Applying ANFIS 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, if we provide proper prediction of future failures, we can reduce maintenance costs. This approach requires using many tools and equipment, including Artificial Intelligence techniques such as neural networks and fuzzy set theories. 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 equipment is based on ANFIS neural network. 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 method has relatively acceptable prediction ability in predicting failure time of equipment according to environment conditions that makes easy the predictive maintenance planning.

[Mehdi Nakhzari Moqaddam, Dr. Alireza Shahraki. **Applying ANFIS neural network in predictive maintenance of thermal power plant industry.** *N Y Sci J* 2014;7(12):94-101]. (ISSN: 1554-0200). http://www.sciencepub.net/newyork. 12

Keywords: ANFIS neural network; predictive maintenance; thermal power plant

1. Introduction

Maintenance includes planned activities that make acceptable systems [2]. Period before 1950 is called without preventive repair periods. Preventive maintenance was introduced in 1950 and Total predictive maintenance in 1960. 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. 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. 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 [8]. This study implements ANFIS fuzzy neural networks in predictive maintenance.

Some researchers have studied the function of neural networks in identifying failure. He and et al. have studied a Feed forward multilayer network based on machine detection methods and have introduced determined fuzzy relations between failure signs and their reasons and nonlinear relations between inputs and outputs of network [4]. Becraft and Lee have studied development of Artificial Intelligent system as a mean for detecting failure in chemical process factories with large dimensions [6].

Bansal, Evans and Jones conducted a study on application of real time predictive maintenance system for production machinery based on neural network approach. In this study, neural network learning feature was used for non linear recording in order to identify machine parameters for machine movement that in turn prevents form high costs of measuring machine [11].

Molina et. al. combined neural networks with expert system for predictive maintenance (NNMP), according to them are proper approach for predictive control systems and the reason is the high relationship between data and abnormal conditions while expert systems try to imitate operator responses and analyze variables like human, neural networks overcome these limitations and try to analyze non linear relationships between different signs.

In this study ARTMAP architecture is used to detect different status in order to prevent from unfavorable modes in future time [10].

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. Studying Document and equipment manufacturer instruction, 13 factors are important in maintaining equipment including:

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 five sub systems of lubrication, hydraulic, cooling, fuel 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, 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 cooling system include water circulation pump, cooling fan, belts and conservator water tanks. 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.

1-3- Neuro- Fuzzy network

Today's, in engineering majors, using neural networks has been increased because other methods are time consuming and with less accuracy. On the other hand, according to lack of formulation and neural network dynamic, it is good idea for engineering modeling and estimation [15].

In Fig 1, the main structure of a neural network is demonstrated. Fuzzy logic is a kind of perspective to issues; Fuzzy logic is used for Expert System design. Expert Systems simulate universal rules. 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 [16].

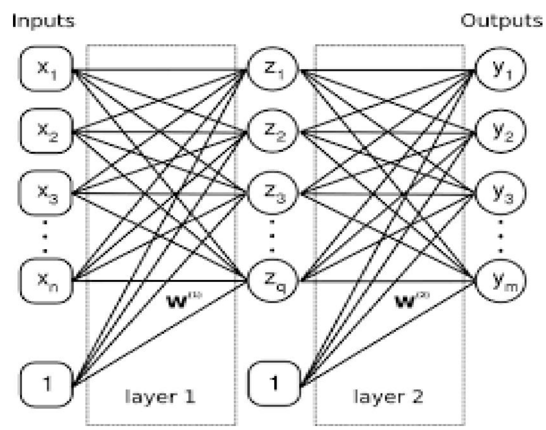

Fig.1: main structure of artificial neural network

Fuzzy- neural networks use a combination of two learning ability and parallel processing of neural networks and approximate Fuzzy inference methods. Neural networks are definite resolve of issues that are learned in system and are unpredictable and Fuzzy logic is solution for problems that their space is not absolute and cannot reach absolute response; then application of neural networks and Fuzzy logic can improve thermal power plant maintenance planning. In this study, ANFIS neural adaptive learning method is used on data that have been collected over 2 years daily. Distributed Control System (DCS) is used for data collection and Matlab, Spss and other similar software are used for data analysis.

This information include measured amount by accurate tool sensors, equipment failure and its date, manufacturer company information on basic and important equipment of Plant.

Adaptive- neural learning has performance similar to neural networks. Adaptive- neural learning techniques provide method for fuzzy modeling approach in line with information learning from data set.

ANFIS creates a Fuzzy Inferential System (FIS) using a set of input/ output data. Member function parameters of this system are justified through propagation algorithm or combining it with method of least squares. This justification operation allows Fuzzy systems to learn its structure from data set. Parameters related to membership functions change over learning process. Calculating these parameters (or their justification) is facilitated through a gradient vector. This gradient vector provides measuring factor for modeling utility of fuzzy inference systems' parameters. After providing gradient vector, other optimization procedures can be used for optimization of parameters and error reduction. ANFIS using propagation method or combining it with method of least squares estimates membership function parameters.

ANFIS creates a Fuzzy Inferential System using a set of input/ output data. This data is in matrix form with equal columns and effective components on equipment failure of each system plus one that last column is an output that is related to failure of each system at the time of applying inputs [17].

2- Adaptive Neuro- Fuzzy Inference System Application Procedure (ANFIS)

ANFIS adaptive neuro- Fuzzy learning method is used for effective important data on each sub system. Data that has been collected over 2 years daily, according to Fig. 2 is given to ANFIS adaptive neuro- Fuzzy inferential system with sugeno function as input matrix and after training, environmental real amounts are entered into this structure and then analyze output results.

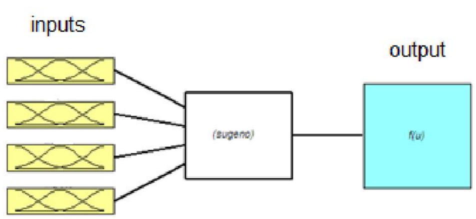

Fig.2: Anfis structure for a system sample (Resource: study findings)

3- Results of Adaptive Neuro- Fuzzy Inference System Application Procedure (ANFIS)

3-1- Lubricating system

The main structure of using this method is shown in Figs 3 and 4. Four effective factors on system failure include humidity, temperature, and voltage and turbine vibrancy.

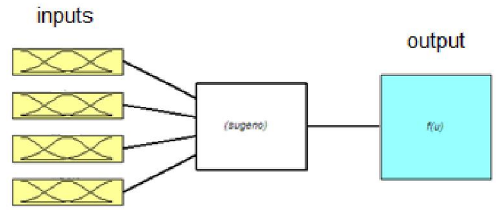

Fig 3: Anfis structure for lubricating system (Resource: study results)

In Fig 4, logic performance of Anfis structure has been shown; in which the relationship between 4 inputs, one output, 81 rules of Anfis and 12 Fuzzy functions have been shown.

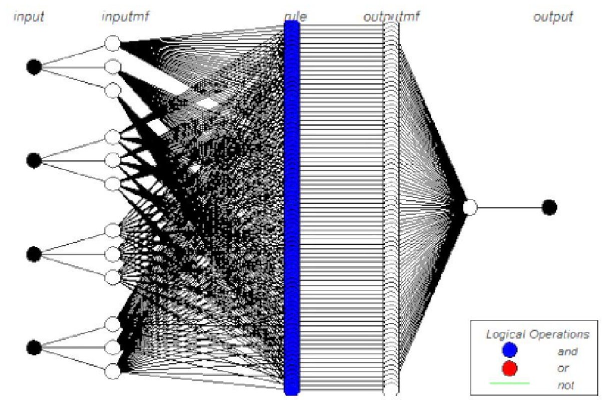

Fig 4: Logic structure of Anfis structure for lubricating system (Resource: study results)

a =

15.4940	30.1260	60.9730	20.8630	1.0000
15.4980	29.8700	68.3290	21.5920	1.0000
15.4950	29.2780	73.2380	21.9020	1.0000
15.4940	30.1090	74.1160	22.3760	1.0000
15.4940	29.7530	72.6090	21.5350	1.0000
15.4900	30.6720	71.5850	21.0080	1.0000
15.5090	30.3490	67.9500	22.1470	1.0000
15.5040	30.0250	58.4520	23.6110	1.0000
15.4930	31.2240	24.0610	22.6840	1.0000
15.4900	31.1750	51.5750	21.7220	1.0000
15.5040	30.4400	70.8840	23.0270	1.0000
15.5200	29.6100	71.8570	23.9150	1.0000
15.5220	30.0160	76.7470	23.7920	1.0000
15.5240	30.4530	77.9740	23.7640	1.0000
15.5180	30.7580	69.0410	24.0430	1.0000
15.5200	31.8840	50.2820	23.8600	1.0000
15.5170	29.9240	58.0110	22.8520	1.0000
15.5190	31.1610	64.9860	23.1150	1.0000
15.4900	28.5800	68.1600	20.7570	1.0000
15.4870	35.7110	34.6280	23.0180	1.0000
15.4910	35.7580	49.0210	22.2810	1.0000
15.4920	36.9170	58.2500	23.4370	1.0000
15.0820	29.2570	52.0700	22.6500	1.0000

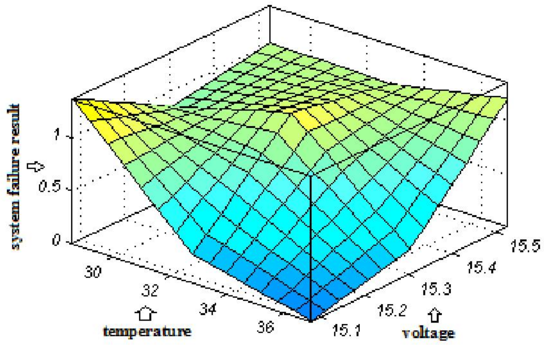

Fig 5: system failure result in terms of temperature and voltage components changes (Resource: study findings)

Table 1: Comparing practically results of ANFIS method

Voltage	Temperature	Humidity	Turbine vibrancy	Prediction	Accuracy	Row
15.49	34	57	22.5%	96%	yes	1
15.45	35	66	23.7%	76.4%	yes	2
15.45	32	66	22.9%	96%	yes	3
15.45	34	73	23.8%	66.3%	yes	4
15.45	30	42	23%	85.8%	no	5

3-2- Hydraulic system

The main structure of using this method is shown in Fig 6. Five effective factors on system failure includes humidity, temperature, voltage, and hydraulic line pressure and turbine vibrancy.

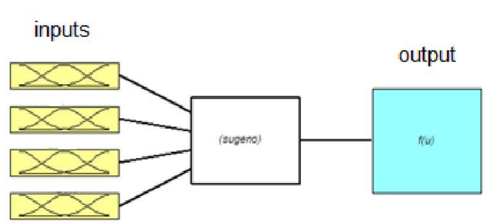

Fig 6: Comparing Anfis structure for hydraulic system (Resource: study results)

Input matrix for Matlab software is like **a** matrix. In Fig 5, lubricating system failure has been shown in terms of temperature and voltage changes that are the most important effective parameters. As in graph figure, by oil temperature reduction and voltage reduction, system failure will increase that is proper prediction. For practical test of system failure prediction accuracy in Fig 6, we measure environmental data 5 times with data designed ANFIS and proper output with reality.

In Fig 7, logic performance of Anfis structure has been shown; in which the relationship between 5 inputs, one output, 243 rules of Anfis and 15 Fuzzy functions have been shown.

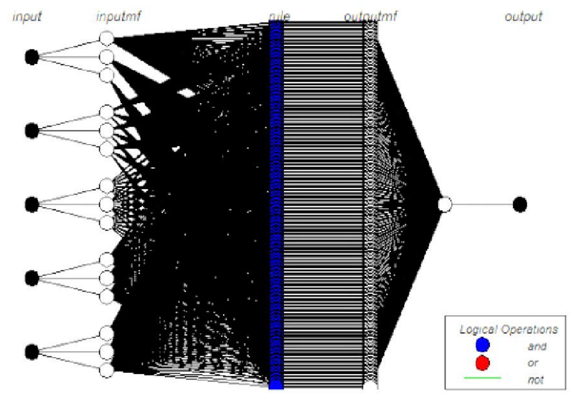

Fig 7: Logic structure of Anfis structure for hydraulic system (Resource: study results)

Input matrix for Matlab software is like **m** matrix.

m =

15.5180	30.7580	69.0410	24.0430	161.2330	1.0000
15.5200	31.8840	50.2820	23.8600	161.2570	1.0000
15.5170	29.9240	58.0110	22.8520	161.2420	1.0000
15.5190	31.1610	64.9860	23.1150	161.1750	1.0000
15.4900	28.5800	68.1600	20.7570	157.1420	1.0000
15.4870	35.7110	34.6280	23.0180	155.1440	1.0000
15.4910	35.7580	49.0210	22.2810	161.0210	1.0000
15.4920	36.9170	58.2500	23.4370	160.9710	1.0000
15.0820	29.2570	52.0700	22.6500	90.6240	1.0000
0.0180	12.4890	50.9480	22.5820	1.9000	1.0000
0.0180	2.4700	71.3580	23.2630	0	1.0000
0.0190	3.1270	78.9730	24.4870	4.0090	1.0000
12.4250	3.0490	70.9870	25.3530	1.7260	1.0000
15.3620	20.7870	65.5300	24.5070	0.9150	1.0000
15.5200	38.8490	54.1720	25.6990	127.6930	1.0000

In Fig 8, system failure result has been shown in terms of two components of turbine vibrancy and hydraulic line pressure changes. As in graph figure, when hydraulic pressure reaches to 100 bar (that indicates hydraulic system is failure as pressure is 160 bar or 0 in normal mode) and when turbine vibrancy reaches its middle mode, system failure increases that is proper prediction. For practical test of system failure prediction accuracy in 11 Fig, we measure environmental data 5 times with data designed ANFIS and proper output with reality.

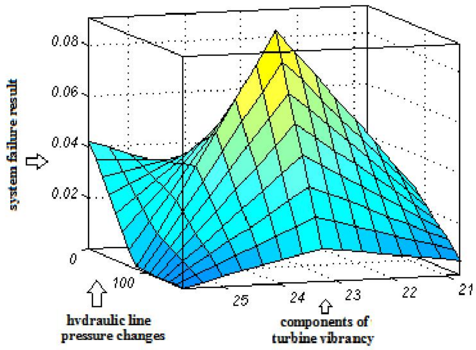

Fig 8: system failure result in terms of two components of turbine vibrancy and hydraulic line pressure changes (Resource: study findings)

Table 2: Comparing practically results of ANFIS method

Voltage	Temperature	Humidity	Turbine vibrancy	Hydraulic	Prediction	Accuracy	Row
15.52	27	64	23	80	96%	yes	1
15.52	28	64	22	120	92%	yes	2
15.52	38	69	23	120	80%	yes	3
15.52	27	60	24	52	56%	yes	4
15.52	38	72	24	161	100%	yes	5

3-3 Fuel system

The main structure of using this method is shown in Fig 9. Five effective factors on system failure includes humidity, temperature, voltage, and Unit load and turbine vibrancy.

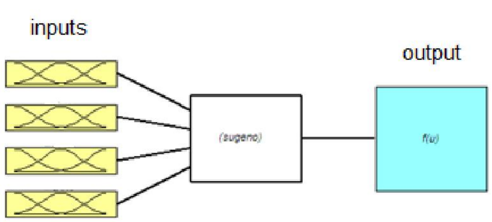

Fig 9: Anfis structure for fuel system (Resource: study results)

In Fig 10, logic performance of Anfis structure has been shown; in which the relationship between 5 inputs, one output, 243 rules of Anfis and 15 Fuzzy functions have been shown.

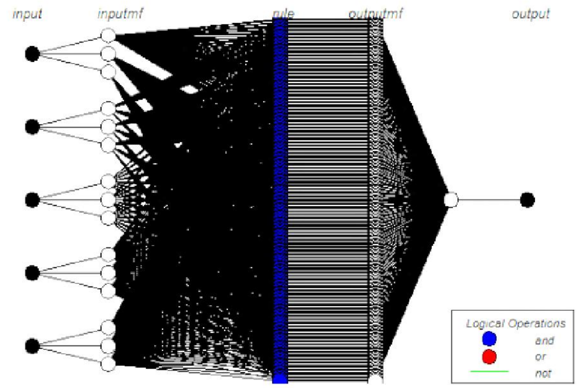

Fig 10: Logic structure of Anfis structure for hydraulic system (Resource: study results)

15.4850	31.0500	70.5700	24.7400	134.6070	1
15.4940	29.9980	77.2750	21.5400	102.4610	1
15.4940	29.3400	72.7370	22.1450	111.6040	1
15.5000	29.9700	73.0350	23.1440	89.5060	1
15.5030	30.4830	69.6310	22.9840	88.2880	1
15.5000	30.3370	78.9300	21.9810	106.0370	1
15.4950	29.9920	48.2180	20.9520	118.2910	1
15.4960	30.4730	32.4830	19.7110	114.3720	1
15.4930	30.6520	35.4320	19.5280	111.1740	1
15.4920	29.9330	54.2170	20.2620	99.9540	1
15.4940	30.1260	60.9730	20.8630	98.6750	1
15.4980	29.8700	68.3290	21.5920	101.5950	1
15.4950	29.2780	73.2380	21.9020	92.6390	1
15.4940	30.1090	74.1160	22.3760	90.3960	1
15.4940	29.7530	72.6090	21.5350	81.6820	1
15.4900	30.6720	71.5850	21.0080	106.0560	1
15.5090	30.3490	67.9500	22.1470	74.8110	1
15.5040	30.0250	58.4520	23.6110	77.0800	1
15.4930	31.2240	24.0610	22.6840	94.4380	1
15.4900	31.1750	51.5750	21.7220	119.5360	1
15.5040	30.4400	70.8840	23.0270	107.3640	1
15.5200	29.6100	71.8570	23.9150	109.2550	1
15.5220	30.0160	76.7470	23.7920	111.8970	1
15.5240	30.4530	77.9740	23.7640	111.8370	1
15.5180	30.7580	69.0410	24.0430	104.7660	1
15.5200	31.8840	50.2820	23.8600	122.8650	1

15.5170	29.9240	58.0110	22.8520	117.3880	1
15.5190	31.1610	64.9860	23.1150	103.0060	1
15.4900	28.5800	68.1600	20.7570	72.5950	1
15.4870	35.7110	34.6280	23.0180	87.5170	1
15.4910	35.7580	49.0210	22.2810	89.5380	1
15.4920	36.9170	58.2500	23.4370	99.0470	1
15.0820	29.2570	52.0700	22.6500	70.0320	1
0.0180	12.4890	50.9480	22.5820	0.1960	1
0.0180	2.4700	71.3580	23.2630	0.1990	1
0.0190	3.1270	78.9730	24.4870	0.2040	1
12.4250	3.0490	70.9870	25.3530	0.2080	1
15.3620	20.7870	65.5300	24.5070	0.2090	1
15.5200	38.8490	54.1720	25.6990	94.4420	1
15.4430	33.2190	70.3650	25.9000	56.3520	1
15.3820	20.7290	51.4600	25.2070	13.5850	1
15.5330	37.1080	65.5220	24.7790	103.1600	1
15.5350	33.2670	70.1070	25.4070	101.0470	1
15.5350	33.8300	81.8830	24.6710	101.1530	1
15.5340	33.1040	64.0090	25.4850	84.8850	1
15.5340	33.2030	66.6520	25.6810	77.9560	1
15.5350	33.9780	68.6680	26.0470	87.7850	1
15.5330	35.7730	66.6830	26.0640	118.9250	1

Input matrix for Matlab software is like **j** matrix. In Fig 11, system failure result has been shown in terms of two components of voltage and humidity changes. As in graph figure, when humidity increases, system failure will increase that is proper prediction. Zero voltage shows that equipment failure is very low and this is due to equipment out of work. For practical test of system failure prediction accuracy in Fig 12, we measure environmental data 5 times with data designed ANFIS and proper output with reality.

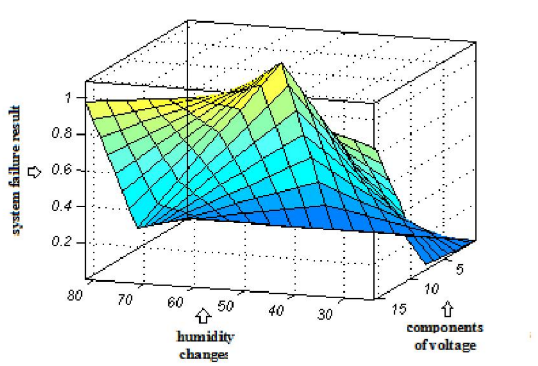

Fig 11: system failure result in terms of two components of voltage and humidity changes (Resource: study findings)

Table 3**:** Comparing practically results of ANFIS method

Voltage	Temperature	Humidity	Turbine vibrancy	Unit load	Prediction	Accuracy	Row
15.54	24	69	23	41	93%	yes	1
15.54	24	69	25	115	99%	yes	2
15.54	36	69	25	115	100 %	yes	3
15.54	12	69	25	115	53%	no	4
14.83	12	35	25	115	36%	no	5

3-4- Cooling system

The main structure of using this method is shown in Fig 12. Four effective factors on system failure include humidity, temperature, voltage and atmospheric pressure.

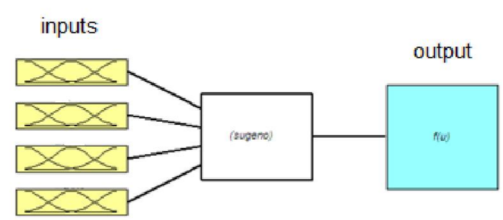

Fig 12: Anfis structure for fuel system (Resource: study results)

In Fig 13, logic performance of Anfis structure has been shown; in which the relationship between 4 inputs, one output, 81 rules of Anfis and 12 Fuzzy functions have been shown.

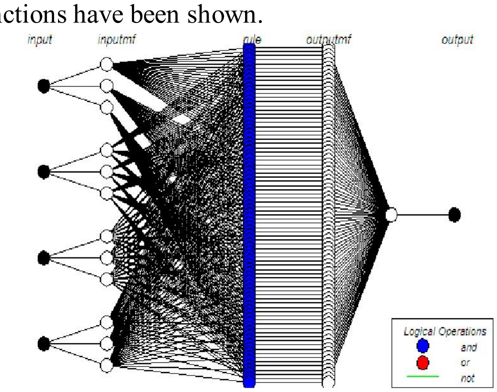

Fig 13: Logic structure of Anfis structure for cooling system (Resource: study results)

Input matrix for Matlab software is like **h** matrix. In Fig 14, system failure result has been shown in terms of two components of voltage and atmospheric pressure changes. As in graph figure, when atmospheric pressure increases, system failure will increase that is proper prediction. For practical test of system failure prediction accuracy in Fig 15, we measure environmental data 5 times with data designed ANFIS and proper output with reality.

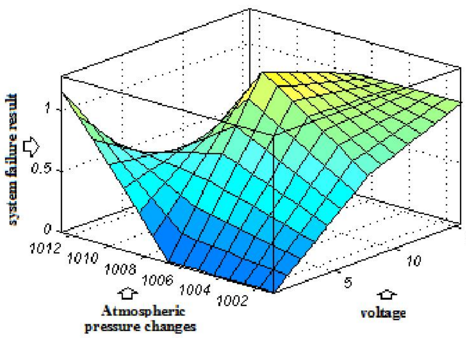

Fig 14: system failure result in terms of two components of voltage and Atmospheric pressure changes (Resource: study findings)

0.0155	1.0014	0.0727	0.0221	0.0010
0.0155	1.0029	0.0730	0.0231	0.0010
0.0155	1.0039	0.0696	0.0230	0.0010
0.0155	1.0029	0.0789	0.0220	0.0010
0.0155	1.0032	0.0482	0.0210	0.0010
0.0155	1.0039	0.0325	0.0197	0.0010
0.0155	1.0032	0.0354	0.0195	0.0010
0.0155	1.0019	0.0542	0.0203	0.0010
0.0155	1.0015	0.0610	0.0209	0.0010
0.0155	1.0027	0.0683	0.0216	0.0010
0.0155	1.0024	0.0732	0.0219	0.0010
0.0155	1.0031	0.0741	0.0224	0.0010
0.0155	1.0045	0.0726	0.0215	0.0010
0.0155	1.0030	0.0716	0.0210	0.0010
0.0155	1.0027	0.0679	0.0221	0.0010
0.0155	1.0027	0.0585	0.0236	0.0010
0.0155	1.0048	0.0241	0.0227	0.0010
0.0155	1.0012	0.0516	0.0217	0.0010
0.0155	1.0016	0.0709	0.0230	0.0010
0.0155	1.0021	0.0719	0.0239	0.0010
0.0155	1.0024	0.0767	0.0238	0.0010
0.0155	1.0024	0.0780	0.0238	0.0010
0.0155	1.0023	0.0690	0.0240	0.0010
0.0155	1.0019	0.0503	0.0239	0.0010
0.0155	1.0032	0.0580	0.0229	0.0010
0.0155	1.0018	0.0650	0.0231	0.0010
0.0155	1.0061	0.0682	0.0208	0.0010
0.0155	1.0031	0.0346	0.0230	0.0010
0.0155	1.0039	0.0490	0.0223	0.0010
0.0155	1.0019	0.0583	0.0234	0.0010
0.0151	1.0067	0.0521	0.0227	0.0010
0.0000	1.0125	0.0509	0.0226	0.0010
0.0000	1.0124	0.0714	0.0233	0.0010
0.0000	1.0105	0.0790	0.0245	0.0010

Table 4: Comparing practically results of ANFIS method

Voltage	Atmospheric pressure	Humidity	Temperature	Prediction	Accuracy	Row
15.52	1007	51	22	99%	yes	1
15.52	1007	55	20	96%	yes	2
15.52	1009	55	20	56%	no	3
15.4	1007	55	20	98%	yes	4
15.4	1010	75	24	50%	no	5

3-5- Electric system

The main structure of using this method is shown in Fig 15. Four effective factors on system failure include humidity, temperature, voltage and Unit load.

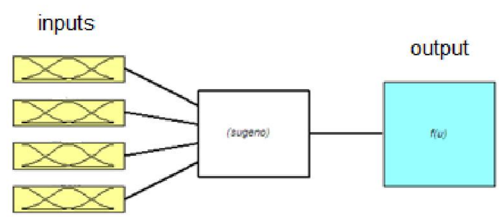

Fig 15: Anfis structure for electric system (Resource: study results)

In Fig 16, logic performance of Anfis structure has been shown; in which the relationship between 4 inputs, one output, 81 rules of Anfis and 12 Fuzzy functions have been shown.

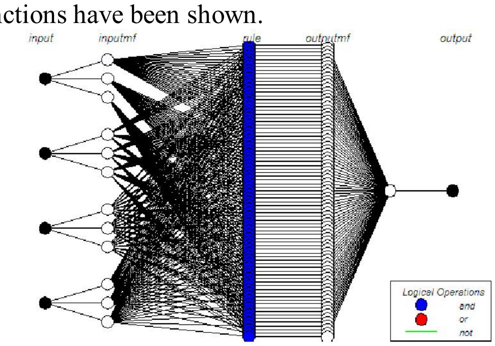

Fig 16: Logic structure of Anfis structure for electric system (Resource: study results)

Electric system matrix is entered into Matlab software. In Fig 16, system failure result has been shown in terms of two components of temperature and Unit load changes. As in graph figure, when Unit load increases, system failure will increase that is proper prediction. Also, in graph figure, temperature of 25° is a temperature that intensifies failure in electric system. For practical test of system failure prediction accuracy in Fig 17, we measure environmental data 5 times with data designed ANFIS and proper output with reality.

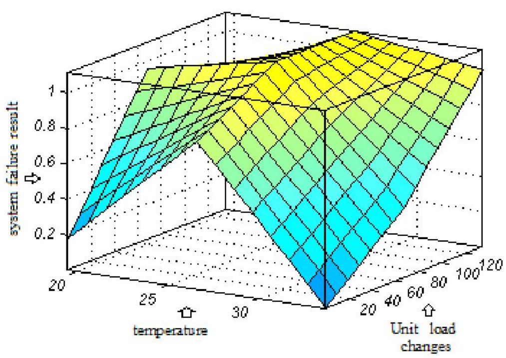

Fig 17: system failure result in terms of two components of temperature and Unit load changes (Resource: study findings)

Table 5: Comparing practically results of ANFIS method

Voltage	Temperature	Humidity	Unit load	Prediction	Accuracy	Row
14.98	31	29	98	95%	yes	1
15.5	32	33	57	84%	no	2
15.5	46	28۲	57	94%	yes	3
15.5	65	28	57	97%	yes	4
15.57	82	25	134	100 %	yes	5

4- Conclusion

Using Neuro- Fuzzy network and studying results, it was found that having resulted components values of each system failure time, we can obtain rules that can predict failure percentage of each thermal power plant systems acceptably per new values. Then, combining neural network and Fuzzy logic methods positively effects on planning gas power plant maintenance.

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12/13/2014