them from each other. In the meantime, it is much more difficult to distinguish NOR, SYS, STR and CYC patterns, IT and US patterns, and DT and DS patterns. Figure 5 shows the boxplot of CCPs.

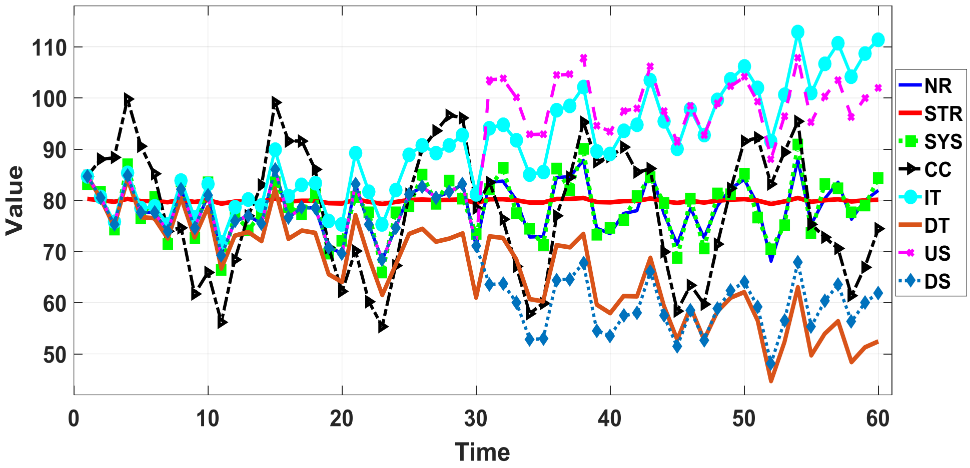

Figure 4. Eight patterns simultaneously

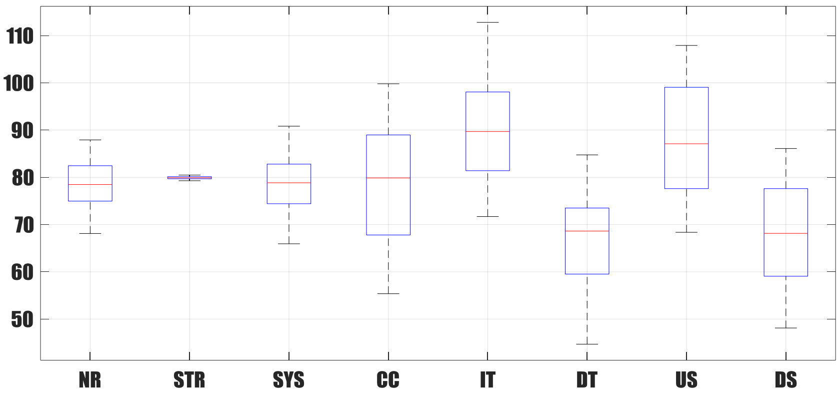

Figure 5. Boxplot of CCPs

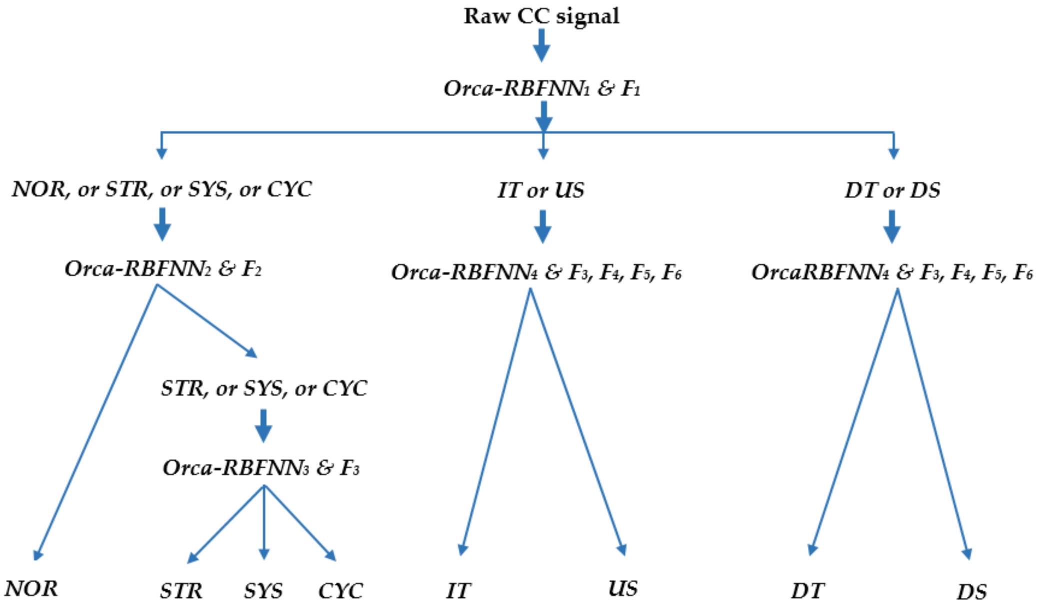

Figure 6. Main steps of the proposed method

In the proposed method, five RBFNNs with a new learning algorithm based on the OOA are used as the main classifiers and a combination of shape and statistical features is used as the input of different RBFNNs. In the proposed method, unlike the previously developed methods, which use a set of shape or statistical features as input, the features are used intelligently and in different steps. The structure of the proposed method is shown in the Figure 6.

In the developed method, four shape features introduced in [25], a shape features introduced in [26] and a statistical feature presented in [27] have been used at different steps. These features include:

F_1) the slope (S) of the least-square line representing the pattern [25].

F2) Mean of signal [27]

F_3) the area between the pattern and the mean line [25].

F_4) the slope difference between the least-square line and the line segments representing a pattern [25].

F_5) the area between the pattern and its least-square line (APSL) [25]

F_6) MVSASTI: the maximum value of variation in signal amplitude in a short time interval [27].

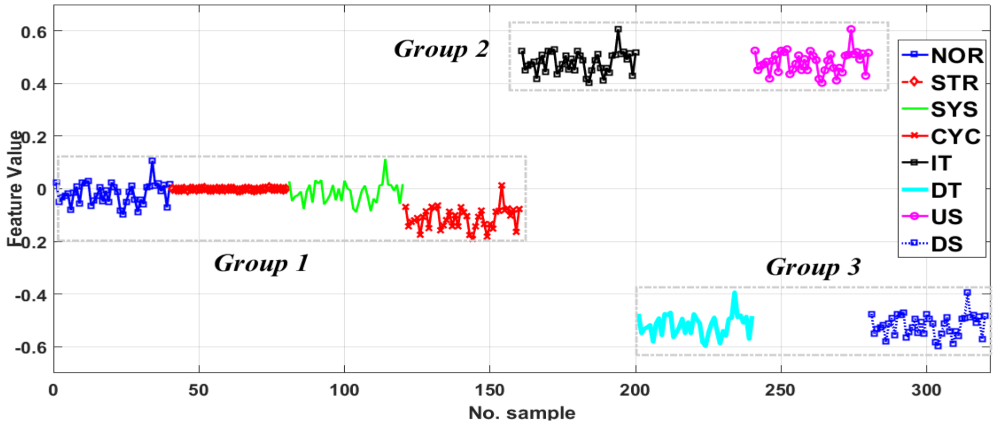

Figure 7. F_1 value for CCPs

In the first stage of decision-making, using F_1 and $RBFNN_1$, the eight CCPs are divided into three groups. As shown in Figure 7, the value of F_1 is almost the same for NOR, SYS, STR and CYC patterns (first group of patterns), IT and US (second group of patterns), and DT and DS (third group of patterns). In this study, 100 samples are for each pattern and 40% of data are used for training purpose. The illustrated values in Figures 7 to 11 are related to training dataset. In training dataset, there are 40 samples of each pattern, so the number of samples drawn in the figures is 320 ($8\ CCPs \times 40 = 320$).

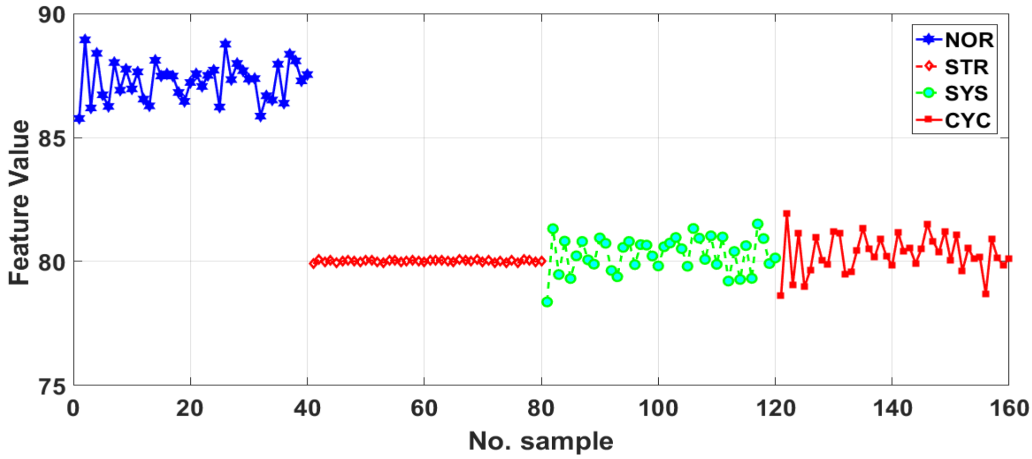

Figure 8. F_2 value for CCPs in Group 1

After the patterns are divided into three groups, the final separation must be performed in each of these groups. In the first group, the four patterns of NOR, SYS, STR and CYC must be distinguished. The F_2 and F_3 are used for this purpose. The value of F_2 is shown in Figure 8. Using F_2, and $RBFNN_2$, the normal pattern can be distinguished from other group 1 patterns with 100% accuracy.

In the first group, three patterns including SYS, STR and CYC remain, which are separated by the F_3 in the next step. The value of this feature is shown in Figure 9. It can be seen that the value of this feature has a completely different value for SYS, STR and CYC patterns, and these patterns can be separated with high precision. Therefore, using the properties of F_2 and F_3, the patterns of group one can be easily distinguished.

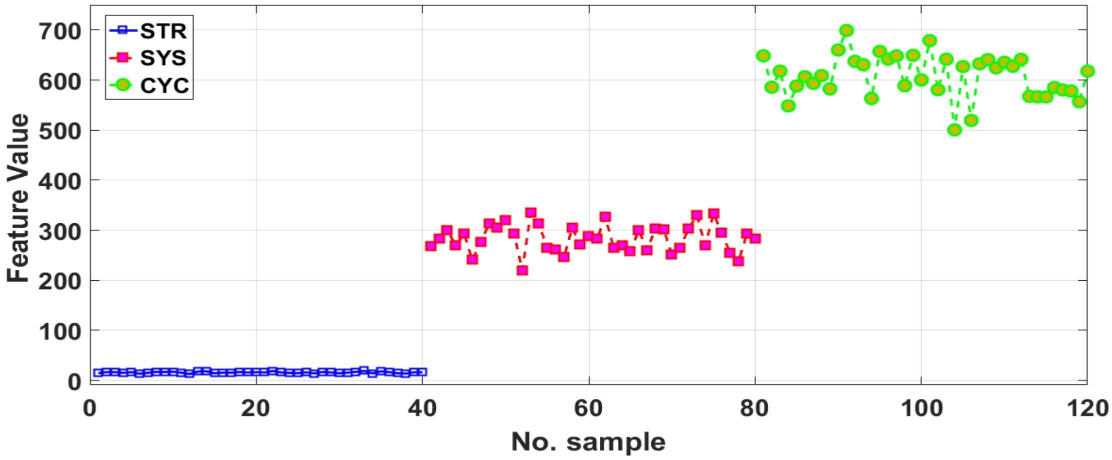

Figure 9. F_3 value for STR, SYS and CYC

The main problem in distinguishing CCPs is the separation of trend and shift patterns. In the proposed method, we face this problem in the second and third groups. As can be seen from Figures 4 and 5, these two patterns overlap strongly and their separation from each other may be done with a high error. To overcome this problem, four shape properties (F_3, F_4, F_5 and F_6) whose values are almost distinct for these patterns have been used as effective features. These features are shown for trend and shift patterns in Figures 10 and 11. For all these features, the shift pattern has a higher value than the trend pattern.

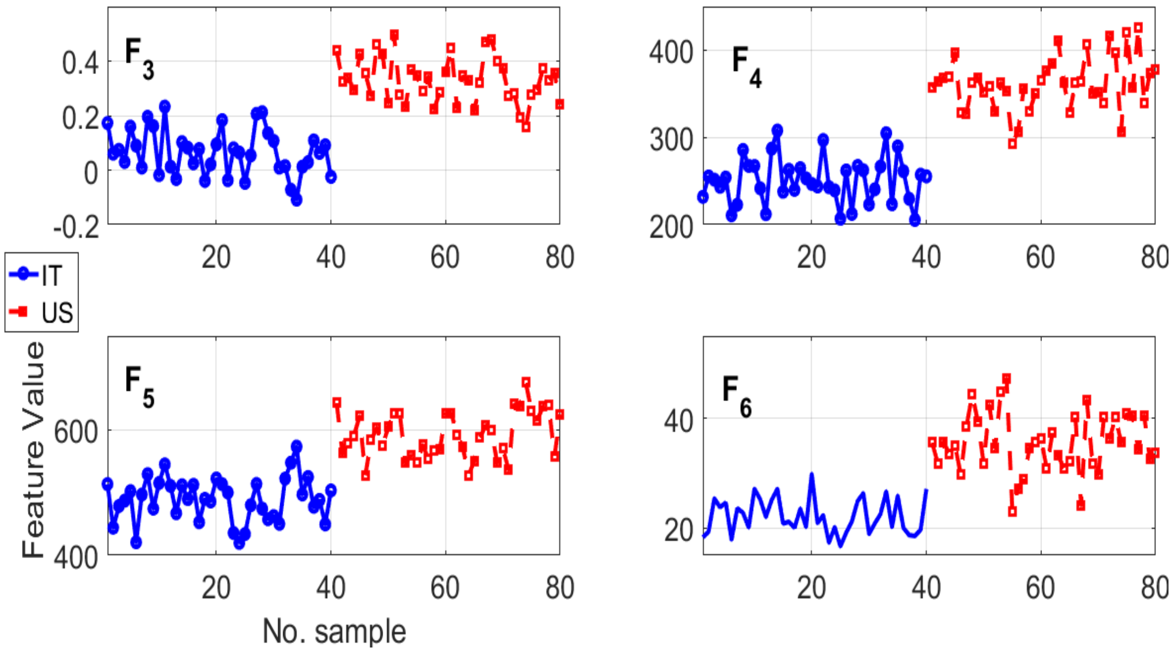

Figure 10. F_3, F_4, F_5 and F_6 value for CCPs in Group 2

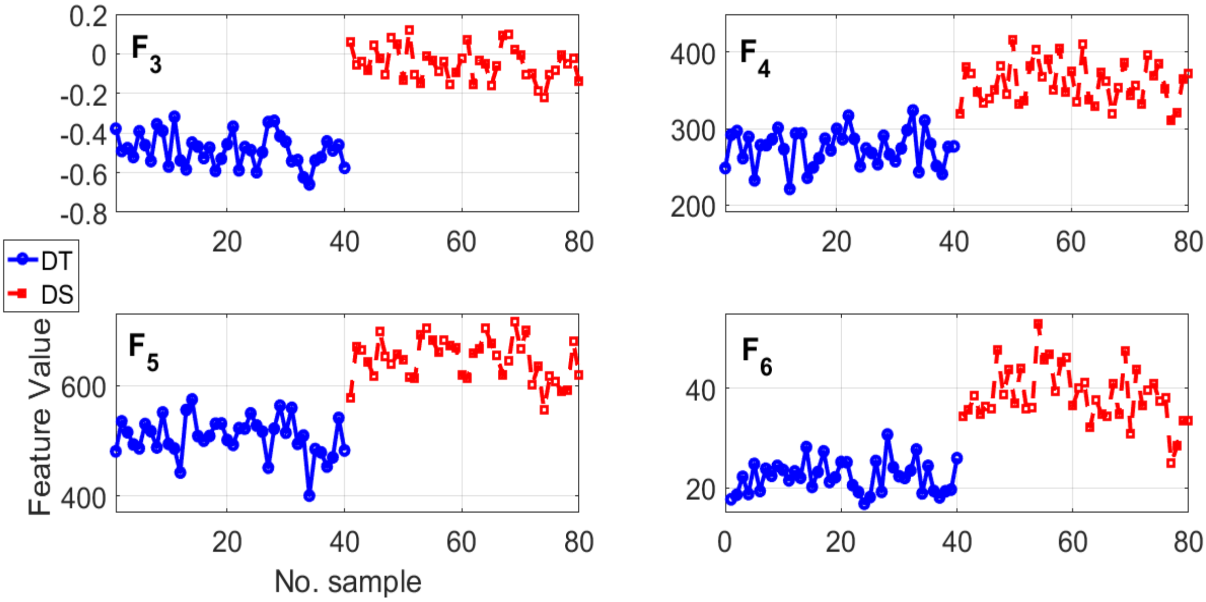

Figure 11. F_3, F_4, F_5 and F_6 value for CCPs in Group 3

The simplest way to train a RBFNN is to equate the number of RBFs with the number of training data in which the cluster centers are determined randomly, or using the K-Means algorithm. However, in this situation, the generalization capability of the trained network will be reduced and it will have poor performance on the test data. Therefore, the structure of the RBFNN, including center, the number of RBFs and their spread, is of great importance and must be carefully selected. In recent years, meta-heuristic optimization algorithms and machine learning have been successfully applied on engineering problems [28- 34]. In the proposed method, the number of RBFs, centers and their spread will be selected by the OOA. An example of an answer is shown by Eq. (3).

$$\begin{aligned} Orca &= [N_{RBFs} \quad C_1 \quad C_2 \quad .... \quad C_{Nc} \quad S_1 \quad S_2 \quad .... \quad S_{Nc}] \\ C_i &= [x_1 \quad x_2 \quad .... \quad x_{\dim}],\ i = 1, 2, ..., \ N_{RBFs} \end{aligned} \tag{3}$$

4. Simulation Results

4.1. Dataset

To evaluate the performance of the proposed method, 100 samples for each pattern are produced using the formulas presented in [5]. In these formulas, v_i is the amount of a standard normal variate at i-th ($i = 1,2,3, \dots 58, 59, 60$) time point and S_i is the monitored signals at i-th time point. Consequently, different control chart patterns of length 60 for a normal process with mean (μ) and standard deviation (Sd) can be produced by the following formulas:

1. NOR:

$$S_j = \mu + v_i\sigma, \qquad \mu = 80.0\,, Sd = 5.0 \tag{4}$$

2. STR:

$$S_j = \mu + r_i\sigma', \quad 0.2 \times Sd \le Sd' \le 0.2 \times Sd \tag{5}$$

3. SYS:

$$S_j = \mu + v_i Sd + d \times (-1)^i, \qquad 1 \times Sd \le d \le 3 \times Sd \tag{6}$$

4. CYC:

$$S_j = \mu + v_i Sd + a sin(2\pi i/T), \quad 1.5 \times Sd \le a \le 2.5 \times Sd \ \ \& \ \ 8 \le T \le 16 \tag{7}$$

In this equation, "a" represents the amplitude of cyclic variation and "T" shows the period of a cycle.

5. IT:

$$S_j = \mu + v_i \times Sd + ig, \qquad 0.05 \times Sd \leq g \leq 0.1 \times Sd \tag{8}$$

6. DT:

$$S_j = \mu + v_i \times Sd - ig, \qquad -0.1 \times Sd \leq g \leq -0.05 \times Sd \tag{9}$$

In Eq. (8) and (9), "g" represents the magnitude of gradient for the trend patterns.

7. US:

$$S_j = \mu + v_i \times Sd + Ls, \quad L = 1 \;\; if \; i \geq P, \quad else \; L = 0 \tag{10}$$

8. DS:

$$S_j = \mu + v_i \times Sd - Ls, \quad L = 1 \;\; if \; i \geq P, \quad else \; \mathrm{L} = 0 \tag{11}$$

In Eq. (10) and (11), "L" is a parameter which determining the shift position and "s" represents the magnitude of the shift. We have generated 800 samples $[Input]_{60\times800}$ (100 sample per pattern). To show the performance analysis of the proposed system, 40% of the data is used for training and 60% for testing the proposed method.

4.2. Effect of Network Structure

In the first experiment, unprocessed data (as in Figure 4) was used as network input and network performance was evaluated for different value values of parameters s. In this experiment, only one RBFNN was used for classification and the number of RBFs was considered 320 (equal to the number of samples in the training dataset). For data clustering, K-Means algorithm is used, which is the usual algorithm for clustering in MATLAB. The value of spread has also increased from 0.1 to 10 in 0.5 steps. The obtained results are listed in Table 1. In the next experiment, the number of RBFs is set to 50, which is less than the samples in the training dataset. The obtained results have been shown by Figure 12. It can be seen that the performance of the RBFNN with 50 RBFs is better than the RBFNN with 320 RBFs. It can be observed that there is no linear relationship between spread and RBFNN's accuracy. In fact, the second layer in RBFNN, performs the final classification based on the distance of samples from their related RBF and determined spread. Hence, the value of spread has vital role in recognition accuracy. These experiments showed the importance of number of RBFs, centers and their spreads. Therefore, their value must be determined carefully.

Table 1. The performance of RBFNN using unprocessed inputs

Spread	No. of RBFs	RA (%)	Width	No. of RBFs	RA (%)
0.5	320	90.54	10.5	320	93.86
1	320	92.76	11	320	93.56
1.5	320	92.78	11.5	320	93.11
2	320	92.90	12	320	93.15
2.5	320	92.96	12.5	320	93.22
3	320	93.61	13	320	93.41
3.5	320	93.69	13.5	320	92.40
4	320	93.46	14	320	93.28
4.5	**320**	**94.93**	14.5	320	93.15
5	320	94.17	15	320	92.63
5.5	320	93.39	15.5	320	92.65
6	320	92.41	16	320	92.19
6.5	320	93.52	16.5	320	92.47
7	320	92.62	17	320	92.65
7.5	320	92.87	17.5	320	92.32
8	320	91.49	18	320	92.33
8.5	320	91.81	18.5	320	91.17
9	320	92.76	19	320	91.11
9.5	320	92.19	19.5	320	91.15
10	320	92.96	20	320	91.05

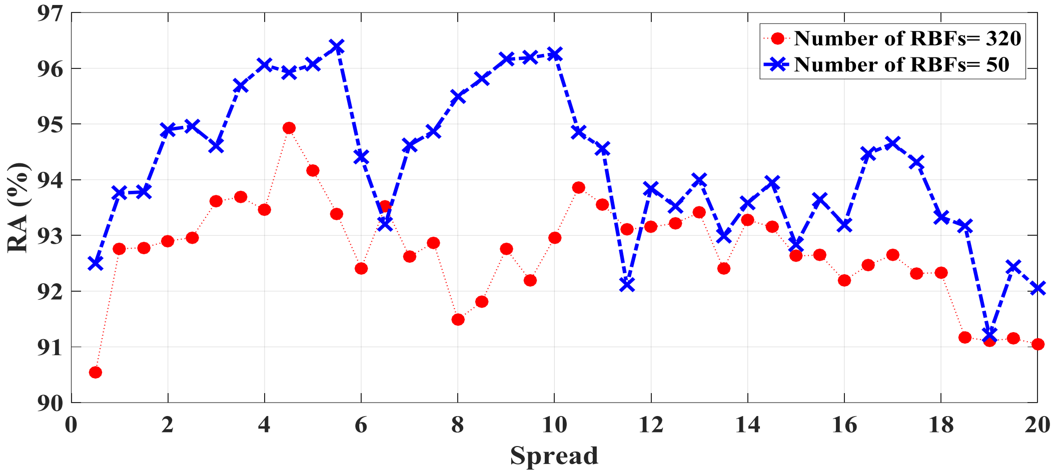

Figure 12. Impact of spread and number of RBFs on network's performance

In previous experiments the effect of spread on RBFNN performance was investigated and it was seen that there was no linear relation between the spread value and RBFNN's performance. In the new experiment, the effect of RBF numbers will be investigated. For this purpose, the number of RBFs is changed from one to 320 and the value of spread is fixed. From Figure 13, it can be seen that the performance of RBFNN is highly dependent on the number of RBFs. Based on these experiments it is clear that the RBFNN performance is highly dependent on RBFs number and spread value.

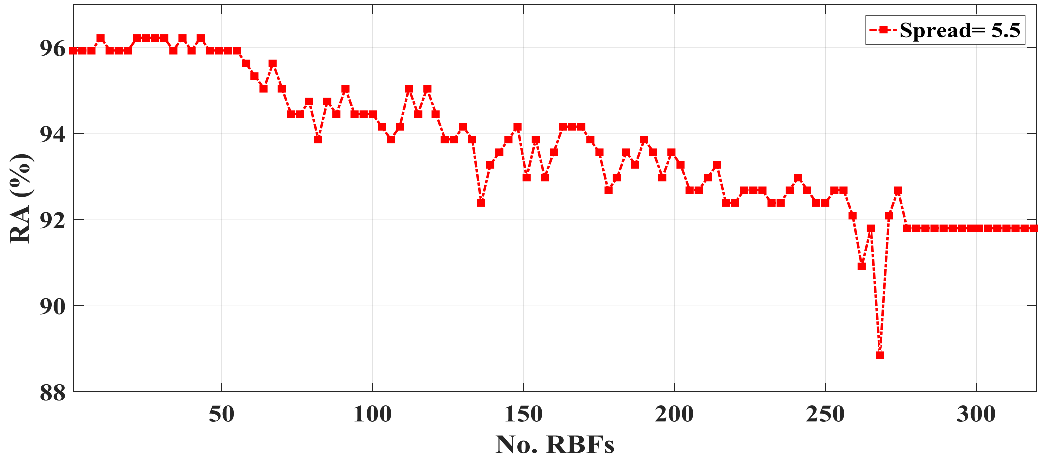

Figure13. The effect of RBF number on network performance (spread= 5.5)

4.3. Performance of the OOA-RBFNN

K-means clustering algorithm is one of the most practical and common clustering techniques. The goal of this algorithm is to group input dataset points into distinct non-overlapping sub-groups. K-means clustering algorithm has good performance when the clusters have a kind of spherical shapes. However, this algorithm suffers as the geometric shapes of clusters deviates from spherical shapes. Moreover, K-means clustering algorithm is considerably sensitive to the initial randomly selected cluster centers, and there is high chance to get trapped in local minima. To overcome these problems, in this study, the use of orca algorithm for clustering data is proposed. Moreover, optimal number of RBFs and their spread is selected by OOA.

In the next experiment, we used different shape and statistical features introduced in the literature. In this experiment, OOA is used for clustering and optimization. The obtained results are listed in Table 2. In this experiment, we have used nine shape features introduced in [25], 15 shape features introduced in [41], and six statistical features introduced in [27]. It can be seen that using new features has increased the recognition accuracy.

Table 2. Performance of Optimized RBFNN using different features

Input type	Clustering method	Input dimension	Spread	No. RBFs	RA (%)
Shape feature [25]	OOA	9	1.854	18	98.54
	K-means		1.699	18	98.03
Shape feature [41]	OOA	15	1.541	21	98.21
	K-means		1.498	22	97.69
Statistical feature [27]	OOA	6	0.768	12	98.37
	K-means		0.805	7	97.82

In the next experiment, the performance of the proposed method is investigated. In this experiment, shape and statistical features are used intelligently in different steps and RBFNN's parameters are selected by OOA. The optimal parameters are listed in Table 3 and the confusion matrix is shown in Figure 14. The proposed method can recognize CCPs with high accuracy, 99.4%.

Table 3. RBFNN's parameters selected by OOA

Classifier	Number of RBFs	Spread
$RBFNN_1$	16	1.654
$RBFNN_2$	9	0.972
$RBFNN_3$	11	0.673
$RBFNN_4$	8	1.076
$RBFNN_5$	8	1.113

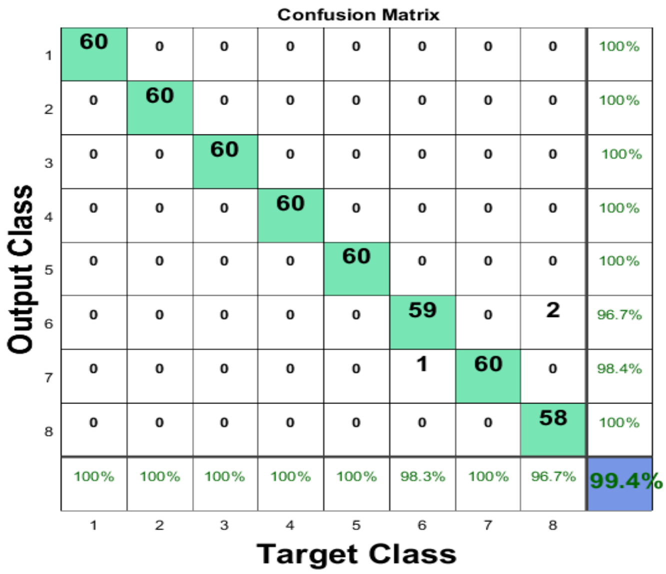

Figure 14. Confusion matrix of the proposed method

4.4. Comparison with Different Classifier

The performance of the proposed classifier has been compared with other classifiers for investigating the capability of the proposed classifier, as indicated in Table 4. In this respect, adaptive neuro-fuzzy inference system (ANFIS), probabilistic neural networks (PNN), Multi layered Perceptron (MLP) neural network with different training algorithm such as Back propagation (BP) learning algorithm, with Resilient propagation (RP) learning algorithm and Levenberg Marquardt (LM) are considered. In this experiment, we used the proposed steps and features. It can be seen from Table 4 that the proposed method has better recognition accuracy than other classifiers.

Table 4. Comparison the performance of proposed classifier with other classifiers.

Classifier	Parameters	Recognition accuracy (%)	Standard deviation
PNN	Spread=0.641	97.64	$\pm$2.27
ANFIS	Radii=0.176	98.77	$\pm$0.42
MLP (BP)	Number of hidden layer= 3	96.62	$\pm$2.75
MLP (RP)	Number of hidden layer= 2	98.55	$\pm$1.05
MLP (LM)	Number of hidden layer= 3	99.06	$\pm$0.71
OOA-RBF	**Table 3**	**99.41**	**0**

4.5. Comparison and Discussion

Control charts are among the essential management control tools. Nowadays, implementation of the control charts in any process are very easy by using the modern computer technology. Hence, data collection and analysis can be fulfilled and carried out on a microcomputer or a local area network terminal in real-time or even on-line at the work center. Recently, several methods have been introduced by researchers for CCPs recognition. In these methods, different classifiers, different features, and different CCPs are investigated. Considering the different number of CCPs, using different databases and assigning a different ratio of training/testing have made the direct comparison impossible. For these reasons, we just mentioned the reported results in the literature. Table 5 compares some different methods in case of the considered CCPs, classification accuracy, classifier type, and the input vector type.

Table 5. A Comparison with different methods

Ref	No. patterns	Input signal	Input dimension	Method	Accuracy (%)
[25]	six	Original signal	60	ANN (MLP)	94.22
[25]	five	Shape feature	9	ANN (MLP)	99.00
[6]	five	Original signal	60	ANN (MLP)	97.73
[27]	six	Statistical features	60	ANN (MLP)	96.79
[7]	six	Original signal	60	LVQ	92.31
[7]	six	Original signal	60	LVQ optimized by Bees algorithm	95.47
[8]	six	Original signal	60	WNN	97.70
[9]	eight	Shape features	8	ANN	96.13
[10]	seven	Shape features	8	CART	97.36
[11]	eight	Shape features	32	ANN	96.66
[12]	six	Shape & Statistical features	3	Opt-SVM	99.58
[13]	six	Shape & Statistical features	5	ANN	99.16
[14]	6	Frequency features	15	Opt-SVM	99.30
[15]	6	Euclidean distance	6	RBF	99.26
[17]	five	Shape features	7	Expert system	95.21
[18]	seven	Original signal	60	SNN	98.61
[19]	seven	Fuzzy features	6	ANN (MLP)	99.65
[20]	six	Frequency features	5	MLP-SVM	99.51
[21]	six	Shape & Statistical features	**7**	Fuzzy	99.01
Proposed method	**eight**	**Raw data**	**60**	**OOA-RBFNN**	**99.41**

5. Conclusion

Production of high quality of goods has a direct relationship with customer satisfaction. Therefore, monitoring the process in factories is very important issue. Due to these issues, in this study, a new method for identifying CPPs was proposed with the aim of monitoring the production process, in which the RBFNN was used as a classifier. The combination of shape and statistical features was also used as input. In order to evaluate the performance of the proposed method, several experiments were performed. The obtained results revealed that intelligent application of different features and optimization of RBFNN leads to highest accuracy.

Conflict of Interest Statement

The authors declare no conflict of interest.

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