Classification of the Mixture Disturbance Patterns for a Manufacturing Process

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***Abstract*—The success of integration of Statistical Process Control (SPC) and Engineering Process Control (EPC) has been reported in recent years. However, the SPC Control Chart Pattern (CCP) has become more difficult to be classified due to the fact that the process disturbances were embedded in the system. Although some studies have focused on the classification tasks for a manufacturing process, they only considered the individual or basic disturbance type in a process. There has been very little research addressed on the classification of mixture of individual disturbance in a SPC-EPC system. The purpose of the present study is therefore to propose an effective way to deal with the classification of mixture CCPs for a SPC-EPC process. Because of its excellent performance on classification tasks, this study employs the Artificial Neural Network (ANN) approach to recognize the mixture patterns of the underlying disturbances. Simulation results revealed that the proposed SVM scheme is able to effectively identify various mixture types of disturbances for an SPC-EPC system.**

***Index Terms*—disturbance, mixture pattern, artificial neural network, SPC, EPC**

I. Introduction

The Statistical Process Control (SPC) charts have been widely used in monitoring the manufacturing processes. The function of SPC chart is to trigger an out-of-control signal when a disturbance was intruded into a process. Typically, when an observation falls outside the control limits, the process is said to be out of control. The process personnel should start to investigate the root causes for the underlying disturbances. If the root causes can be correctly determined and removed, the process improvement can be quickly achieved. However, the determination of root causes may be difficult in practical applications.

Another indication of out-of-control is that the Control Charts Patterns (CCPs) exhibit unnatural structures [1]. Different kinds of disturbances possess different type of CCPs. Different kinds of CCPs would be associated with certain root causes which adversely upset the process. For example, a shift disturbance pattern is typically associated with the new methods or new raw materials. As a consequence, the issue of how to effectively classify those unusual CCPs is very important for the SPC applications.

In addition, because the typical SPC charts may be ineffective when process outputs are correlated, the engineering process control (EPC) is combined with SPC to help controlling tasks. The correlated measurements of a process may cause high false alarm rates in an SPC application. When SPC chart possesses a high false alarm rate, a plotted point which is fallen outside the control limits does not necessarily imply that the process is unstable. Consequentially, the SPC signal may be misjudged the status of the underlying process. Unfortunate the correlated measurements often exist in practical processes [2]-[11]. EPC is able to effectively tune the correlated process, and it can be used to overcome the correlation difficulty. However, the use of EPC could cause the problem of embed underlying disturbance patterns.

Because of its easy use and powerful classification capability, Artificial Neural Network (ANN) has been widely used in many practical applications. Also, ANN is a powerful data-driven and a self-adaptive computational tool which possesses the capability of capturing nonlinear and complex characteristics of a manufacturing process with a high degree of accuracy. Therefore, this study employs ANN technique to serve as the classifier for identify the mixture CCPs of an SPC-EPC system.

The rest of this paper is structured as follows. Section 2 addresses the structure of an SPC/EPC system and describes the difficulties for controlling the auto correlated process. The concept of the proposed ANN approach is discussed in Section 3. The experimental results and discussions are given in Section 4. The final section concludes this study.

II. The Models

The commonly used integrated moving average with order of 1 (i.e., IMA (1, 1)) is considered to be the process noise in this study. Additionally, this study assumes that the manufacturing process can be described by a zero order model with the IMA (1, 1) noise; that is: [7], [9]:

$$Y_{t+1} = qX_t + d_{t+1} \tag{1}$$

$$d_{t+1} = \frac{(1-\theta B)a_t}{(1-B)}$$

where

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Y_{t+1}: the process measurement at time $t+1$

d_{t+1}: the noise at time $t+1$, and it is represented by an IMA(1,1) process,

θ: the parameter of an IMA(1,1) process,

X_t: manipulated variable's value at time t,

q: the system gain, and it is a parameter, and

B: backward shift operator, and it is defined as: $Y_t B^j = Y_{t-j}$ for j=1, 2,

Giving the process model in Equation (1), a suitable EPC is usually employed as follows [7]:

$$x_t = -\frac{(1-\theta)}{q} \sum_{j=-\infty}^{t} y_j \tag{2}$$

Typically, the disturbances may interrupt the process at any time. When a disturbance has occurred, the process can be reformulated as follows.

$$Y_{t+1} = qX_t + d_{t+1} + D_{t+1} \tag{3}$$

where D_{t+1} is a certain disturbance at time $t+1$.

In this study, we consider three types of individual disturbances for a process, and they are described as follows [12], [13].

$$\text{Systematic: } D_{t+1}=D^{SYS}_t = g \times (-1)^t + a_t \tag{4}$$

$$\text{Cycle: } D_{t+1}=D^{CYC}_t = \sin(2\pi t/\psi)U_t + a_t \tag{5}$$

$$\text{Mixture: } D_{t+1}= D^{MIX}_t=D^{SYS}_t + D^{CYC}_t \tag{6}$$

where

DSYSt: systematic disturbance value at time t,

g: magnitude of the systematic pattern in terms of, and it is assumed to follow a uniform distribution with the range of (1.0, 3.0),

DCYCt: cycle disturbance value at time t,

Ut: cycle amplitude, and it is assumed to follow a uniform distribution with the range of (1.5, 2.5),

ψ: cycle period, and it is assumed ψ =8.

DMIXt: mixture type of systematic and cycle disturbance value at time t.

Fig. 1 shows the patter of systematic disturbance in a process. In Fig. 1, the first 50 observations were generated from an in control state of a process, and a systematic disturbance was intruded into the process after observation 51. Fig. 2 shows the corresponding EPC actions which were described in Eq. (2).

Fig. 3 displays the pattern of a cycle disturbance in a process. Same as in Figure, the first 50 observations in Fig. 3 were generated from an in control state, the observations 51 to 200 were generated from an out-of-control state which had a cycle disturbances. Fig. 4 shows the corresponding EPC actions which were used to tune the cycle disturbance.

Fig. 5 shows the pattern of a mixture types of systematic and cycle disturbances. That is, in Fig. 5, the first 50 observations were generated from an in control state and the observations 51 to 200 were from the mixture of systematic and cycle disturbance. Fig. 6 demonstrates the corresponding EPC actions which were used to tune the mixture type of the disturbance.

By observing the Fig. 1, 3 and 5, one can notice that the classification of those disturbance patterns is very difficult. Accordingly, the issue of classification of CCPs for an SPC-EPC system becomes a promising research topic.

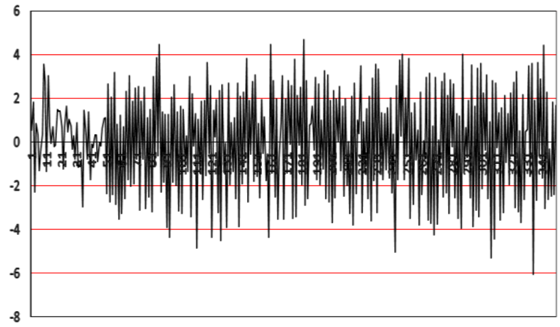

Figure 1. The process outputs with the presence of a systematic disturbance after time 50.

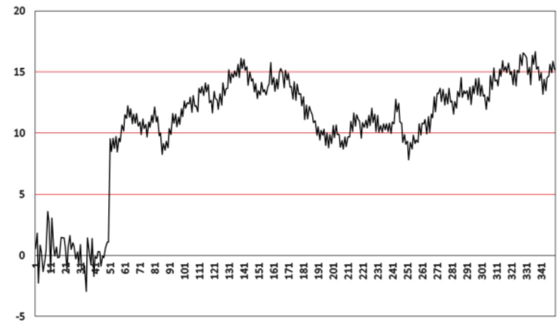

Figure 2. The values of EPC with the presence of a systematic disturbance after time 50.

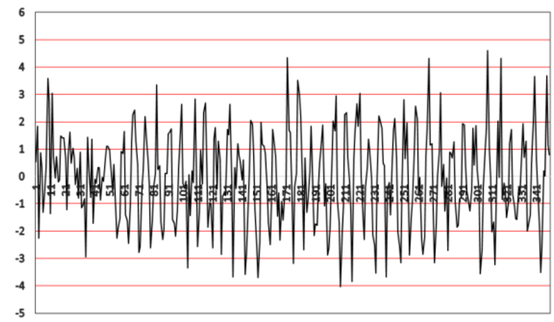

Figure 3. The process outputs with the presence of a cycle disturbance after time 50.

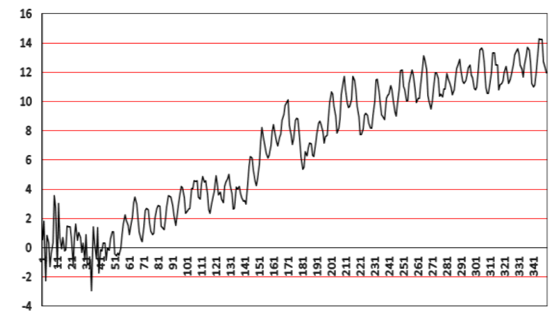

Figure 4. The values of EPC with the presence of a cycle disturbance after time 50.

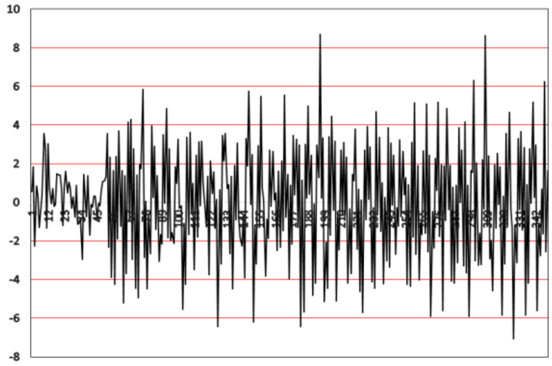

Figure 5. The process outputs with the presence of a mixture type of systematic and cycle disturbance after time 50.

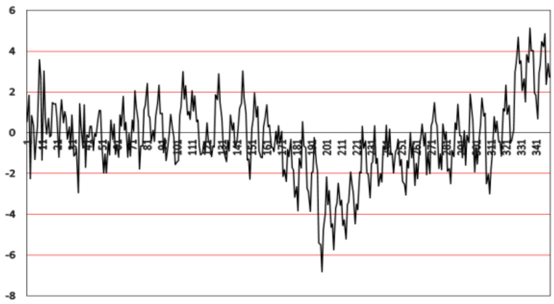

Figure 6. The values of EPC with the presence of a mixture type of systematic and cycle disturbance after time 50.

III. Artificial Neural Network

A neural network is a massively parallel system comprised of highly interconnected, interacting processing elements based on neurobiological models. Due to its associated memory characteristic and its generalization capability, ANN has been increasingly utilized for modeling non-stationary processes [14]-[21]. ANN is a massively parallel system comprised of highly interconnected, interacting processing elements, or units that are based on neurobiological models. ANNs process information through the interactions of a large number of simple processing elements or units, also known as neurons. Knowledge is not stored within individual processing units, but is represented by the strength between units [14].

The ANN nodes can be divided into three layers: the input layer, the output layer, and one or more hidden layers. The nodes in the input layer receive input signals from an external source and the nodes in the output layer provide the target output signals. The output of each neuron in the input layer is the same as the input to that neuron. For each neuron j in the hidden layer and neuron k in the output layer, the net inputs are given by [22]

$$net_j = \sum_i w_{ji} \times o_i \text{ , and } net_k = \sum_j w_{kj} \times o_j \qquad (7)$$

where i (j) is a neuron in the previous layer, oi (oj) is the output of node i (j) and wji (wkj) is the connection weight from neuron i (j) to neuron j (k). The neuron outputs are given by

$$o_i = net_i$$

$$o_i = \frac{1}{1+\exp^{-(net_i+\theta_i)}} = f_i(net_i, \theta_i) \qquad (8)$$

$$o_k = \frac{1}{1+\exp^{-(net_k+\theta_k)}} = f_k(net_k, \theta_k) \qquad (9)$$

where netj (netk) is the input signal from the external source to the node j (k) in the input layer and θ_j (θ_k) is a bias. The transformation function shown in Equations (8) and (9) is called sigmoid function and is the one most commonly utilized to date. Consequently, sigmoid function is used in this study.

The generalized delta rule is the conventional technique used to derive the connection weights of the feedforward network. Initially, a set of random numbers is assigned to the connection weights. Then for a presentation of a pattern p with target output vector tp=[tp1, tp2, ..., tpM]T, the sum of squared error to be minimized is given by

$$E_p = \frac{1}{2}\sum_{j=1}^{M}(t_{pj} - o_{pj})^2 \qquad (10)$$

where M is the number of output nodes. By minimizing the error Ep using the technique of gradient descent, the connection weights can be updated by using the following equations:

$$\Delta w_{ji}(p) = \eta \delta_{pj} o_{pj} + \alpha \Delta w_{ji}(p-1) \qquad (11)$$

where for output nodes

$$\delta_{pj} = (t_{pj} - o_{pj}) o_{pj} (1 - o_{pj}) \qquad (12)$$

and for other nodes

$$\delta_{pj} = (\sum_k (\delta_{pk} \times w_{kj}) o_{pj} (1 - o_{pj}) \qquad (13)$$

Note that the learning rate affects the network's generalization and the learning speed to a great extent.

The input to the ANN is the values of the process outputs. The ANN output consists of one node. This output node indicates the classification of the process status. The value of 0 concludes that the process is in control, and the value of 1 indicates that the process is out-of-control.

IV. Simulation Results and Discussion

Suppose a manufacturing process is monitored by the SPC-EPC mechanism. This process can be represented by Eq. (3), and the process parameters are arbitrarily chosen as q=0.5 and $\theta = 0.8$. Also, we assume that the process is tuned with the use of EPC control action which is represented by Eq. (2).

In order to show the performance of ANN approach, this study performs a series of computer simulations. This study assumes that a systematic disturbances initially intruded alone in the process in a certain period of time, then a cycle disturbance intruded alone in the process in another period of time. Finally, the mixture type of systematic and cycle disturbance started upsetting the process. This study employs the ANN approach to classify those three kinds of disturbances; that is, the systematic disturbance, cycle disturbance and mixture type of systematic and cycle disturbance.

This study uses 2100 and 900 data vectors for the training and testing phases. The first 700 training data vectors are generated from the presence of systematic disturbance alone; the data vectors from 701 and 1400 are generated from the presence of cycle disturbance alone, and the last 700 data vectors are generated from the mixture type of systematic and cycle disturbance. The testing data structure is same as the training data structure. The first 300 data vectors are involved with systematic disturbance alone, the data vectors from 401 and 600 are involved with cycle disturbance alone, and the last 300 data vectors are involved with the mixture type of systematic and cycle disturbance.

For ANN designs, this study uses the notation, {ni-nh-no} to represents the number of neurons in the input layer, number of neurons in the hidden layer and number of neurons in the output layer, respectively. The inputs nodes of the ANN classifiers contain the EPC action (X) and process outputs (Y). The output contains one node, Z. This node represents the prediction of the process status. The values of 1, 2, and 0 represent that the underlying disturbance is systematic, cycle, or mixture type, respectively. The learning rate is set to be either one of the two typical values, 0.01 or 0.001.

After performing the ANN classification tasks, we obtain the results which are shown in Table I. In Table I, the first column indicates that the disturbance types which we want to correctly classify. The second column of Table I is the parameter setting for the ANN classifier, and the corresponding accurate classification rate (ACR) are displayed in the third column.

Observing Table I, we can see that the values of ACR are 100%, 97.6% and 90.3% for systematic, cycle and mixture type, respectively. The corresponding parameter settings are all {2-5-1}.

TABLE I. ACR FOR THREE KINDS OF DISTURBANCES

Disturbance type	Parameters $\{n_i\text{-}n_h\text{-}n_o\}$	ACR
SYS	{2-5-1}	100%
CYC	{2-5-1}	97.6%
Mixture of SYS-CYC	{2-5-1}	90.3%

V. CONCLUSION

An integrated SPC-EPC mechanism is a good approach to monitor a manufacturing process. However, because EPC would compensate the underlying disturbances, the CCPs are difficult to be classified.

This study proposes the ANN approach to classify three kinds of process disturbances. The performance of the proposed ANN approach is confirmed through a series of computer simulations. The proposed ANN approach is simple to use and effective in categorizing the mixture type of disturbance patterns. In this study, we only consider the systematic, cycle and their mixture type of disturbances, an attempt to classify more mixture type of disturbances should be a valuable contribution to the future research. Also, the use of other machine learning classifiers, such as support vector machine and random forest, could be employed to classify the disturbance patterns for a multivariate SPC/EPC system.

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