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RADIAL BASIS AND LVQ NEURAL NETWORK ALGORITHM FOR REAL TIME FAULT DIAGNOSIS OF BOTTLE FILLING PLANT

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Original scientific paper

In this study, an Artificial Neural Network (ANN) is developed to find faults rapidly on a pneumatic system. The data were saved and evaluated considering system is working perfectly and faults are predetermined. These faults include having no bottle, a nonworking cap closing cylinder B, a nonworking bottle cap closing cylinder C, insufficient air pressure, water not filling and low air pressure faults. The signals of six sensors were collected during the entire sequence and the 18 most descriptive features of the data were encoded to present to the ANNs. Two different ANNs were applied for interpretation of the encoded signals. The ANNs tested in the study were learning vector quantization (LVQ) and radial basis network (RBN). The performance of LVQ and RBN was found to be fine with the presented procedures for a system having very repetitive sequential data.

Keywords: *artificial neural network, bottle filling plant, fault diagnosis, pneumatic*

Algoritam radijalne osnove i LVQ algoritam neuronske mreže za pravovremenu dijagnozu greške pogona za punjenje boca

Izvorni znanstveni članak

U ovom je radu razvijena umjetna neuronska mreža (ANN) za brzo pronalaženje grešaka na pneumatskom sustavu. Podaci su prikupljeni i procijenjeni smatrajući da sustav radi savršeno, a greške su unaprijed predviđene. Greške uključuju manjak boce, ne funkcioniranje cilindra B za stavljanje poklopca, neispravni cilindar C za stavljanje poklopca na boce, nedovoljan tlak zraka, voda se ne puni i nizak tlak zraka. Tijekom postupka prikupljeni su signali šest senzora te je za ANN kodirano 18 najkarakterističnijih obilježja podataka. Primijenjene su dvije različite umjetne neuronske mreže (ANN) za interpretaciju kodiranih signala. Umjetne neuronske mreže testirane u ispitivanju bile su "learning vector quantization (LVQ)" i "radial basis network (RBN)". Ustanovilo se da te dvije vrste umjetnih neuronskih mreža dobro funkcioniraju u primijenjenim postupcima u sustavu u kojem se sekvencijski podaci ponavljaju.

Ključne riječi: *dijagnoza greške, pneumatski, pogon za punjenje baca, umjetna neuronska mreža*

1 Introduction

Automation has changed the manufacturing industry over the years and made it much more competitive. Today, following technological changes is necessary to stay in the competitive world market. Pneumatic system is an economical, unpolluted, and easily maintainable choice for the automation. Sequential movements can be programmed to repeat the tasks many times in these systems. However, generally the manufactured parts will be wasted and the cost will increase in case of coming across a problem. So, it is essential to identify the problems and their cause as quickly and accurately as possible to be able to operate with minimum break. Main solution is to place sensors to critical locations and to encode the signals in order to obtain the data set describing the problem and cause [1].

ANN is one of the best options in clarification of the encoded signals obtained from pneumatic systems. The ANNs correlate the inputs with the desired outputs which indicate the problems and their source. Currently, ANNs are mainly used in many systems such as rotating machine parts, automobile engines, bearings, hydraulic servo-valves, servomotors, wood sawing machines, check-valves, march-motors, electric motors, gears, gearboxes, hydraulic systems, pumps, gas turbines, Fisher Rosemount valves, compressor, and etc. The most frequently used ANN algorithms in fault diagnosis are Levenberg Marquart, Back propagation, Neuro-fuzzy, Art-Kohonen, LVQ (Learning Vector Quantisation), RBF (Radial Basis Function) algorithms, SOM [2], ART [3], and SVM [4].

Learning vector quantization methods (LVQ) algorithm is used mostly in classification of pattern recognition [5]. It has been shown that LVQ methods create a very practicable alternative to the traditional approaches. Their speed in learning is considerably higher due to the very simple computations while their classification accuracy is as much as that of any other NN algorithms. Therefore, the LVQ algorithm is an excellent method for nonlinear separation and a novel scheme for fault diagnosis [6].

Another neural network algorithm called an RBN type of network is a subgroup of the multilayer feed forward neural networks. One advantage of RBN networks is that they can be trained in a more straightforward manner than neural networks, which are trained with the back propagation algorithm. However, in order to achieve the same accuracy, the RBN network can become larger than the network trained with back-propagation algorithm [7].

Literature review confirms that NN-based systems are effective in handling fault diagnosis tasks. For example, Samantha [8], Chen and Wang [9] developed an ANN to diagnose failure at gears. In their study, the fault is recognized using the data from machine vibrations. A back propagation algorithm was used. In another study, Yang et al. [10] and Wang et al. [11] used the ANN algorithm to analyse rotating parts. Many researchers have worked on predicting the fault of hydraulic and pneumatic systems [12 ÷ 18]. Chen et al. [19] and Hou and Huang [20] have worked on fault diagnosis of production systems.

Jeffries et al. [21] tried to control a bottle filling plant with fuzzy logic. Cooke et al. [22] presented a practical production model based on mass balance equations. The model has modest data requirements and can be initialized with machine mean up and down times and joint unavailability, in addition to fixed line parameters. Lastly, Demetgul et al. [23] proposed GA-NN environment to diagnose the fault and demonstrated that the convenience, accuracy and speed of the system have increased.

In this study, the operation of a pneumatic system was observed by using six sensors. Two types of ANN, Learning Vector Quantization (LVQ) and Radial Basis Network (RBN), were used to interpret the encoded data of the sensors. In this study, we used these algorithms to diagnose failure on bottle filling plants. The following describes the test system used in experiments. Then, methodology used in analysis is explained. Obtained results are discussed and conclusions are given.

2 Test system

The experimental setup is composed of many parts. They are three double-act cylinders, three inductive sensors which indicate if there is a part or not, three electro-pneumatic valves, three limit switches, one step motor, one solenoid valve, three pressure sensors, three linear potentiometers, a data acquisition card, a multiplex board and a computer as shown in Fig. 1. The pressure sensors being used give data between 0 ÷ 10 V (0 ÷ 10 bar) and the potentiometers give data between 0 ÷ 10 V.

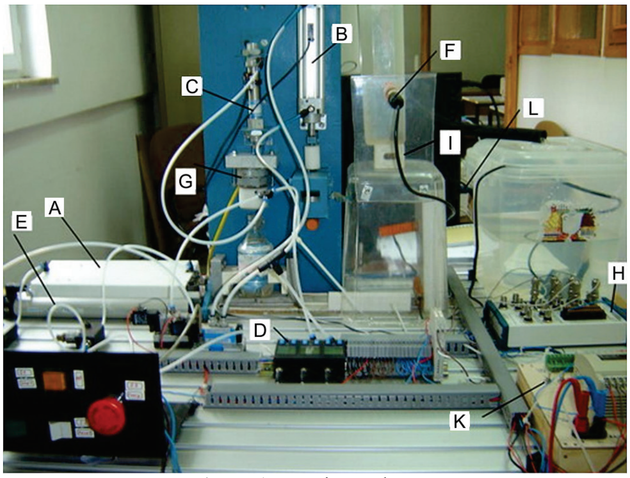

Figure 1 Experimental setup

2.1 Operation of the system and data collection

The parts shown with letters in Fig. 1 are described in Tab. 1. Cylinder A in the experimental setup grasps the empty bottle and moves forward. The system stops working when the bottle sensor notices that there is no bottle. When cylinder A reaches a limit, it switches to solenoid valve I shown in Fig. 1, which opens and fills the bottle with water. There is a water reservoir over the solenoid valve and when water is used up there, water is stored from a bigger reservoir. After the bottle is filled up to the defined level, the solenoid valve is closed by the help of F level inductive sensor. Cylinder A waits for a while after filling up then it moves back. Cylinder A stops when it reaches halfway of its last position. Cylinder B moves back and then cylinder A reaches its last position. Then, the bottle cap closing cylinder C moves down. The cap is tightened and then cylinder C moves back. The step motor runs and closes the cap. Thus, a full process is completed.

A flow diagram of our work is illustrated in Fig. 2. The system is controlled by PLC. Analog sensors are pressure sensors and linear potentiometers placed at different parts of the system. Pressure sensors measure between 0 ÷ 10 bar, work with current between 4 ÷ 20 mA and with 2 % errors. Pressure sensors are placed to the entry of valves and pressure difference of the system is measured with analog measurement equipments. 1 V is equal to 1 bar in these sensors outputs. Linear potentiometers are placed next to cylinders. 1 V is equal to 15 mm in these sensors outputs. MATLAB 7.0 is used to develop our software in this work.

Table 1 Parts of experimental setup shown in Fig. 1

A	Cylinder A
B	Cylinder B
C	Cylinder C
D	Pressure sensor
E	Linear potentiometer
F	Inductive sensor
G	Step motor
H	Multiplex board
I	Solenoid valve
K	PLC
L	DAC

The Data Acquisition Card is gathering the data taken from sensors which are placed to the different parts of the pneumatic system. LVQ and Radial Basis Function are used as ANN algorithms. The user gives values to variables and gets results on the user interface as shown in Fig. 2.

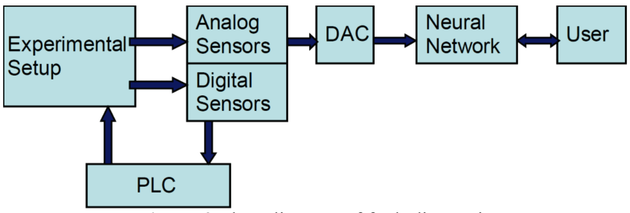

Figure 2 Flow diagram of fault diagnosis

2.2 Characteristics of the signals of the sensors at different operating conditions

Any implication of an abnormality in the operating conditions is defined as fault and the related equipment is referred as being faulty. A more specific definition of faults can be explained by using substantial degradation in system performances. This could be because of changes in the system parameters or a fault of equipment measuring inaccurate values. Users request and sometimes require suppliers to build up systems which will decrease/prevent faults and their consequences. The most common way implemented today is to use maintenance schemes/plans that notify the user to replace the parts before faults. The alternative way is to provide a monitoring scheme to observe the processes. It could be integrated within the process in such a way that faults, their causes and locations could be detected when they occurred. In consequence, it is clear that fault detection, fault location, fault diagnosis and fault correction are principal functions in creating a monitoring scheme [24].

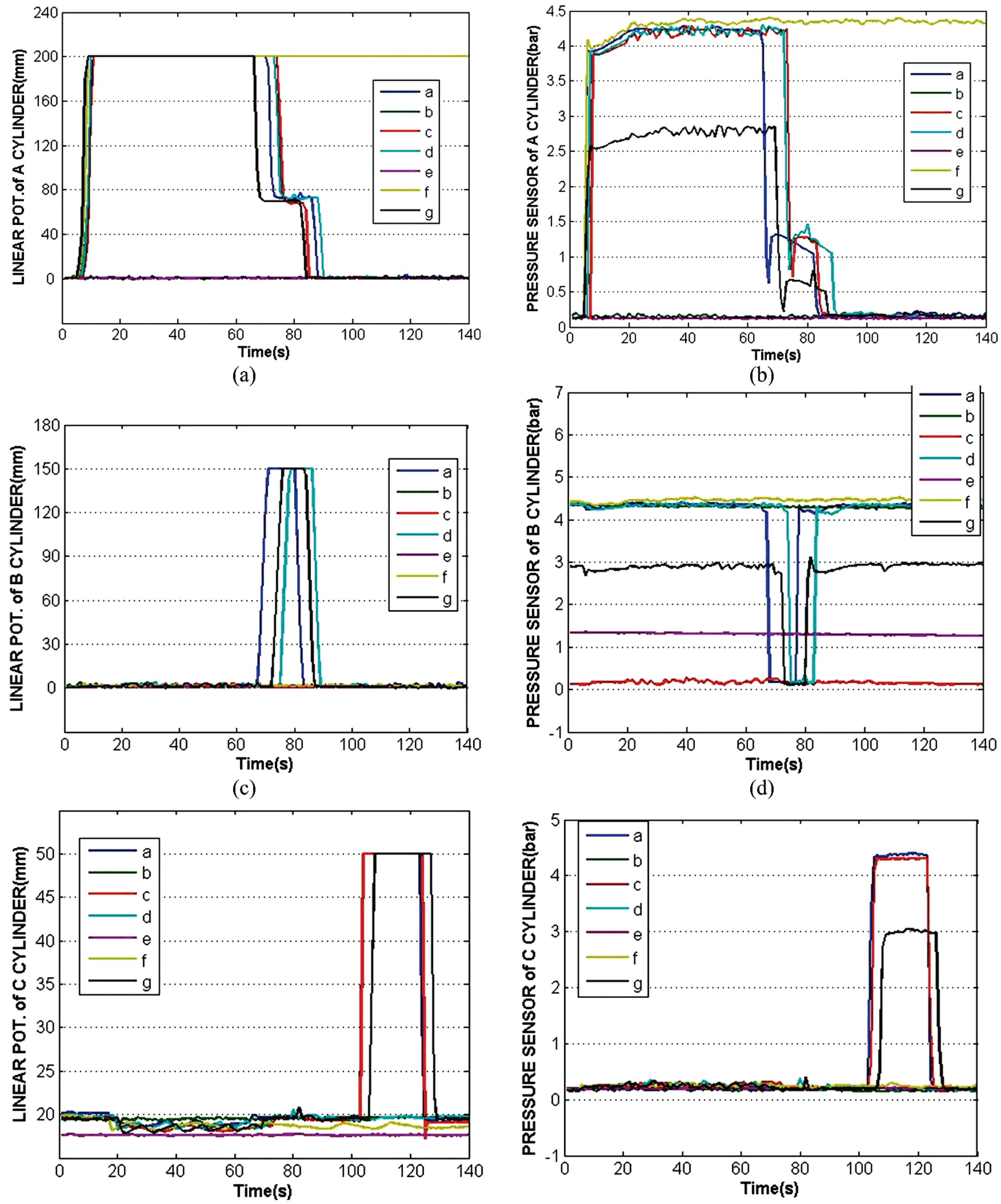

Figure 3 Failures at experimental setup (continued):
(a) Cylinder A linear potentiometer, (b) Cylinder A pressure sensor, (c) Cylinder B linear potentiometer, (d) Cylinder B pressure sensor, (e) Cylinder C linear potentiometer, (f) Cylinder C pressure sensor

Table 2 Failures occurring at experimental setup

a	Normal
b	No bottle
c	Bottle cap closing cylinder B is not working
d	Bottle cap closing cylinder C is not working
e	Air pressure not sufficient
f	Water is not filling
g	Low air pressure

In Fig. 3, pressure change in A, B, and C valves and change in location of A, B, and C cylinders are given. These graphs are drawn for 140 second-intervals. In Tab. 2, description of each letter shown in the figure is given. (a) in Fig. 3 represents the data taken from 6 sensors while there is no failure on system. (b) represents the data before the bottle is placed in its first position as in Fig. 3. Because there is no bottle, the process will not complete. Values taken will be close to zero during the process. (c) represents the data when the air is not compressed to cylinder B. Although the cap closing cylinder is not working, the process is completed. Thus, bottles reach the limit without closing cap. (d) represents the data when the cylinder C in Fig. 3 is not working. This cylinder, in normal conditions, is moving down and closing the cap over the bottle by means of a step motor. Because the cylinder did not go down, a cap will not be pressed over the bottle. (e) represents the data when there is air pressure not sufficient in system and no part is moving. Certainly, air pressure must be sufficient in order for the system to work. (f) represents the data when water is not filling even though cylinder A moves forward. Solenoid valve, shown in Fig. 1 as I, provides filling of water. Water reservoir is over the solenoid valve. When the reservoir becomes empty, it is filled with water from the next, bigger, reservoir by means of motor. If water is not filling when cylinder A moves forward, it means that water is not pumped to small reservoir or that there is a problem with the solenoid valve. Finally, (g) represents the data when the air pressure in the system is low. This results in a longer processing time and consequently, a more costly production. If air pressure in the system is not enough, the process will not work.

3 Learning Vector Quantization (LVQ)

LVQ was first proposed by Kohonen for classifying patterns with inherent class intersections. The core of the Learning Vector Quantization classifier is based on the nearest-neighbor method by calculating the Euclidean distance. The LVQ algorithm is used to approximate the theoretical Bayes decision borders using piecewise linear decision surfaces [25]. It is shown that the accuracy of the LVQ algorithm is very close to the decision-theoretic Bayes limit even in problematic instances. The learning rule in LVQ network is based on the competence of process elements in Kohonen layer with each other. The one whose process element reference vector is nearest to input vector wins the competence analysis. Distance of its process element is calculated as in Eq. (1) while d represents the distance between input vector $\boldsymbol{X}$ and reference vector $\boldsymbol{A}$ [26].

$$d_i = \|A_i - X\| = \sqrt{\sum_j (A_{ij} - x_j)^2}. \quad (1)$$

Weights of network are changed according to Eq. (2). λ represents learning coefficient in this equation. It is gradually decreased to zero. The reason for this is to be able to stop the change in input vector when it comes too near to the reference vector and to prevent it from moving back to the opposite side.

$$A_y = A_e + \lambda(X - A_e). \quad (2)$$

When the winner process element is from a wrong class, the weight vector decreases the input vector. So, when the same position occurs again, this detraction is made to prevent that same process element from prevailing. In this case weights are changed as shown in Eq. (3).

$$A_y = A_e - \lambda(X - A_e). \quad (3)$$

The outputs of process elements in Kohonen are multiplied with weight values which join process elements to the output layer. The output of network is calculated as shown in Eq. (4).

$$Ç_i = \sum_j Ç_j^k \alpha_{ki}. \quad (4)$$

In Fig. 4, change in position of cylinder A, B, C and change in pressure of cylinder A, B, C are taken as input. Their data are shown in Fig. 3. Outputs of network are normal and faulty. Kohonen Layer neuron numbers are selected 10. It is shown in Tab. 3.

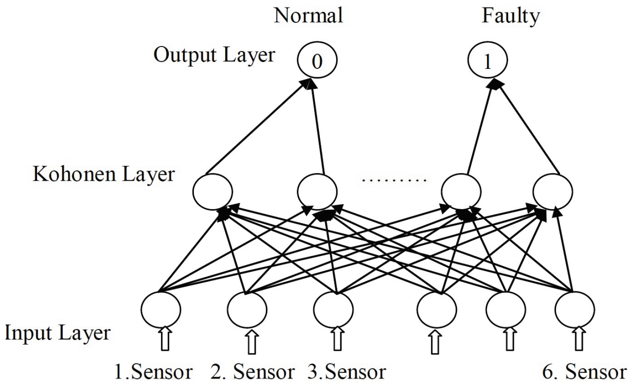

Figure 4 LVQ Structure

Six different trials are made as shown in Tab. 3 to find out the most appropriate variable values, which let the network work with maximum performance. Performance of the network is 99 % at the second trial, value of hidden layer neurons number is taken as 10. At the third, fourth, fifth, and sixth trials, different learning rate values are attempted but their performance could not match the value of the second trials. Learning rate value of network is taken as 0,1.

Table 3 LVQ Training performances

Training number	Hidden layer neurons number	Learning rate	Performance %
1	5	0,1	90
2	**10**	0,1	**99**
3	20	0,1	89
4	10	0,3	95
5	10	0,6	90
6	10	0,9	88

As a result of the trials shown in Table 3, hidden layer neuron number, learning rate and iteration number of LVQ network are taken respectively as 10; 0,1 and 1000 as shown in Tab. 4.

Table 4 LVQ Learning parameter

Hidden layer neurons number	10
Learning rate	0,1
Iteration number	1000

4 Radial Basis Network (RBN)

RBNs are composed of simple elements operating in parallel. Biological nervous systems inspired the composition of these elements. In nature, connections between neurons (elements) determine the function. In RBN, learning rule serves as a procedure for modifying the values of the connections (weights and biases) between neurons. Commonly RBNs are trained so that a particular input leads to a specific target output. The design of a RBN in its most basic form consists of three separate layers: input layer, hidden layer and output layer. The hidden layer contains a number of RBF neurons, and each of them represents a single radial basis function. The output layer provides the response of the network to the activation patterns applied to the input layer [27]. The architecture of the RBN is shown in Fig. 5.

From the centre layer to the output layer, an adoptable and linear transformation is performed. Output of network is shown at Eq. 5.

$$I_k = \|X - c_k\| = \sqrt{\sum_{i=1}^{N}(X_i - c_{ki})^2},\ k = 1, 2, 3,.., N. \qquad (5)$$

Output of neuron is shown at Eq. (6).

$$V_k = \mathrm{e}^{\frac{I_k}{\sigma_k^2}}. \qquad (6)$$

Free parameters adoptable to radial bases networks are centre vectors; width of radial functions and output layer weights. Because output layer is linear, it could be easily found by weights slope reduction or linear optimization methods. Although centres could be selected among inputs randomly or constantly, to improve the performance of radial-base network, various methods are developed to adopt centre vectors and width. Centre vectors could be determined by adopting learning with tutor algorithms according to slope reduction method or grouping among input samples or self-adopting methods [26]. The network structure is shown in Fig. 5. The learning phase has two steps: unsupervised learning and supervised learning. The difference between them is that external prototypes are used as target outputs for specific input patterns and that new connection weights, giving closer output values, are determined by a learning algorithm which network introduced.

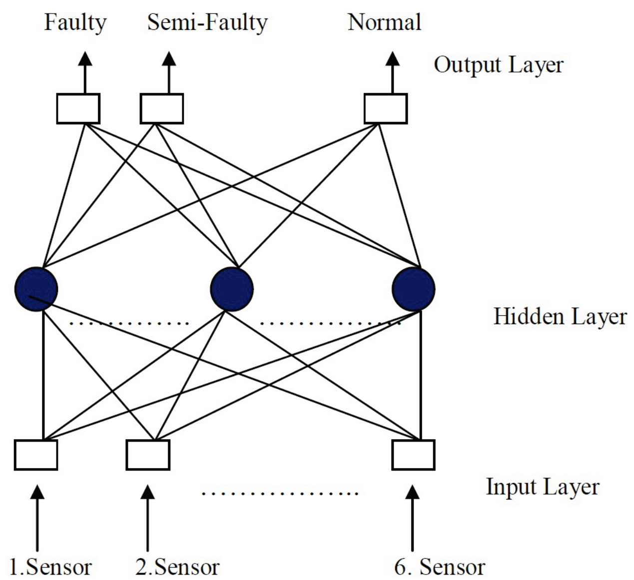

Figure 5 Radial Basis Network Structure

Inputs and outputs of developed network are given in Fig. 5. Change in position of cylinder A, B, C and change in pressure of cylinder A, B, C is taken as inputs of network. The data of change in position and pressure are shown in Fig. 3. "Normal", "Semi-Faulty" and "Faulty" states are taken as outputs of network. The amount of the least square of error is taken as 0,002 and spread constant for radial basis layer is taken as 50.

5 Results and discussion

The signals were encoded by identifying the time that their value went over 3 V and fell below 3 V. In the case the reading was maximized, the average of the sampled values was used. Training data was taken when all of fault condition happens two times.

Sensors, given in the first row of testing results Tab. 5, "1" and "2" are pressure sensor A and its linear potentiometer, "3" and "4" are pressure sensor B and its linear potentiometer, "5" and "6" are pressure sensor C and its potentiometer. The system gets 140 data from each sensor. Then it is observed that the quantity of data from each sensor that was obtained is close to 1. "2" shows the failures and finds that "Normal", "No bottle", "Bottle cap closing cylinder B is not working", "Bottle cap closing cylinder C is not working", "Air pressure not sufficient", "Water is not filling", and "Low air pressure failures".

Table 5 Learning Vector Quantization (LVQ) Outputs (S: Sensor)

Faults	1. S	2. S	3. S	4. S	5. S	6. S
F1: Normal	1	1	1	1	2	1
F2: No bottle	2	2	2	2	2	2
F3: Bottle cap closing cylinder B is not working	1	1	2	2	2	1
F4: Bottle cap closing cylinder C is not working	1	1	1	1	2	2
F5: Air pressure not sufficient	2	2	2	2	2	2
F6: Water is not filling	2	1	2	2	2	2

In "No bottle" failure, sensor "6" gives output values close to 2 because the system is not working. In "Bottle cap closing cylinder B is not working" failure, sensors "3" and "4" give output values close to 2. The reason why sensor "5" gives values close to 2 is that the network gives wrong outputs. If "Bottle cap closing cylinder C is not working", sensors "5" and "6" give output values close to 2. Sensor "5" is the linear potentiometer of cylinder C. Sensor "6" is the pressure sensor of valve C. When "Air pressure is not sufficient", output value of network becomes close to 2. In failure "Water is not filling", output values of required movement as just half of movement is done when forward gives 0,5 go. This means that it belongs to the failed sensors group. Value of linear potentiometer is taken as 1. And it is included in the non-problematic group. Other sensor values are acquired as close to 2. Because water did not fill due to lack of water cylinder B and C did not work.

Table 6 RBN (Radial Basis Network) outputs

Faults	1. S	2. S	3. S	4. S	5. S	6. S
F1	−0,0008	−0,00087	−0,00029	0,002522	−0,00089	0,00034
F2	0,7166	1,29020	−0,00204	−0,00013	0,94116	1,07360
F3	0,75136	1,22310	0,47639	1,33940	0,003045	0,014428
F4	−0,0003	0,002166	0,043256	0,001727	−0,00073	0,008282
F5	0,50513	0,49020	0,009651	0,001581	0,000536	−0,00359
F6	0,54261	0,44261	0,40815	0,38570	0,48674	0,27870

Tab. 6 shows Radial Basis Network results. Sensors, given in first row of testing results Tab. 6, "1" and "2" are pressure sensor A and its linear potentiometer, "3" and "4" are pressure sensor B and its linear potentiometer, "5" and "6" are pressure sensor C and its potentiometer. Data in columns gives the output values of the artificial neural network. Then, to diagnose the failure, the quantity of data acquired by the sensor that is close to 1 is determined. Output values are shown in "Normal", "No bottle", "Bottle cap closing cylinder B is not working", "Bottle cap closing cylinder C is not working", "Air pressure not sufficient", "Water is not filling", and "Low air pressure faults".

In "No bottle" failure, sensor "6" gives output values close to 0 because the system is not working. In "Bottle cap closing cylinder B is not working" failure, sensors "3" and "4" give output values close to 0 and the others to 1. Sensor "3" is the linear potentiometer of cylinder B. Sensor "4" is the pressure sensor of valve B. If "Bottle cap closing cylinder C is not working", sensors "5" and "6" give output values close to 0. Sensor "5" is the linear potentiometer of cylinder C. Sensor "6" pressure sensor corresponds to valve C. When "Air pressure is not sufficient", output values of network become close to 0. In failure "Water is not filling", output values of required movement as just half of movement is done when going forward give 0,5 and others give output values close to 0. Because water did not fill due to the lack of water, cylinder B and C did not work. When the pressure of the system is not sufficient, while output values of network should be close to 1, sensors give output values as between 0,3 and 0,55.

6 Conclusions

ANN could think partly like a human and make a decision as an expert. In this work, predicted or occurred faults on a system are diagnosed initially by taking analogue data from linear potentiometers and pressure sensors. Besides, ANN is trained with training inputs and how much ANN is trained or experienced is tested with test inputs. It is possible to apply these network real-time industry problems. ANN will be trained after sensors on the system are connected to ANN. Then, training data will be compared with taken data when a failure occurs in the system and the fault will be diagnosed. Thus, fault diagnosis will be done immediately. Besides, the results point out that the network can accurately estimate fault levels unnoticeable through the training step. This information is critical for the pneumatic system since it can be used to detect the problems and assist to maintenance scheduling of the valves, cylinders and other parts. It is believed that this work makes an important contribution in the area of pneumatic systems which are enhanced by the ability of real-time fault diagnosis.

- In this work, it is seen that LVQ network gives better results because LVQ performance is 99 %. But LVQ divides failures into two groups: "Failed" and "Normal". RBF network divides failures into 3 groups: "Normal", "Failed" and "Semi-Failed". RBF performance is 87 %. LVQ network is better than RBF network in terms of performance.
- The experimental results demonstrated that the trained network is capable of detecting and identifying various faults as they occur separately.
- Neural network diagnoses faults on the plant, where "No bottle", "Cap closing cylinder B is not working", "Bottle cap closing cylinder C is not working", "Air pressure is not sufficient", "Water is not filling" and "Low air pressure faults".
- It is possible to find any problem by using normal Neural Network to get information where the fault is. However, ANN also can be used for different systems and purposes where initial aim is to find the fault simultaneously.
- The developed algorithm is flexible, it can be used for different systems for finding the faults In addition, it is observed that the algorithm is very capable of programming for many industrial plants having pneumatic systems.
- Moreover, this experimental system could be used for educational purposes.

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