Applying Perceptron Neural Network in Predictive Maintenance of Thermal Power Plant Industry

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Abstract: With the advent of predictive maintenance (maintenance) in 1980, dramatic changes were happened in maintenance planning of equipment. As predictive maintenance is depended on failure prediction of equipment in use, this approach requires using many tools and equipment, including Artificial Intelligence techniques such as neural networks. Thermal power plant activity is among industries that maintenance costs are important for them and using predictive maintenance has economic justification. Thermal power plant function is so that any failure in each subsystem will suspend power generation and will cause more costs. In this study, predicting failure in thermal power plant sub- systems is based on Perceptron multilayer network model with levenberg marquardt algorithm. For this purpose, thermal power plant 500 MW manufactured by Siemens Co, in East Iran has been considered as case study. Study results show that the model has prediction ability of MSE=0.1877 mean squared error in predicting failure time of equipment according to environment conditions that makes easy predictive maintenance planning in terms of visit numbers and required services and timely procurement of parts and storage costs.
[Mehdi Nakhzari Moqaddam, Dr. Alireza Shahraki. **Applying Perceptron neural network in predictive maintenance of thermal power plant industry.** *Researcher* 2014;6(12):49-55](ISSN: 1553-9865). http://www.sciencepub.net/researcher. 8

Key words: Perceptron multilayer neural network; predictive maintenance; thermal power plant

1. Introduction:

Machine failure happen when one component, structure or system cannot reach planned aim. Maintenance includes planned activities that make acceptable systems [1-5]. Preventive maintenance included prevention based on time until 1970 and was based on services and basic maintenance. With the continuous expansion of awareness and TPM since 1970, continuous expansion of equipment technical conditions was begun [6-8]. In 1980, predictive maintenance or maintenance based on conditions or equipment status replaced preventive maintenance. Predictive maintenance plays important role in TPM as it identifies their status using new methods of examining technical conditions of equipment at the time of operation by identifying depreciation signs or possibility of imminent failure [9-12]. Predictive maintenance includes continuous collection and interpretation of data related to production conditions and the main component operation of the equipment, failure prediction and identifying appropriate maintenance strategies [13,14]. In recent years, artificial intelligent networks have been used in pattern identification applications and failure detection issues; one advantage of using artificial intelligent networks is the ability to identify patterns that are imprecise. This study is for implementation of neural networks in predictive maintenance of Plants [15,16,17].

Some researchers have studied the function of neural networks in identifying failure. Wangand Knapp has studied on Backpropagation neural network application in CNC machine failure detection using oscillatory data. Becraft and Lee have studied development of Artificial Intelligent system as a mean for detecting failure in chemical process factories with large dimensions [18-23]. Wang, Javadpur and Knapp have provided a real time neural network based on status control system for mechanical equipment circulation, in this study, another type of neural network has been used named ARTMAP that has been developed by Karpenter et. Al in 1992, in this method, network training is a combination of training with supervisor and training without supervisor [24-28]. Also, in this model, new information on machine status are controlled consistently by oscillatory data. Lucifredi, Mazzieri and Mrossi compared two Multiple Linear Regression statistical methods and one developed method called dynamic kriging technique and neural networks in order to recognize the best technique for control and supervise systems. The study results show ineffectiveness of statistical methods in getting an optimal response [29,30]. Combining these methods with neural network is effective in predicting optimal maintenance time.

In this study, Perceptron multilayer neural networks are used on data that have been collected over 2 years daily. Then results are analyzed. Excel, Matlab, Spss and other similar software are used for data analysis and DCS system is used for data collection. This information include measured amount by accurate tool sensors, equipment failure and its date [31,32].

1-2- Thermal Power Plant

A power plant that is known with Generating Station and Power Plant names is an industrial installation for electric generation. All power manufactures have one automated power generator rotor (rotating) that transforms mechanic energy by relative motion between magnetic field and one conductor to electric energy and it is available based on fuel type and technology. Studying Document and equipment manufacturer instruction, 13 factors are important in maintaining thermal power plant equipment including [33-35]:

1. Humidity

2. Temperature
3. Atmospheric pressure
4. Unit's hours of Operation
5. Unit's Trip numbers
6. Unit's production energy
7. Unit's production capacitive energy
8. Frequency (turbine round)
9. Generator voltage
10. Turbine vibrancy
11. E. G. V. Close parentage
12. Fuel control valve percentage
13. Unit's start number

The main sub systems of thermal power plant (gas) on which more maintenance activities are done, including lubrication, cooling, fuel, hydraulic and electric.

The main components of lubrication system include main pumps and lubrication reserve, Vent Fan, filters, turbine jacking pumps and generator. Effective factors on system failure are as below.

Humidity, temperature, Unit's hours of operation, oil line pressure, lubricating system, Unit's production energy, bus voltage, low voltage, turbine vibrancy, E. G. V. Closing percentage, Unit's Trip numbers.

The main components of cooling system include water circulation pump, cooling fan, belts and conservator water tanks. Effective factors on system failure are as below.

Humidity, temperature, atmospheric pressure, Unit's hours of operation, Unit's trip numbers, Unit's production energy, 15 volts bus voltage, Unit's Start numbers.

The main components of Fuel system include fuel transportation pumps (injection, forwarding), fuel line filters and fuel line valve control. Effective factors on system failure are as below.

Humidity, temperature, Unit's hours of operation, trip numbers, Unit's production energy, frequency, 15 volts bus voltage, turbine vibrancy, E. G. V. Closing percentage, fuel valve control, Unit's Start numbers.

The main components of hydraulic system include main and reserve pumps, cooling fan, Heaters and oil line filters. Effective factors on system failure are as below.

Humidity, temperature, Unit's hours of operation, trip numbers, Unit's production energy, 15 volts bus voltage, turbine vibrancy, E. G. V. Closing percentage, fuel valve control percentage, Unit's Start numbers.

The main components of electric system include Transformator, Diesel, Battery, Feeder and Generator excitation system. Effective factors on system failure are as below.

Humidity, temperature, Unit's hours of operation, trip numbers, Unit's production energy, Unit's production capacitive energy, frequency, 15 volts bus voltage, Unit's Start numbers. Neural networks are dynamic systems that transform hidden rule or knowledge beyond data into network structure by patterning from neural system function and human brain through processing on experimental data and solve complex problems relying on learning ability and parallel processing [15].

1-3- Neural networks

Neural networks can be called electronics models that are made from human brain neural structure. Learning and training mechanism of brain is based on experimentation. Electronics models of natural neural networks are based on this pattern, and the way of dealing with problem by these methods is different from calculation methods by computer systems [36].

Neural network is made of many neural cells with great and continuous processing that is used in parallel solving of problems. Neural networks learn through examples. They are not planned for a special task. Examples must be selected with high accuracy or network maybe created incompletely. Here there is no way to understand that a system is failures unless an error occurs [38,39]. An artificial network is a set of neurons, however artificial neurons work like vital neurons; thus, it takes different inputs with many weights and produces an output that is depended on input [40].

When a neural network is made of putting so many neurons beside each other, we will have a network that its behavior is depended on b and w in addition to f output function. In such a great network, many b and m parameters must be quantified by network designer [41].

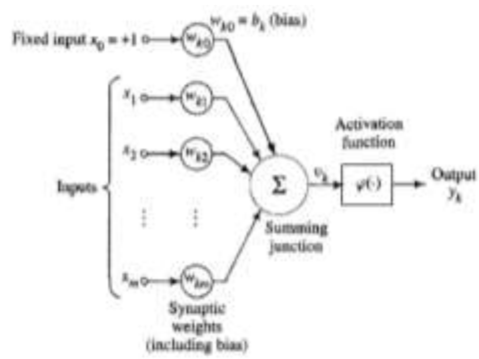

Fig .1: Neuron mathematic model

This process is known as learning process in neural networks terminology. In fact, in a real experiment when input signals of a great network are connected, network designer trains network through measuring output and selecting b and w parameters that desired output is obtained. When such a network was trained per a set of inputs for creating desired outputs, we can use it to solve a problem including a combination of inputs [42].

2- Perceptron neural network method application Procedure

In this method, firstly, input values are normalized. For this purpose, data are transformed; so that data are in [L, H] distance. This is done using below equation:

Eq. 1

$$X_{scaled} = mX_i + b$$

Where

Eq.2

$$m = \frac{H - L}{X_{max} - X_{min}}, \quad b = \frac{X_{max} \cdot L - X_{min} \cdot H}{X_{max} - H_{min}}$$

In above equation, L and H are low and high boundaries of normalization distance and are considered 0 and 1, respectively. Xmin and Xmax are the minimum and maximum values of Xi, respectively, that above equation can be simplified as below.

Eq. 3

$$X_n = \frac{2(X - X_{min})}{X_{max} - X_{min}} - 1$$

For each number related to a special variable, a weight according to the least error is given so that this variable is applied in associative sub system, then the sum of all variables are added for each status. Weights must be so that their sum equals to 1.

Eq. 4

$$N_i=(w_1x_1+w_2x_2+\ldots+w_nx_n)$$

Where $w_1+w_2+\ldots+w_n=1$

Then an artificial neural network for example according to Fig. 2 is designed in Matlab software, so that the best weight creates the least error. The process of using this method is shown in 3 Fig.

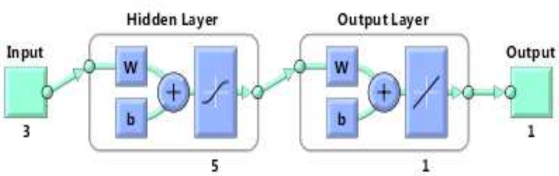

Fig. 2: Sample of designing neural network (Resource: study results)

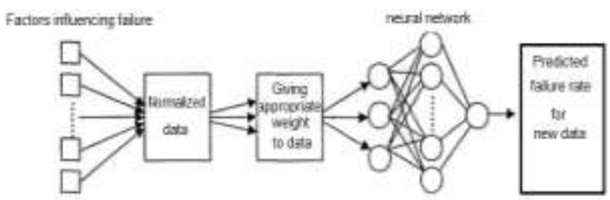

Fig. 3: implementation process of multilayer Perceptron neural network method (Resource: study results)

Levenberg-marguardt training method is used for training multilayer Perceptron neural network. In this method, input data are as weighted sum of normalized numbers and output function is each system failure. The mean square errors index (Eq. 5) shows error magnitude, also, root mean square error or root mean square deviation (Eq. 6) is the difference between predicted amount by model or statistical estimator and real amount [43].

Eq. 5

$$MSE=\frac{1}{n}\sum_{i=1}^{N} e(t)^2$$

Eq. 6

$$RMSE=\frac{1}{n}\sum_{i=1}^{N} (y-x)^2$$

3- Results of Perceptron neural network method application

3-1- Lubricating system

Levenberg- Marquart algorithm is used for designing neural network and Random method is used for data classification and Mean Squared Error is used for Performance. Network hidden layers are considered ten layers. (According to Fig. 4) for neural network training, 70 % of data is considered for training, 15% for Validation and 15% for testing.

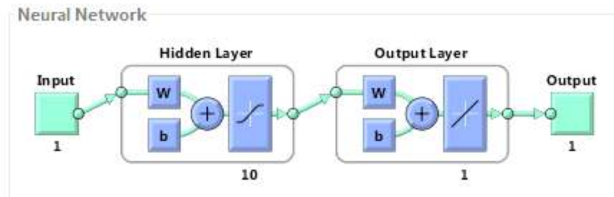

Fig. 4: Designed network for lubricating system (Resource: study results)

In 5 Fig, two types of error calculation values are calculated and shown on experimental data, MSE and RMSE. Also, in 6 Fig, the best performance of neural network has been show 0.019557 per Performance that occurs in first stage of training.

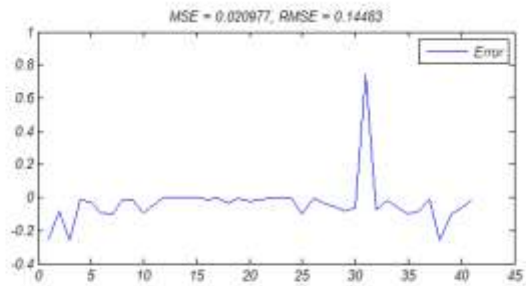

Fig. 5: results of Matlab software process for error calculation (Resource: study results)

Error is as below:

$$MSE=\frac{1}{n}\sum_{i=1}^{N} e(t)^2 \quad = 0.020977$$

$$RMSE=\frac{1}{n}\sum_{i=1}^{N} (y-x)^2 \quad = 0.14483$$

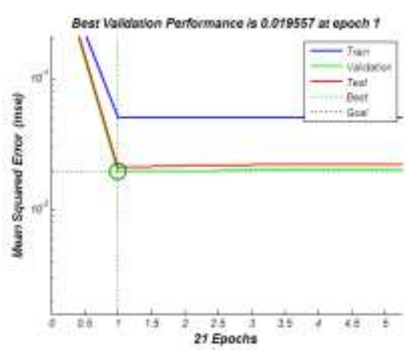

Fig. 6: the best performance of neural network (Resource: study results)

3-2- Hydraulic system

Levenberg- Marquart algorithm is used for designing neural network and Random method is used for data classification and Mean Squared Error is used for Performance. Network hidden layers are considered four layers. (According to Fig. 7) for neural network training, 70 % of data is considered for training, 15% for Validation and 15% for testing.

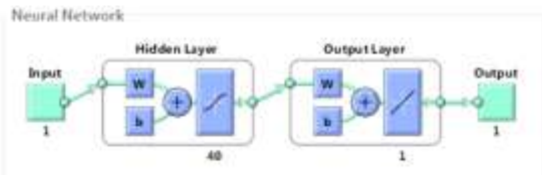

Fig. 7: Designed network for hydraulic system (Resource: study results)

In 8 Fig, two types of error calculation values are calculated and shown on experimental data, MSE and RMSE.

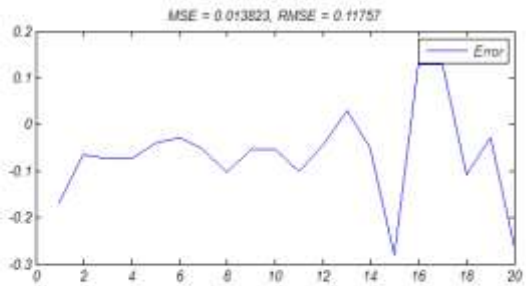

Fig. 8: results of Matlab software process for error calculation (Resource: study results)

Error is as below:

$$MSE=\frac{1}{n}\sum_{i=1}^{N} e(t)^{2} \quad = 0.013823$$

$$RMSE=\frac{1}{n}\sum_{i=1}^{N} (y-x)^{2} \quad = 0.11757$$

In 9 Fig, the best performance of neural network has been show 0.012244 per Performance that occurs in first stage of training.

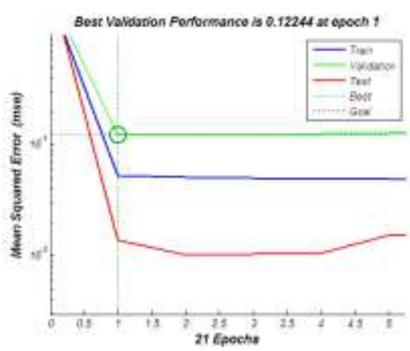

Fig. 9: the best performance of neural network (Resource: study results)

3-3- Cooling system

Levenberg- Marquart algorithm is used for designing neural network and Random method is used for data classification and Mean Squared Error is used for Performance. Network hidden layers are considered five layers. (According to Fig. 10) for neural network training, 70 % of data is considered for training, 15% for Validation and 15% for testing.

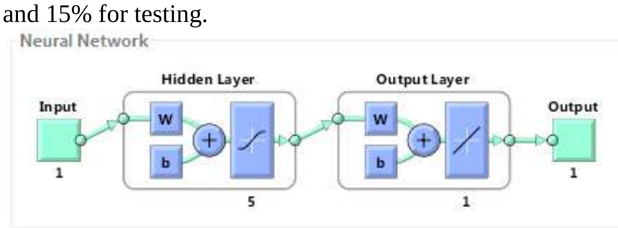

Fig. 10: Designed network for cooling system (Resource: study results)

In 11 Fig, two types of error calculation values are calculated and shown on experimental data, MSE and RMSE.

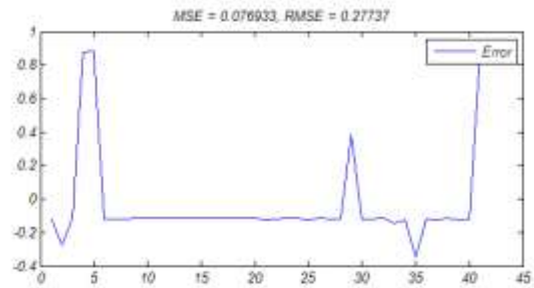

Fig. 11: results of Matlab software process for error calculation (Resource: study results)

Error is as below:

$$MSE=\frac{1}{n}\sum_{i=1}^{N} e(t)^{2} \quad = 0.076933$$

$$RMSE=\frac{1}{n}\sum_{i=1}^{N} (y-x)^{2} \quad = 0.27737$$

In 12 Fig, the best performance of neural network has been show 0.013218 per Performance that occurs in first stage of training.

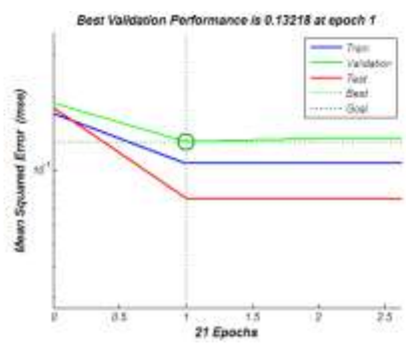

Fig. 12: the best performance of neural network (Resource: study results)

3-4 Fuel system

Levenberg- Marquart algorithm is used for designing neural network and Random method is used for data classification and Mean Squared Error is used for Performance. Network hidden layers are considered thirty layers. (According to Fig. 13) for neural network training, 75 % of data is considered for training, 15% for Validation and 10% for testing.

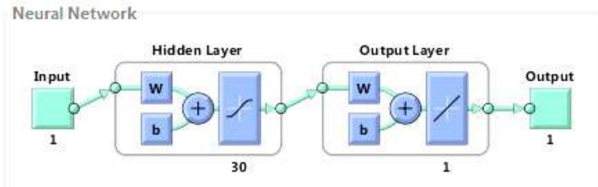

Fig. 13: Designed network for Fuel system (Resource: study results)

In 14 Fig, two types of error calculation values are calculated and shown on experimental data, MSE and RMSE.

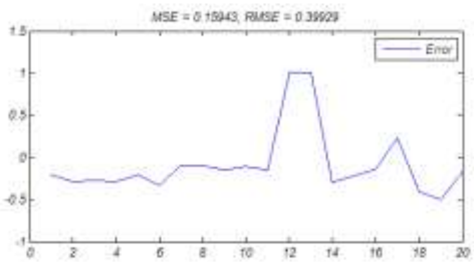

Fig. 14: results of Matlab software process for error calculation (Resource: study results)

Error is as below:

$$MSE=\frac{1}{n}\sum_{i=1}^{N} e(t)^{2} \quad = 0.15943$$

$$RMSE=\frac{1}{n}\sum_{i=1}^{N}(y-x)^{2} \quad = 0.39929$$

In 15 Fig, the best performance of neural network has been show 0.20678 per Performance that occurs in second stage of training.

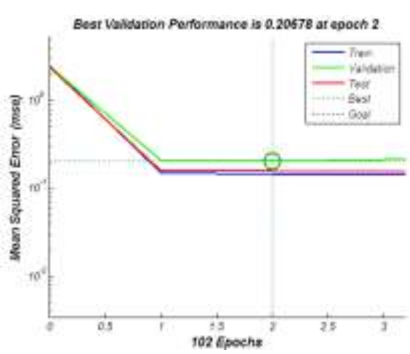

Fig. 15: the best performance of neural network (Resource: study results)

In the case of first row, prediction seems accurate due to the high humidity and high temperature and function of 109 MW compared to second row.

4-5- electric system

Levenberg- Marquart algorithm is used for designing neural network and Random method is used for data classification and Mean Squared Error is used for Performance. Network hidden layers are considered twenty layers. (According to Fig. 16) for neural network training, 75 % of data is considered for training, 15% for Validation and 10% for testing.

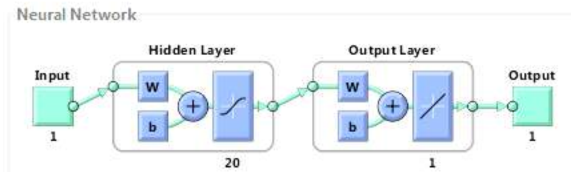

Fig. 16: Designed network for Electric system (Resource: study results)

In 17 Fig, two types of error calculation values are calculated and shown on experimental data, MSE and RMSE.

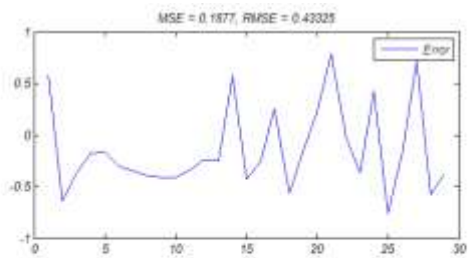

Fig. 17: results of Matlab software process for error calculation (Resource: study results)

Error is as below:

$$MSE=\frac{1}{n}\sum_{i=1}^{N} e(t)^{2} \quad = 0.1877$$

$$RMSE=\frac{1}{n}\sum_{i=1}^{N}(y-x)^{2} \quad = 0.43325$$

In 18 Fig, the best performance of neural network has been shown 0.22098 per Performance that occurs in 150th stage of training.

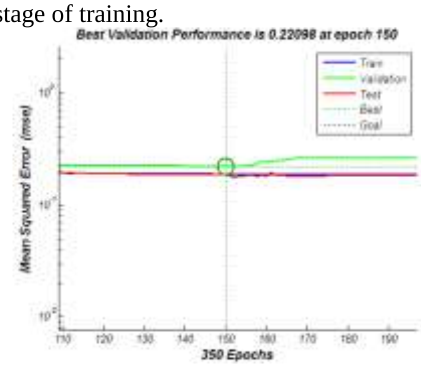

Fig. 18: the best performance of neural network (Resource: study results)

4- Conclusion

Using neural network method and studying results, it was found that we can predict failure rate per effective inputs on system failure with acceptable percent of error prediction in all five systems' power plant equipment (The maximum mean square error of MSE= 0.1877). Predicting equipment failure, we can estimate human resources, needed tools for equipment maintenance and number of services before failure and then used these parameters in maintenance planning. As a result, using neural network methods positively effects on planning gas power plant maintenance.

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12/13/2014