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Fault diagnosis of pneumatic systems with artificial neural network algorithms

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ABSTRACT

Pneumatic systems repeat the identical programmed sequence during their operation. The data was collected when the pneumatic system worked perfectly and had some faults including empty magazine, zero vacuum, inappropriate material, no pressure, closed manual pressure valve, missing drilling stroke, poorly located material, not vacuuming the material and low air pressure. The signals of eight sensors were collected during the entire sequence and the 24 most descriptive features of the data were encoded to present to the ANNs. A synthetic data generation process was proposed to train and test the ANNs better when signals are extremely repetitive from one sequence to other. Two artificial neural networks (ANN) were used for interpretation of the encoded signals. The tested ANNs were Adaptive Resonance Theory 2 (ART2), and Back propagation (Bp). ART2 correctly distinguished the perfect and faulty operations at all the tested vigilance values. It classified 11 faulty and 1 normal modes in seven or eight categories at the best vigilance values. Bp also distinguished perfect and faulty operations without even the slightest uncertainty. In less than 10 cases, it had difficulty identifying the 11 types of possible faults. The average estimation error of the Bp was better than 2.1% of the output range on the test data which was created by deviating the encoded values. The ART2 and Bp performance was found excellent with the proposed encoding and synthetic data generation procedures for extremely repetitive sequential data.

1. Introduction

Almost all manufacturers need to automate their facilities and follow the technological changes to stay competitive in the world market (Angeli & Smirni, 1999). If the speed of the moving objects is not critical, pneumatic systems are a cheap, clean, and easy to maintain alternative for the automation. These systems repeat a programmed sequence many times. When the system encounters a problem, generally the manufactured parts will be wasted and the cost will increase (Demetgul, 2006). It is necessary to detect the problems and their source as quickly and accurately as possible to continue operating with minimum interruption. Sensors are installed at the critical locations and their signals are carefully encoded to obtain the smallest and best descriptive data set. ANNs are a good choice for interpretation of the encoded sensory signals for most pneumatic systems. The ANNs correlate the inputs with the desired outputs which indicate the problems and their source. In this study, the operation of a pneumatic system was monitored by using eight sensors. Two ANNs (Adaptive Resonance Theory 2 (ART2) (Carpenter & Grossberg, 1987), and Back propagation (Bp) (Rumelhart, Hilton, & Williams, 1986)) were used to interpret the encoded data of the sensors.

Many researchers have developed diagnostic methods by using ANNs to detect the problems of march-motors, electric motors (Bayır & Bay, 2004), rotating machine parts (Rajakarunakaran, Venkumar, Devaraj, & Rao, 2008), automobile engines, bearings, hydraulic servo-valves, servomotors, check-valves (Seong et al., 2005), wood sawing machines, metal cutting operations, gears, gearboxes (Chen & Wang, 2000; Samanta, 2004; Wuxing, Tse, Guicai, & Tielin, 2004), hydraulic systems (Demetgul, 2008; Sandt et al., 1997), pumps (Karkoub, Gad, & Rabie, 1999), gas turbines, Fisher Rosemount valves (Karpenko & Sepehri, 2002; Karpenko, Sepehri & Scuse, 2003), and compressors. Some of the commonly used ANN algorithms in fault diagnosis are Bp, ART2, Levenberg Marquart, Neuro-fuzzy (Wang, Golnaraghi, & Ismail, 2004), (Self Organization Feature Maps) SOFM (Jams a-Jounela, Vermasvuori, Enden, & Haavisto, 2003), (Learning Vector Quantisation) LVQ, and (Radial Basis Function) RBF algorithms (Parlos, Kim, & Bharadwaj, 2004).

Shi and Sepehri used LVQ and Neuro-fuzzy algorithms to diagnose the failure of the cylinder and valves of pneumatic system. They used only one pressure sensor to monitor the system (Shi & Sepehri, 2005). In this study, a realistic manufacturing operation

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was simulated by using a modular production system (MPS). The normal and faulty modes were detected by using the signals of eight transducers including three pressure sensors, a linear potentiometer and 4 P/E (pneumatic to electric) switches.

Depending on the training process, ANNs are classified as unsupervised and supervised neural networks (Masters, 1995). One unsupervised (ART2) and one supervised (Bp) ANNs were used in this paper. Unsupervised neural networks such as ART2 may start to monitor the considered operation without any training. It will generate new categories when the characteristics of the data changes. The vigilance of the ART2 has to be adjusted very carefully in order to create the minimum number of categories and be able to classify the perfect and defective cases correctly. Bp is a supervised ANN which requires a training process to allow the algorithm to select the proper parameters. Bp is the most commonly used ANN since it can be used for classification and mapping. It requires extensive training data which covers all the possible combinations to work properly. In this study, synthetic data was generated by slightly deviating the encoded values and excellent results were obtained. Bp has to be trained very carefully with artificially generated data to cover large number of possibilities if almost the identical values are received from the sensors during the normal operation of the system.

In the following sections, the theoretical background, test system, proposed monitoring system, results and conclusions are presented.

2. Theoretical background of the tested ANNs

Two different ANNs were used in this study and evaluated on their performance and convenience. The unsupervised neural network was the easiest to use and calibrate. Use of Bp was a complete challenge and needed to generate synthetic data from the experimentally encoded parameters. Once the synthetic data was generated, we used the same data to evaluate the sensitivity of the ART2 and Bp.

ART2 network was introduced by Carpenter and Grossberg (Tansel, Mekdeci, & McLaughlin, 1995). The network simulates the learning of the biological systems. It generates a self-organized stable pattern during the inspection of the data. It can be used in real time for monitoring the diagnostic applications without any previous training. When the input characteristics and the feedback expectancies are matched within the allowable tolerance, adaptive resonance occurs and the data is classified with one of the previously created categories. Otherwise, a new category is created. The most important task is the selection of the vigilance of the neural network to create the minimum number of categories without classifying normal and faulty cases in the same category (McGhee, Henderson, & Baird, 1997; Yang & Han, 2004).

Bp (Karpenko, Sepehri, & Scuse, 2003) is the most widely used neural network. It systematically optimizes large numbers of simple transfer functions located on different layers to represent the relationship between the input and the output. Generally, training takes a very long time since the neural network makes millions of iterations to obtain the best fit for the transfer functions. After the training, a complex and non-linear mapping is obtained between the input and output variables (Venkatasubramanian, Rengaswamy, Kavuri, & Yin, 2003). The Bp estimates the output parameters very quickly once the training is completed. Thus, given the input/output pairs, the network can have its weights adjusted by the Back propagation algorithm to capture the non-linear relationship (Tansel, Wagiman, & Tziranis, 1991). It is necessary to be very careful during the training of the Bp type of neural network. Since it maps the input and the output variables it has no measure of the distance between the known cases and a presented case. Simply stated, if a user trains the neural network only a limited space of the variables, the estimation of the Bp at the other vector spaces are almost random.

3. Test system

In this study the operation of the didactic modular production system (MPS) from the Festo Company was used to evaluate the performance of a combination of eight sensors and ANN (Hussain & Frey, 2005). The MPS stations are presented in Fig. 1 (Taskin, 2007).

The principal objective of the developed didactic prototype was to examine the cylindrical work pieces for proper height and material type. A hole was drilled on each workpiece and they were sorted according to their material type. As the name implies, the plant consist of different modules. The modules are again grouped in five stations. A brief description of the five stations and their operation are outlined in the following sections and presented with a schematic in Fig. 2.

3.1. The stations of the Festo MPS didactic plant

3.1.1. Distribution station

This section of the plant consists of a pneumatic feeder and a transfer module. The feeder module pushes one workpiece at a time from the magazine and moves it the range of the transfer module. The transfer module picks up the workpiece with a vacuum suction cap and moves to the next station after rotating it 180°.

3.1.2. Testing station

The testing station consists of a test spot, a lifting apparatus, a linear potentiometer to measure the thickness of the workpieces and a conveyor module. The test spot is equipped with three different types of proximity sensors, namely, inductive, capacitive and optical. The capacitive proximity sensor detects whether there is a workpiece or not. The inductive proximity sensor detects whether the workpiece is metallic or non-metallic and the optical proximity sensor detects whether the workpiece is black or not. The lifting module moves the workpiece up and brings it in front of the linear potentiometer. After the thickness of the workpiece is measured, a pneumatic cylinder mounted on the lifting module pushes the workpiece either to the conveyor or to the slider and off to the scrape area depending on whether or not it passes the thickness test.

3.1.3. Processing station

A hole is drilled on the workpiece at this station. The station consists of a rotary indexing table, a drilling module and an inspection module to confirm the drilled hole. The rotary indexing table has four sections. These sections are 90° apart from each other. Position 1 is for receiving the workpiece from the conveyor belt. The drilling operation takes place at the position 2. There is an inspection module for the drilled holes at position 3. Position 4 is for delivering the workpiece to the next station.

3.1.4. Handling station

This station is used to transfer the materials to the last unit of the MPS: the sorting station. It picks up the workpiece by using a suction cap from position 4 of the rotary table. It rotates the workpiece 180° and places it on the sorting conveyor belt.

3.1.5. Storing station

This station stores processed pieces in different magazines according to their material type. The defective parts are guided through a slider to the scrape area.