Intelligent Integration of SPC/EPC for Quality Control and Fault Diagnosis

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***Abstract*—Traditionally statistical process control (SPC) is used for online process quality monitoring, while engineering process control (EPC) is designed for system auto-regulation for a given output target against the system disturbance. This paper presents the research work of the integration of SPC, EPC, and pattern recognition of Artificial Neural Network (ANN) for system process monitoring, fault diagnosis, and automatic system control. ANN module serves as a pattern reorganizer of SPC chart outputs for fault diagnosis, and also the regulation controller for system automation. The proposed methodology provides an integrated online process of monitoring & regulation for effective process quality control. This paper develops the framework and the structure of the integration of SPC, EPC, and ANN with fault-diagnosis and controller functions. The integration scheme demonstrates the ability of non-random fault auto-recognition from SPC charts and being an effective way to maintain target output by coupling with the automatic control and regulation of the process. A three-tank nonlinear system analysis for fault-diagnosis is illustrated as an example of using this developed methodology.**

***Index Terms*—SPC, EPC, ANN, quality control, fault diagnosis, intelligence**

I. Introduction

In production systems, statistically unstable manufacturing processes can lead to poor product quality that will significantly affect customers' satisfaction and companies' goodwill. A good process control is therefore an essential methodology for corporations to achieve stable product quality. Statistical Process Control (SPC) and Engineering Process Control (EPC), which have been used in quality improvement for decades, are the most effective tools of process control for quality. These two methods focus on different quality strategies. EPC gives sequential adjustments in order to control the quality characteristic of interest without finding the assignable causes [1]. The main goal of EPC is to compensate the effect of inertia and disturbance in the process and to keep the process output on a desired target. EPC are often seen in applications in the chemical industry, where variation is highly auto-correlated. The benefits of using EPC can be concluded as follows [2], [3].

(1) EPC technology is an effective way to reduce the variation of the products for production quality improvement.

(2) EPC enhances plant quality production rate with minimum input and cost.

(3) EPC controller can be simple and adaptive to a production process and a changing environment.

EPC focuses on process regulation that assumes there are other manipulatable variables that can be adjusted to compensate for the drift of the process output and keep the output of the process close to the desired target. It makes no attempt to identify and remove the causes that impact and divert the process output from the target. However, the regulation capability of EPC (from the controller) is not unlimited. When the disturbance to the process is beyond a certain range, EPC (controller) alone is not able to stop the system output diverting from the target (system will be unstable in terms of system control engineering). Hence it is proposed to have a strategy of integration of EPS and SPC by applying SPC to detect non-random patterns which cause the abnormal disturbance to the process. As soon as the type of non-random patterns is identified by SPC, the corresponding root causes should be removed (by process engineers) and the process brought back to a statistical-stable condition. Therefore, SPC is used to detect the existence of an assignable cause that makes the process out of statistical process control. SPC works to achieve product quality by monitoring whether the process is statistically stable by sampling and analysis of data [2]. SPC tools, such as control charts, are used to monitor the stability of process mean and/or process variation by measuring the product quality characteristics of interest. SPC has a long history of worldwide popularity because of the following benefits [1].

(1) SPC is a simple, but effective methodology for online quality monitoring.

(2) SPC in a good design can be used to prevent defects throughout the process.

(3) SPC provides quality information for diagnosis and prognosis for decision making; SPC also provides process capability information.

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The prime idea of the integration of SPC and EPC is to use the function of SPC to monitor and find the assignable cause that resulted in the system being statistically unstable and to use the function of EPC for process automatic control (feedback control) for the reduction of the process variability. This type of integration system with SPC and EPC has been studied as an algorithmic SPC system [4].

II. SPC and ANN Pattern Recognition

SPC control charts can be applied in four main fields: process monitoring, planning, evaluating customer satisfaction, and forecasting [5], [6]. Statistical Process Control charts are technology that displays a graphical line to monitor whether a manufacturing process is in a statistical control. A sequence of data is measured from the samples and is plotted on the graph versus the subgroup number or time. The charts contain central line, upper control limit, and lower control limit. The central line represents the average value of the sample. The upper and lower control limits form a zone where the sample data and the process are in-control. Otherwise, if one or more points are plotted out of the zone, the process is out of control and then corrective actions are required to find causes responsible for this unstable behavior. Multiple standard deviation ($k\sigma$) from the center line ($\overline{x}$) of the process decide the distance of two control limits from central line ($\overline{x} \pm k\sigma$).

Statistical process control charts and Artificial Neural Network (ANN) are two powerful tools for process control and intelligent learning. There are numerous publications and research results introducing ANN [4], [7]. and SPC and their applications [1], [8]-[11]. Among them, H. B. Hwarng *et. al.* [12], D. T. Pham *et al*. [13], C. S. Cheng [14], and R. S. Guh [15] conducted the research with establishing automatic on-line SPC with combination of ANN for continuous improvement of quality and real-time manufacturing process control. The main idea of applying ANNs to SPC is to obtain the function of auto-interpretation of patterns of SPC control chart online [16].

Pattern Recognition (PR) plays the essential role in characterization of patterns in deviated data. PR procedure involves three processing levels [17]: filtering, feature extraction, and classification. Artificial Neural Network (ANN) is one of the most popular pattern recognition tools in industrial applications, which has the advantages of self-organization, simple computational operations, and parallelity.

A. *Engineering Process Control*

Engineering Process Control (EPC) focuses on process adjustment, which aims to detect whether processes output has deviated, or is deviating, and to take proper counteraction with input, then make the output response back to the target value. The deviation of process occurs due to phenomena such as continuous variation in input materials, effects of environmental covariates, process variables, or unknown forces that impact the process. In the past, process control device played the role in adjusting manipulated variables; however, it demands that all actions of sensing, measurement, comparison, and correction are embedded in the device hardware. In order to eliminate hardware cost, some automatic means are utilized based on quantitative models of different operational strategies, including discrete-time control, PID control, artificial neural network, expert systems, etc. These various forms of feedback control schemes are used for making the required compensation in the control level in order to offset the output deviation.

The primary task of EPC is for devising algorithms to manipulate the adjustable process variables in order to reach the desired process behaviour, namely, output values close to pre-set target values [18]. The EPC controller measures one or more of the process conditions which provide an automatic counteraction to any change in the condition in order to maintain a balanced state, or called steady state, which is defined as “a characteristic of a condition such as a value, rate, periodicity, or amplitude exhibiting only negligible change, over an arbitrary long period of time” (Instrument Society of America Standard on Process Instrumentation).

B. *Integration of SPC and EPC*

The concept of combining SPC with EPC has been introduced by many studies. The purpose of this technique is not only monitoring assignable causes in a system quality control but also reducing the effect of inertia on predictable quality variables. SPC reduces the variability of the output by detecting and eliminating the assignable causes in the process. EPC reduces the output variability by adjusting one or more controllable inputs. SPC and EPC integration can provide more system improvement by decreasing the variability, where EPC is used to reduce the effect of quality variations, while the purpose of SPC to detect assignable causes for this variation by statistical process monitoring. To this end, control chart can be applied on the error that is the difference between the actual system output (y_t) and the desired system target (T). It is possible also to apply control charts to the adjustable variable (x_t) that contain information for engineers to use in monitoring processes. The objective of this paper is to design SPC and EPC integration system that uses ANN as controller and classifier to control the process, to detect the abnormal disturbance, and to classify the type of disturbance. In EPC, the system may detect ‘output’ diverting from target, but there no further information on which and what type of the disturbance. For more information on ‘disturbance,’ a feed-forward control scheme is adopted. First, when a certain output signal comes out from the system, the ANN controller automatically compares it with the target that has been predetermined. Then the controller starts to adjust manipulated and manage to keep the system actual output close to the target. However, when assignable causes appear in the system, those make the output deviates from the target and the controller cannot bring it back to the normal. The detailed system structure is illustrated in Fig. 1.

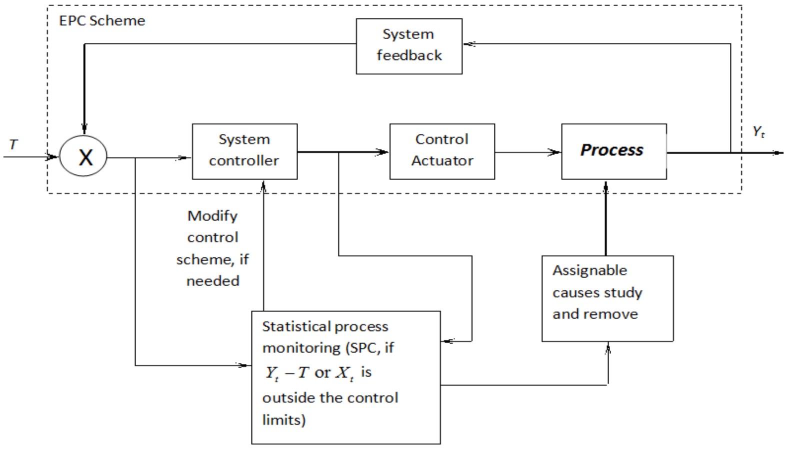


Figure 1. The concept of combining SPC and EPC.

III. SPC/EPC INTEGRATION: THREE-TANK SYSTEM CASE STUDY

A three-tank system is used to simulate the idea of integration SPC and EPC. Three-tank system can be considered as the most used prototype while liquid level control system has a tremendous application field in industry. It is applied in the wastewater treatment plant, the petro chemical plant, and oil/gas systems. The scheme of the system is shown in Fig. 2 [11]. It is composed of three cylindrical tanks connected via valves. Each Tank 1 and Tank 3 has one outlet while Tank 2 has two outlets. Water is fed from the bottom basin into Tank1 and Tank 2 by Pump 1 and Pump 2. The manipulable control inputs are $x_1(t)$ and $x_2(t)$, and the outputs are the water levels in each tank, $y_1(t)$, $y_2(t)$, and $y_3(t)$ respectively. The differential equations for the system dynamics are shown as follows [19]

$$\frac{dy_1}{dt} = q_1(t) - q_{13}(t) \tag{1}$$

$$\frac{dy_2}{dt} = q_2(t) + q_{32}(t) - q_{20}(t) \tag{2}$$

$$\frac{dy_3}{dt} = q_{13}(t) - q_{32}(t) \tag{3}$$

where

$q_{13}(t)$ is the flow between Tank 1 & Tank 3 given by

$$q_{13}(t) = p_1\sqrt{y_1 - y_3}$$

$q_{32}(t)$ is the flow between the Tank 2 & Tank 3 given by $q_{32}(t) = p_2\sqrt{y_3 - y_2}$

$q_{20}(t)$ is the flow between two outlets of Tank 2 given by $q_{20}(t) = p_3\sqrt{y_2}$

$q_1(t)$ is the flow into Tank 1, given by $q_1(t) = p_4 x_1$

$q_2(t)$ is the flow into Tank 2 given by $q_2(t) = p_5 x_2$

p_1, p_2, p_3 are valve constants and p_4, p_5 are pump constants.

Therefore, the model can be detailed, with system input and output variables, as:

$$\begin{aligned} \frac{dy_1}{dt} &= p_4 x_1 - p_1\sqrt{y_1 - y_3} \\ \frac{dy_2}{dt} &= p_5 x_2 + p_2\sqrt{y_3 - y_2} - p_3\sqrt{y_2} \\ \frac{dy_3}{dt} &= p_1\sqrt{y_1 - y_3} - p_2\sqrt{y_3 - y_2} \end{aligned} \tag{4}$$

The dynamics of the system can be simulated and studied by Simulink [21] directly.

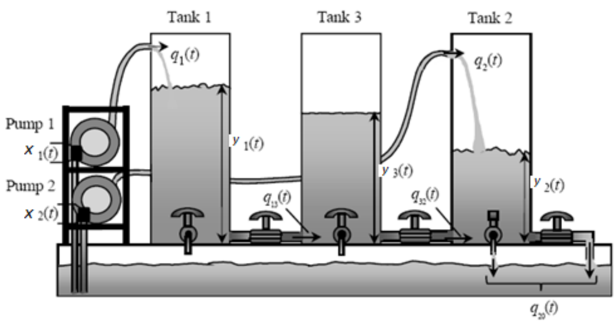


Figure 2. Three-tank system

EPC control scheme with adaptive control (Fig. 3), using Artificial Neural Network (ANN), consists of three elements. They are the plant, the neural network identifier, and the neural network controller. The difference between the outputs from the plant and the outputs from the identifier, the error, will be used to adjust the weights of the neural network. Then the controller sends the predictive signal back to the plant and the neural network identifier for the next step of weight update adaptively. Feed forward neural networks are used to build the inverse and the direct models. Input and outputs data sets are simulated using the three tank system to build both inverse and direct models. Training and validation datasets are produced to appropriately design these models. The inverse model is connected in series with the system, and a direct model is placed in parallel with plant.

To study the combination of EPC/SPC controls and ANN system controller for quality, the dynamics and control of three-tank system are simulated in Simulink using controller blocks. Multilayer perceptron (MLP) neural network is selected, which is commonly used for modelling nonlinear systems and implementing general-purpose of non-linear controller [20], as both neural network controller and the neural network identifier in the system. The control scheme of three-tank system with neural network identifier and controller in Simulink is presented in Fig. 3 [21].

To study the system dynamics and the function of the combination of EPC/SPC, different kinds of source blocks in Simulink are used to generate the desired target signals and to change the target value in a specified time horizon. Source blocks are also used to generate (simulated) disturbances for the system in order to be detected by ANN pattern recognizer [22]. After building the control charts using the error signal between the desired output and the target, ANN pattern recognizer is adopted for control charts classification. Different types of disturbances to the system can be produced by a single block or multiple blocks. The pattern recognizer from SPC in the system has been well-trained for 7 different types of random and non-random control chart patterns. These control chart patterns are defined in Besterfield (2013) [23] according to Western Electric Handbook. All patterns are illustrated in Fig. 4.

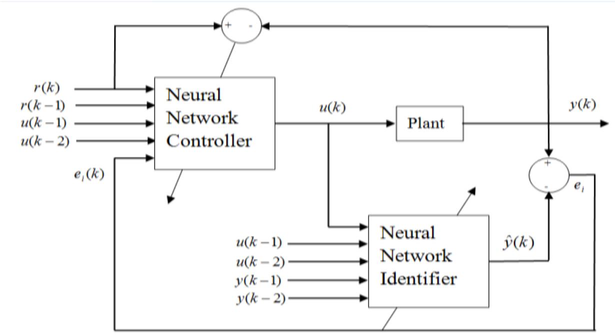
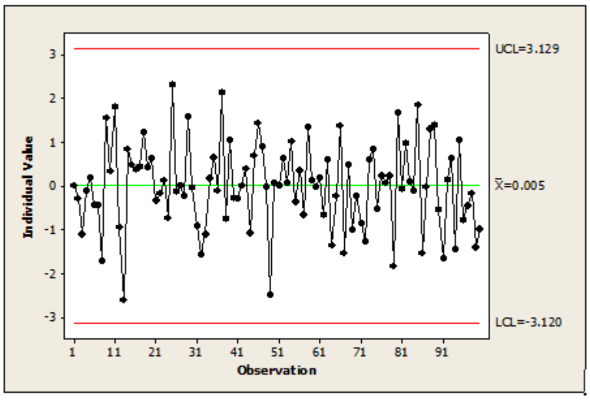
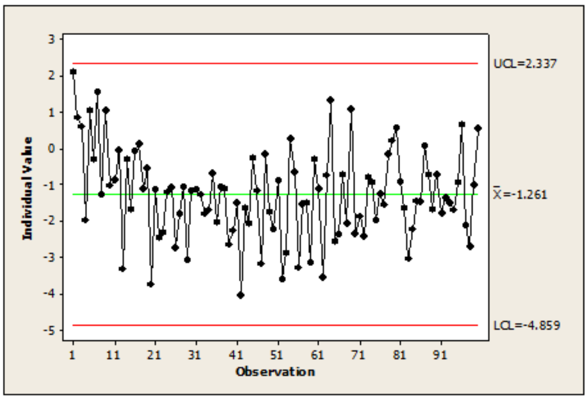


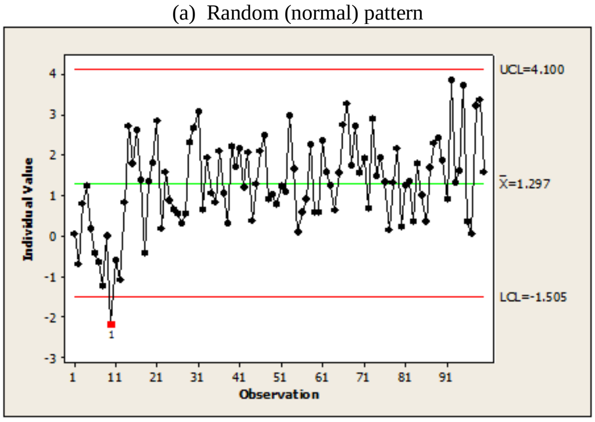
Figure 3. Principle of NN adaptive controller system



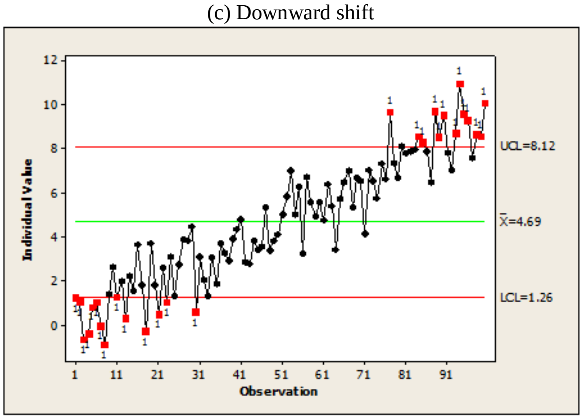
(a) Random (normal) pattern



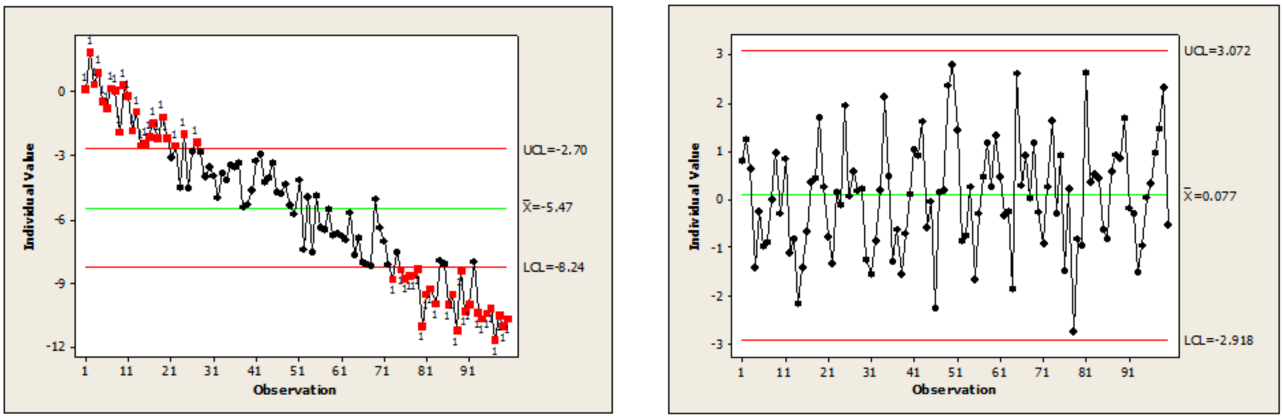
(c) Downward shift



(b) Upward shift



(d) Upward trend



(e) Downward trend (f) Cyclic trend

Figure 4. Common patterns of control chart in SPC: (a) Random (normal) patter; (b) Upward shift; (c) Downward shift; (d) Upward trend; (e) Upward shift; (f) Cyclic trend

ANN pattern recognizer is also pre-trained using the simulated control charts in different types, then this recognizer is connected to classify different types of control chart generated using the error signal between the output and the desired reference. Different error signals may result depending on the simulated (added) disturbance to the system. By correlating the classified control chart type and the disturbance type, control action will be determined by the controller.

Table I illustrates the formulas and parameter of seven control chart patterns [24]. In order to avoid over-fitting, the total 1050 input-output vector-pairs data for each generated sample are divided into three subsets. The first subset, including 700 available data points, is used for training process, which computes the gradient, update weights and bias of the network. The second subset, including 175 available data points, is used for validation process, which is used to monitor the performance of the network during the training process. The third subset, including 175 data points, is used for testing process, which is used to test the trained network and to verify the performance during training.

TABLE I. FORMULAS AND PARAMETERS OF SEVEN CONTROL CHART PATTERNS

Pattern Types	Formula of d(t)	Ranges of Parameter	Parameter Description	Quantity for training, validating, and testing
Upward Trend	$d*t$	$0.10\sigma \le d \le 0.26\sigma$	d :trend slope in term of σ	150
Downward Trend	$d'*t$	$-0.26\sigma \le d' \le -0.1\sigma$	d' :trend slope in term of σ	150
Cycle	$a*\sin(2\pi t/\Omega)$	$1.0\sigma \le a \le 3.0\sigma$ $\Omega = 4,5,6,7,8$	a :cycle amplitude in term of σ Ω :cycle period	150
Systematic	$m*(-1)^t$	$1.0\sigma \le m \le 3.0\sigma$	m: magniture	150
Upward Shift	$u * s$	$u = 0 or 1$ $1.0\sigma \le s \le 3.0\sigma$	u or u' : determining the position of shifting (μ=0 :before shifting ; μ=1 :after shifting) s: shift magnitude in term of σ	150
Downward Shift	$u'*s$	$u' = 0 or 1$ $-3.0\sigma \le s \le -1.0\sigma$		150
Normal	$x(t) = \mu + 3*\sigma*n(t)$	-	-	150

After the ANN control chart pattern recognizer is established and well-trained, it starts to detect the output signals which are simulated from ANN controller, then compare those under different conditions. Backpropagation (BP) training algorithm is chosen as primary training algorithm to develop the proposed ANN-based control chart pattern recognizer. At the beginning of the network construction, it is divided into two categories based on different number of hidden layers, one and two hidden layer structures. These two structures are used with various number of hidden layer neurons. For one hidden layer structure, the number of neuron is categorized as multiples of tens, i.e. 10, 20, 30, 40, and 50. For the two hidden layer topology, the node number is set to be the same as the one hidden layer topology. The node number of the first hidden layer is either equivalent or larger than that of the second hidden layer. Therefore, different (backpropagation network) BPN structures are established. Four learning algorithms, Resilient Backpropagation (RBP), Scaled Conjugate Gradient (SCG), Conjugate Gradient Backpropagation (CGB), and Gradient Descent Backpropagation (GDB) are utilized for each BPN to learn on training pairs.

Sigmoid and linear activation functions are used for neural network node-function. Sigmoid function is given by

$$f(a) = \frac{1}{1+e^{-a}}, \; a = WP + b \tag{5}$$

where $\boldsymbol{W}$ is the weight matrix, $\boldsymbol{P}$ is the input matrix and b is the bias.

Mean Squared Error (MSE) is selected to measure the performance and control for BPN training. Four different learning algorithms are tested with designed data sets. By looking at different training results, RBP performs a much better classification accuracy than other three algorithms. In neural network structure design, taking a comparison of different number of hidden layer neurons in the model with RBP training algorithm and sigmoid transfer function, the 30-30-7 produces the highest average classification accuracy, over 92% shown as Table II. Different sampling data points (window size) are used to get higher accuracy.

TABLE II. BACKPROPAGATION PERFORMANCE ON VARIOUS WINDOW SIZE

Window Size	Classification Accuracy on Test data (%)
10	39.02
30	**92.68**
50	78.05
70	73.17
100	68.29

Different disturbances (noise) are simulated and added to the system to determine the ability of the control chart classifier to rule out these signals. Control charts are built using error signals, which is the difference between target and the outputs of the three tank system after adding these noise signals. After determining ANN parameters, including different sizes of window, training algorithms, transfer functions, number nodes of hidden layers, and number of hidden layers. The classifier starts to detect the simulated data from different noise functions. These functions are generated using Simulink. The classification accuracy is shown in Table III. Accuracy is calculated by dividing the number of the correctly classified control charts by the overall number. Results show that no matter what functions are used, including single or combined functions, the ANN classifier can accurately detect the different disturbances, over 91% respectively.

TABLE III. BACKPROPAGATION PERFORMANCE ON THE AVERAGE OF THE SIMULATED DATA FROM DIFFERENT NOISE FUNCTIONS (%)

Different Kinds of Noise Functions	Classification Accuracy on Test Data
Step	95.26
Sine Wave	91.8
Ramp	93.18
Constant	92.4
Combined signals	90.76
Average	92.68

IV. SUMMARY AND CONCLUSION

Disturbances and assignable causes in manufacturing process can result in the deviation of output quality from the desired target even if adaptive controllers are used. The trend of deviated data can be classified as one of several non-random patterns in a view of statistical process control charts. An effective identification of these non-random control chart patterns can greatly narrow down the possible disturbances to be investigated, and significantly reduce the time for diagnosis of unexpected process deviation. Therefore, to establish an integrated process control system with a combination of on-line automatic control (EPC) and disturbance/assignable cause detection (SPC) is necessary. Artificial neural networks possess a great capability to deal with both on-line signal adjustment and control chart pattern recognition/analysis. The objective of this research is to develop an integrated control system which contains two ANN neural network based software prototype sub-systems, ANN adaptive controller and ANN pattern recognizer. For ANN adaptive controller scheme, the inverse neural model connected with the parallel framework of the original neural and the plant model are used. For ANN pattern recognizer, many trials based on back-propagation network are well-trained by plenty of representative training data and a comparative study on the trails based on different sizes of window (input time-lag number of signal), training algorithms, transfer functions, number nodes of hidden layers, and number of hidden layers (ANN structure design and training). The result shows that a single-layer BPN with 30 neurons in hidden layer, RBP learning, and sigmoid transfer function is capable of producing satisfactory classification accuracy over 92%. Using multiple hidden layer BPN seems not capable of outperform the single layer significantly. Finally, the ANN classifier starts to detect the signals which are simulated by different function blocks from Simulink. Error signals (difference between output and target) are used to build control chart. The result shows that the classifier performs excellent accuracy in detecting disturbances through classifying these charts, over 91%.

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