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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.

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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.

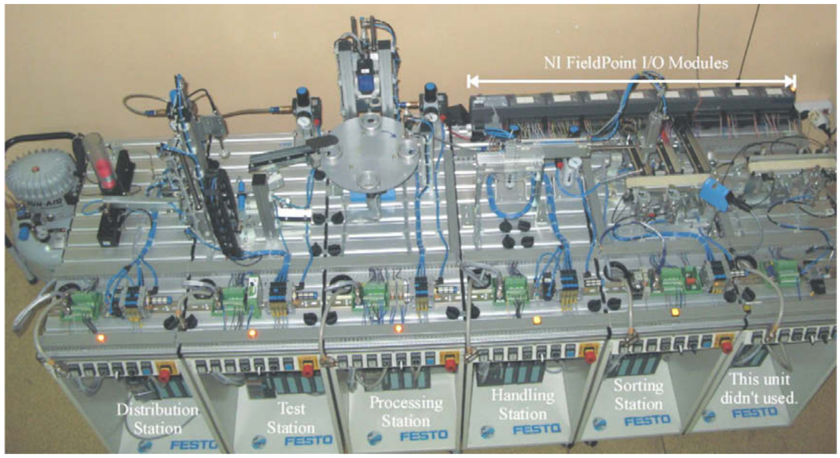

Fig. 1. Festo MPS didactic plant.

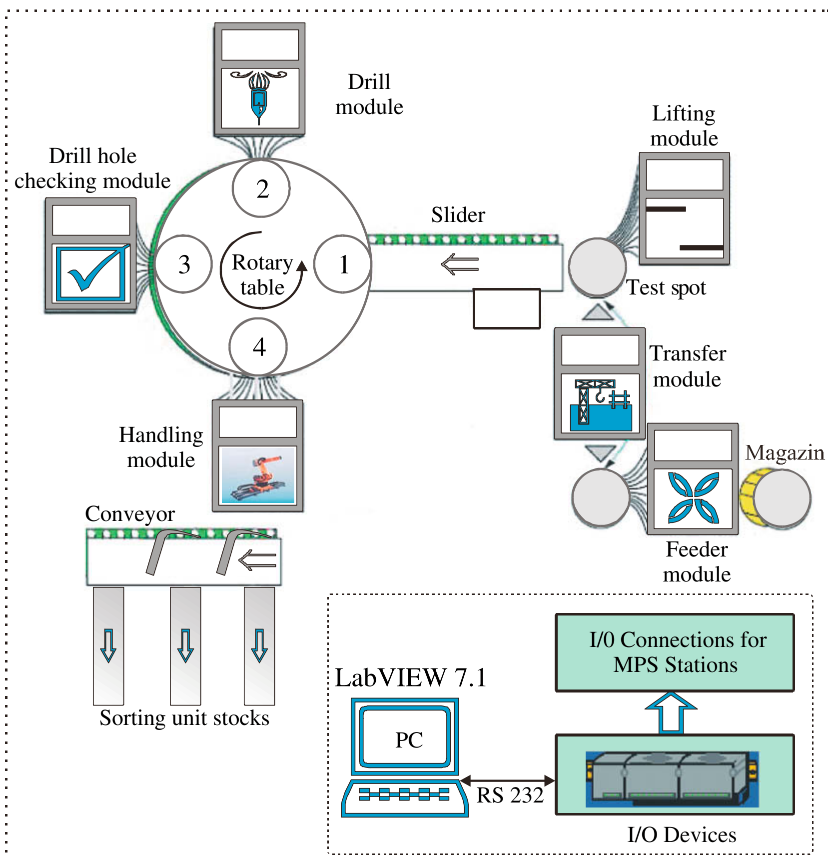

Fig. 2. Schematic of the didactic plant.

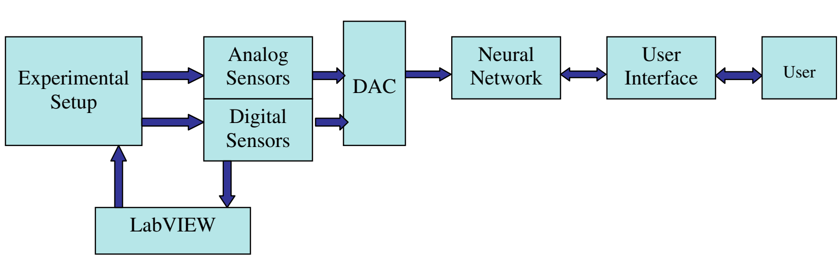

Fig. 3. Flow diagram of fault diagnosis.

3.2. Operation of the system and data collection

Flow diagram of the MPS system is presented in Fig. 3. The system was controlled by LabVIEW. Matlab 7.0 was used to collect the experimental data.

Data acquisition card collected the data from sensors which were located at the different sections of the pneumatic system. Users selected the operation values on the user interface of the flow diagram. Eight sensors were used in the experiments to collect the data. The sensors are listed in Table 1.

4. Proposed encoding and classification method

The sensors provided long data segments during the operation of the system. To represent the characteristics of the system, the sensory signals were encoded by selecting their most descriptive features and presented to ANN.

Typically, the pressure of the system is constant. 6.5 V was subtracted from all the sampled voltages of the pressure sensor defined as S1. The absolute values were calculated and the 10th highest value was selected. To increase the weight of the data, the same value was presented to ANN three times.

The signals of the S2, S3, S4, S5, and S7 were encoded by identifying the time when the value went over 3 V, when it fell below 3 V and the average of the sampled values when the reading was maximum.

Seven values were encoded for the pressure sensor indicated by the S6: when the signal fell below the 3 V, when it went over 3 V, the average of 400 sampled values, the average values when the signal went below 3 V and increased over 3 V, and again the averages when the signal dropped below 3 V and increased over 3 V.

5. Results and discussion

In this section, we cover the signals of the sensors when the system works at the perfect and faulty conditions. The performance of the neural networks will be discussed in the following sections.

5.1. Characteristics of the signals of the sensors at different operating conditions

In this study, the pneumatic system was operated at the normal conditions and at 11 different faulty conditions. The imposed problems are listed in Table 2.

The signals of the linear potentiometer (Fig. 4), magazine optic sensor (Fig. 5), vacuum analog pressure sensor (Fig. 6), material holding P/E switch (Fig. 7), material handling arm pressure sensor (Fig. 8), vacuum information P/E switch (Fig. 9), optic sensor (Fig. 10), and pressure sensor of main system (Fig. 11) are presented at the listed figures. Most of the sensors had unique patterns for the problems except the pressure sensor of the main system and the optic sensor. The level of the signal of the main pressure sensor was almost flat and around the 6.5 V except the one fault: the pressure level of the main pneumatic system was low. Optical system only detected when the drilling did not work and workpiece was removed from the magazine but separated.

Table 1
Sensors used for the diagnostics of the considered MPS system.

Symbol	Sensor
1	Pressure sensor of main system
2	Magazine optics sensor
3	Vacuum information P/E switch
4	Material handling P/E switch
5	Linear potentiometer
6	Material handling arm pressure sensor
7	Vacuum analog pressure sensor
8	Material in the stock optic sensor

The signals of the linear potentiometer (Fig. 4), vacuum analog pressure sensor (Fig. 6), material holding P/E switch (Fig. 7), material handling arm pressure sensor (Fig. 8), and vacuum information P/E switch (Fig. 9) looked like irregularly located square waves with different widths. The magazine optic sensor (Fig. 5) had spike type output. Almost the signal of each one of these sensors was informative enough to detect the defects. This characteristic of the sensory signals simplified the interpretation of the signals by the neural networks. When the experiments were repeated at the same conditions, the signals were almost identical. Use of almost identical cases was like using the duplicate data for training. Since the sensory data was almost identical, the training and testing cases were almost the same too. Under these circumstances, we determined to use only one case at each condition.

5.2. Generation of synthetic data to determine the accuracy and robustness of the ANN

The ideal training and test data of the ANNs are supposed to cover the entire space of all the input variables. Generally, some compromise is necessary when the experimental data is used. When the data of the sensors or encoded parameters are identical or extremely close to each other, using data from multiple tests does not improve the quality of the training and may even be considered as presenting duplicate cases. The ANN is trained only at a very small space of the input variables and the reliability of the system suffers enormously.

In this study, to fill the input variable space better, synthetic cases were generated by increasing and decreasing the encoded parameters by 2%, 4%, 6%, and 8%. This process enabled us to work with nine times more data than the original cases and to train the ANNs within a larger band which covers the ±8% of the input variable space.

5.3. Performance of the ART2 type ANN

Performance of the ART2 was studied first without considering the generated synthetic cases. Later, synthetic cases were also considered to evaluate the robustness of the ANN when the encoded parameters deviates ±8% from the experimental ones.

ART2 was used to classify one perfect and 11 faulty cases at the different vigilance values ranging from 0.92 to 1. For all the vigilance values, ART2 generated one category for the perfect operation case and put the other 11 faulty cases into the different categories. It classified 11 faulty modes in six categories for the vigilance of 0.92. For the vigilance of 1, it created different categories for each one of the faulty cases. These results indicated that even for the lowest vigilance value, the ART2 would not misidentify any of the faulty modes with perfect operation and may be used with confidence. At the vigilance of 0.9995, a different category was created for all the faults except one. The relationship between the vigilance and the number of the created categories for the 12 experimental cases are presented in Fig. 12.

The synthetic data was used to evaluate if ART2 would put these artificial cases in the same category with the original one, classify them in the same category with another original one, or create a new category. Ideally, the artificial cases were supposed to be classified in the same category with the originals. Creation of a new category for the derivative of an original one is not wanted but acceptable. Classifying the derivative of one original in the same category with another experimental one is not acceptable.

ART2 generated only seven categories for the vigilance values between the 0.92 and 0.9365. It put the synthetic cases of the Fault8 and Fault9 in the same category with the Fault11 of the ori-

Table 2
Faults in the system and output values of ANN algorithm.

Faults	Symbol
Normal operation of the MPS	a Normal
Magazine is empty	b Fault1
Vacuum couldnot be started in order to take the material from Distribution Station of MPS	c Fault2
The workpiece was moved with vacuum from the magazine but dropped	d Fault3
The workpiece which was removed from the magazine was separated e	e Fault4
No pressure at the valve which controls the forward motion of the handling arm f Fault5	f Fault5
Handling station manual pressure valve may be closed g Fault6	g Fault6
Drilling isnot working. So, the following moves of the MPS is waiting h Fault7	h Fault7
In the handling unit the workpiece was not located properly for vacuum I Fault8	i Fault8
In the handling unit the material couldnot be vacuumed k Fault9	k Fault9
The material is transported to the sorting unit of MPS, but it didnot pass to the stock l Fault10	l Fault10
The pressure of the MPS is low m Fault11	m Fault11

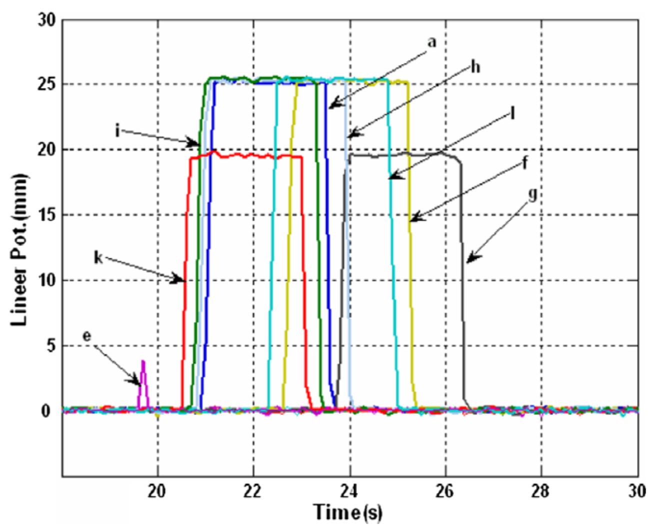

Fig. 4. Linear potentiometer.

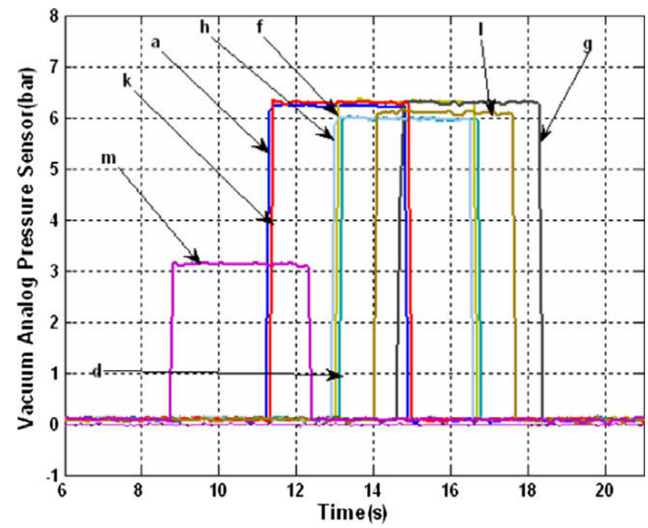

Fig. 6. Vacuum analog pressure sensor.

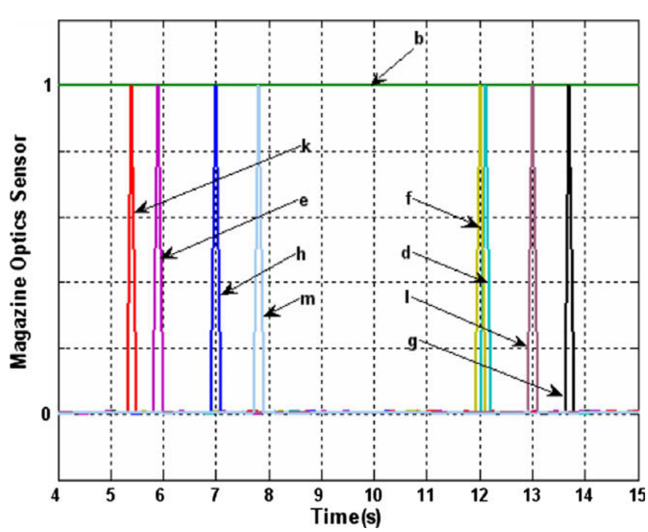

Fig. 5. Magazine optics sensor.

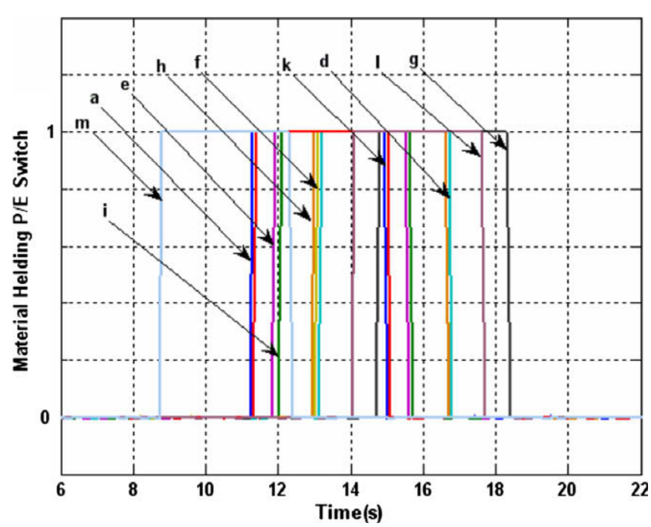

Fig. 7. Material holding P/E switch.

ginal cases. This error was repeated for all the data groups generated at different deviations from the experimental ones. ART2 generated eight categories for the vigilances between the 0.937 and 0.947. The reported confusion disappeared with the addition of one more category. All the artificial cases were classified in the same category with their originals. A total of nine categories were generated for the original data when the vigilance values were between 0.9375 and 0.9865. All of the derivatives of the original data were classified with the originals in the nine categories without any confusion. ART2 generated 10 categories for the original cases and continued to add new ones for each of the derivatives of Fault8 and Fault11 for the vigilance of 0.987. The total number of created

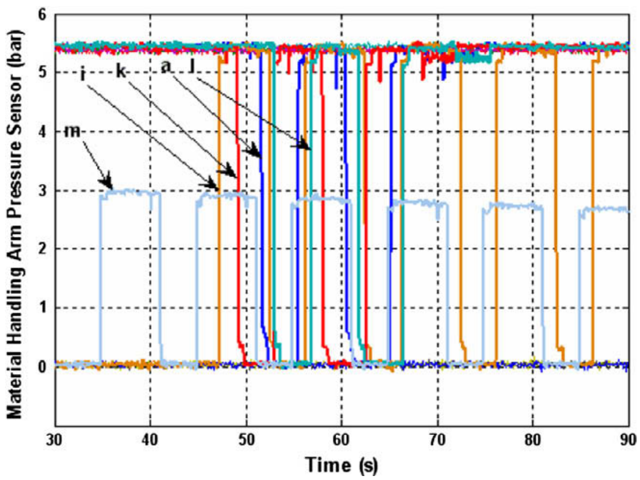

Fig. 8. Material handling arm pressure sensor.

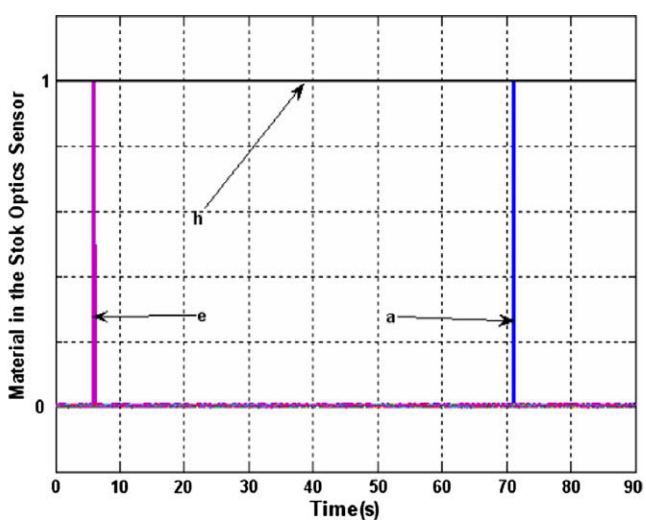

Fig. 9. Vacuum information P/E switch.

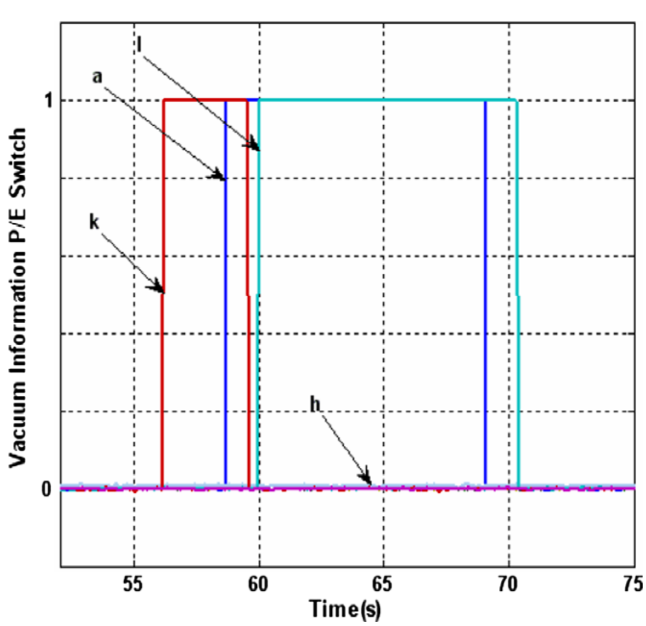

Fig. 10. Optics sensor.

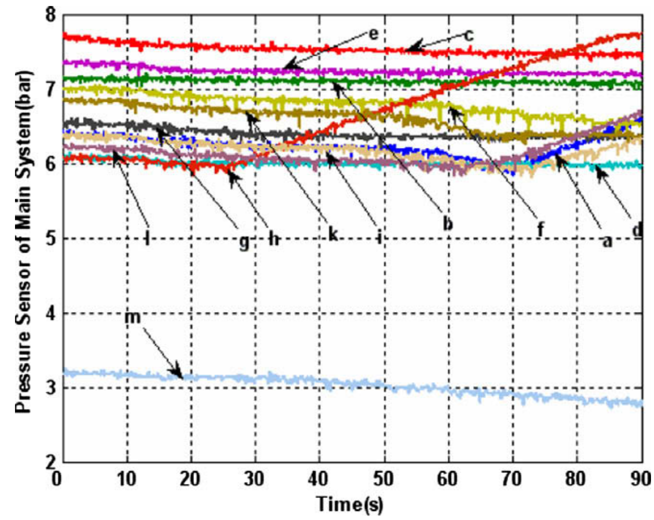

Fig. 11. Pressure sensor of main system.

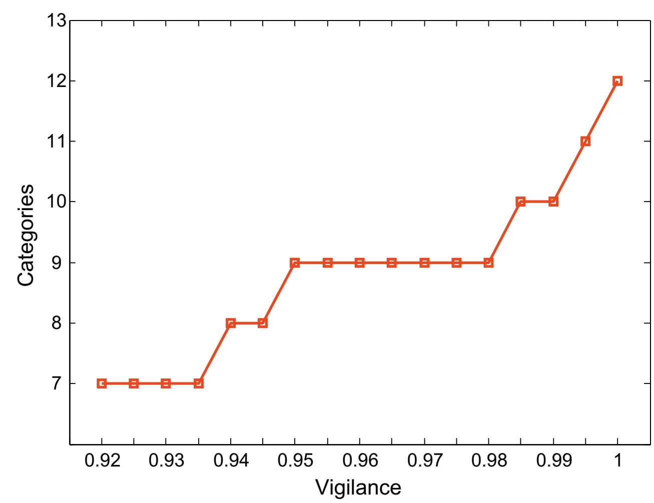

Fig. 12. Performance of the ART2 on the presented.

categories, obtained by inspecting all 108 cases, was 26. For the perfect and the 11 faulty cases, different categories were generated for the vigilance of 1. There were a total of 53 categories created for the original and the artificial cases. The numbers of the created categories at the different vigilance values are presented in Fig. 13.

As observed from the results of this study, the best vigilance values for the ART2 are between 0.9365 and 0.9865. The system will be able to monitor the system without any interruption when it works perfectly and indicate the fault as soon as it encounters problems. Operators will need to inspect the system one more time since it will classify 11 different faults either in seven or eight categories for these vigilance values.

5.4. Performance of the Bp type ANN

The generated synthetic data was essential for the training and testing of the Bp type ANNs with our extremely repetitive data. The Bp had 12 inputs and one output. The value of the output was determined to be 1 for perfect case. For the faults the output was selected as 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.1 for normal, Fault1, Fault2, Fault3, Fault4, Fault5, Fault6, Fault7, Fault8, Fault9, Fault10 and Fault11, respectively. This was chosen in a very prac-

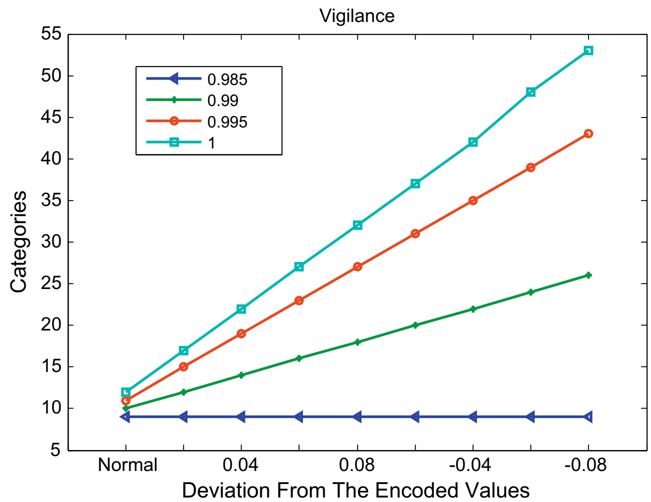

Fig. 13. Performance of the ART2 on the different deviation.

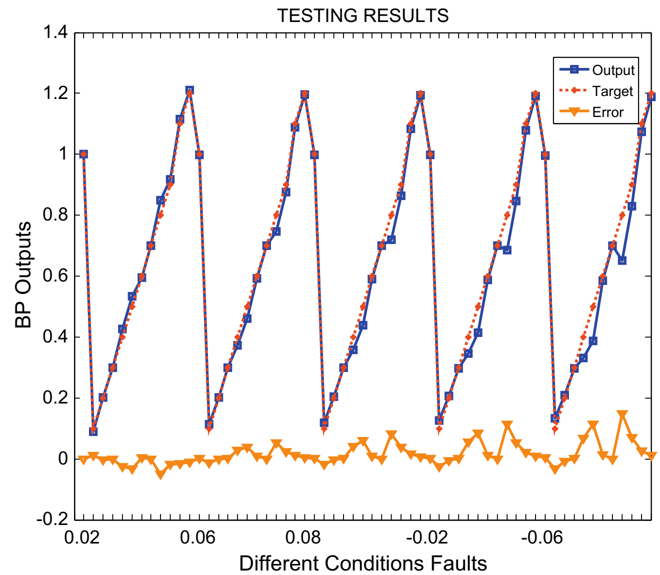

Fig. 15. Bp test results.

tical manner, considering the maximum accuracy which might be tested from a Bp type neural network when the experimental data is involved. 15 nodes were used at the hidden layer after several tests to obtain a compact network with acceptable accuracy. Bp was tested by using 60 cases after it was trained with 48 cases. The encoded values of the original data and the artificial cases generated with +4%, −4% and −8% deviations were used for the training. The deviation of the test cases from the encoded values of the original ones were +2%, +6%, 8%, −2% and −6%. At the final stages of the training, the learning rate and momentum constant were selected to be 0.3 and 0.5, respectively.

The estimations of the Bp type ANN is compared with the experimental and synthetic values in Figs. 14 and 15 for the training and test cases, respectively. The estimation accuracy of the Bp was excellent for the training cases. The perfect operating condition and every fault were accurately identified without any uncertainty. The performance was also excellent when the Bp was tested on the synthetic data with +2% deviations from the encoded experimental data. For 8% and −6% deviations, the perfect and faulty operation modes were always accurately identified. However, at

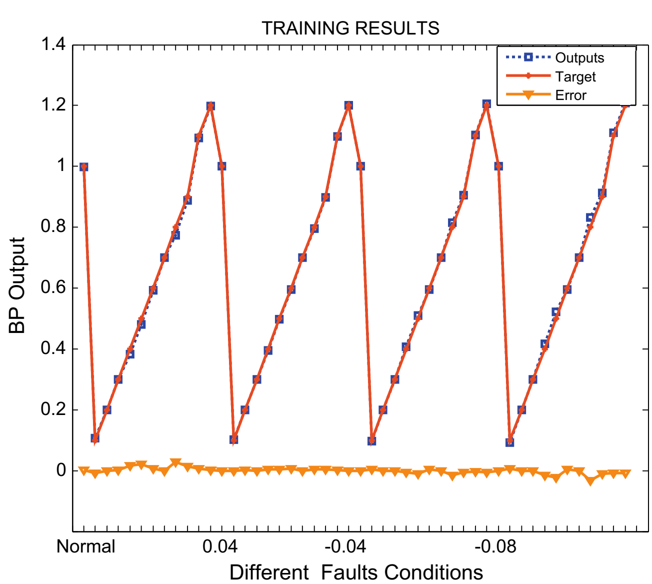

Fig. 14. Bp training results.

these extreme values the Bp started to confuse some of the faults with others.

6. Conclusion

A pneumatic manufacturing system was simulated with modular production system (MPS) and automated monitoring of the system was considered. New procedures were proposed for encoding the sensory signals and generating synthetic data for better training and testing of the data. Performance of the ART2 and BP type ANNs were evaluated by using the experimental and synthetic encoded values.

The pneumatic systems repeat the identical sequence like many other automated assembly systems. The experimental data of each sequence was almost identical at the perfect operation. Similarly, each fault had a unique sensor output which repeated itself. For each one of the perfect operation and 11 faulty modes, sensory signals were encoded only once. The 25 most descriptive features of the sensory signals were calculated and used for each case. To better evaluate the performance of the ANNs, synthetic data was generated by increasing and decreasing the encoded values up to 8% with 2% steps.

ART2 identified the perfect operation. The data of the faulty operations were also detected; however, it could not correctly identify all of the 11 faulty modes unless the vigilance was selected as 1. The best vigilance value was between 0.9365 and 0.9865. The 11 faulty modes were classified by using seven or eight categories.

Bp is a very difficult ANN when the experimental data is concentrated in a very small segment of the input space. When the data almost duplicates, Bp cannot be used. The proposed synthetic data generation approach solved this problem and allowed training and testing of the ANN. The performance of the ANN was excellent with less than 1% average estimation error (respect to the range) for the training cases. For the test data, the average estimation error increased to 2.1%. The perfect and faulty modes were distinguished without the slightest uncertainty for the training and test sets. At the test cases, some of the 11 possible faults were misidentified in less than 10 cases. This is an excellent level of performance for a Bp type ANN.

The results indicated that ART2 and BP type ANNs could be used for the diagnostic of even extremely repetitive automation systems. We recommend the number of the fault modes to be kept below 5 to let the ANNs identify each one of them reliably.

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