

# Application of Data Mining on Fault Detection and Prediction in Boiler of Power Plant Using Artificial Neural Network

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**Abstract**—This paper tries to present a new applied method on detection and prediction of faults for the boiler's burner system of power plant with using data mining and artificial neural network. Boiler/Steam turbine is important equipments in the industry, especially in the electric power industry. Because of the complexity of burner management systems and particularity of its running environment, the fault rate of boiler's burner system is high. So the fault prediction is a difficult problem. The proposed approach includes data mining, data preprocessing i.e. data reduction, data clustering; learning and prediction by artificial neural networks. Boiler/turbine units constitute a critical component of a co-generation system. The operative parameters in boiler's burner system are measured and are characterized to obtain a set of descriptors. These sets are analyzed by data mining approach. Next, these preprocessed data are used as input data of two neural networks which detect and predict the faults in a boiler of power plant. Multiplayer back propagation neural network with four hidden layers, as one of the steps in data mining process is studied. The knowledge extracted by this data mining algorithm is an important component of an intelligent alarm system. Furthermore, using this method is more valuable for the further study.

## I. INTRODUCTION

Boilers are important components in oil refinery, chemical and power industries; they transform water into steam for power generation or other industrial applications. A common boiler fault is the malfunction in boiler's burner system. Early detection of such faults in operation are important; It helps in reducing possible damage to equipments and productivity loss caused by (otherwise) unscheduled boiler shut-down; it also ensures safety for operators. Boiler's burner faults are a special type of faults in process systems that can be frequent. It is mainly the operator who detects, isolate and take action when a fault appears. It can be very hard to distinguish between normal process operation and a developing fault. Early-warning systems can help the process operator to detect faults at an early stage and thus prevent further fault development.

However, boilers are complex systems involving various disturbances, nonlinearities, and time-varying characteristics with many parameters. The values of these parameters must be recorded for each second. This recording makes large volumes of routinely collected temporal data. Unusual events are often characterized by normal parameter conditions sequenced in abnormal combinations that are hidden in large volumes of this temporal data. They may lead to a terrible system failure. The

ability to predict and avoid these rare events is a challenge that could be addressed by an intelligence data mining approaches.

So it is necessary to apply a complete method for providing a satisfactory performance in fault detection and prediction problem. Among various data analyzing and interpreting approaches, the data mining technique is considered an advanced means [1]. The core components of data mining technology have been under development for decades and various models have been developed, for example classical statistics regression analysis, decision tree [2], rough sets [3], and the machine learning based method (e.g. generic programming, artificial neural networks, etc.). These technologies have already been proven successfully in a variety of application domains, such as stock market assessment and prediction [4], medical diagnosis and protein structure discovery [5,6], analysis of insurance packages [7], detect of useful information from the power system data bases [8,9] and structural health monitoring [10,11]. However, the application of the data mining technique to handle massive nuclear power plant quake-proof information is a new attempt.

In this research, an effective and applied method on detection and prediction of faults for the boiler's burner system of power plant is presented, taking into account boiler parameters. Boiler/Steam turbine is important equipments in the industry, especially in the electric power industry. Because of the complexity of burner management systems and particularity of its running environment, the fault rate of boiler's burner system is high. So the fault prediction is a difficult problem. The proposed approach includes data mining, data preprocessing i.e. data reduction, data clustering; learning and prediction by artificial neural networks. Boiler/turbine units constitute a critical component of a co-generation system. The operative parameters in boiler's burner system are measured and are characterized to obtain a set of descriptors. These sets are analyzed by data mining approach. Next, these preprocessed data are used as input data of two neural networks which detect and predict the faults in a boiler of power plant. Multiplayer back propagation neural network with four hidden layers, as one of the steps in data mining process were studied. The knowledge extracted by this data mining algorithm is an important component of an intelligent alarm system. Application of the proposed scheme to industrial case studies

shows the advantages of proposed method. Furthermore using this method is more valuable for further study.

Briefly, this paper is organized as follows; Section II briefly introduces some important components of boiler model, Section III presents the proposed fault detection and prediction data mining approach, Section IV shows the results of simulation case studies. Finally, Section V offers some concluding remarks.

## II. DESCRIBE OF BOILER MODEL

Boiler means equipment, where fuel burns and heat is transferred from flue gas to energy transfer medium, which is heated up or phase change (boiling) happens. In order to ensure efficient combustion and compliance with the emissions standards, boilers must be operated and maintained according to the manufacturer's instructions.

Boiler/Steam turbine is important equipments in the industry, especially in the electric power industry. Because of the complexity of burner management systems and particularity of its running environment, the fault rate of boiler's burner system is high. So this paper is focused on detection and prediction of faults in boiler's burner system. Basically the boiler is consisted of several components but in this research just the effective parameters on fault in burner system are recognize and applied for simulation; such as [12]: Fuel pressure, Fuel temperature, Fuel flow, Atomizing pressure, Condition of full-load generation, Output pressure of F.D.Fan, Air box pressure, Steam pressure of boiler, Steam temperature of boiler, Damper condition, Fuel filtering, Drum oscillation, Situation of pneumatic valves, Photocell condition,

Sequence in equipments of burner system, Change on cooling fans and Condition of soot blower.

Figure 1 shows elements and connections of the boiler and heating system.

## III. PROPOSED FAULT DETECTION AND PREDICTION METHOD

The efficiency of the traditional data analysis method is impaired significantly in view of the huge volume of data and as the inaccessibility of profound information hidden inside the data limits the improvement of management level and enhancement of economic profits. The power plants need for rapid data accessing and collecting techniques to replace the tradition crude data analysis methods. So a new approach based on intelligent data mining is proposed. This method includes of four steps and the artificial network is used in one of steps of this method.

One of the advantages of the data-mining approach is its ability to generate previously unknown models using essentially unlimited number of quantitative and qualitative parameters. The discovered models are then validated and tested without the need for full understanding of the process physics. This quick discovery of usable models involving qualitative and quantitative parameters with data-mining algorithms may offer an effective paradigm for combustion research. The key to successful detection of faults with a data mining approach is in parameter reduction, data preprocessing, statistical analysis, time segmentation, and event labeling. As shown in Fig. 2, this mining approach can be described as follows: Step 1: data collection, Step 2: data pre-processing, Step 3: model estimation by ANN, Step 4: test and interpretation.

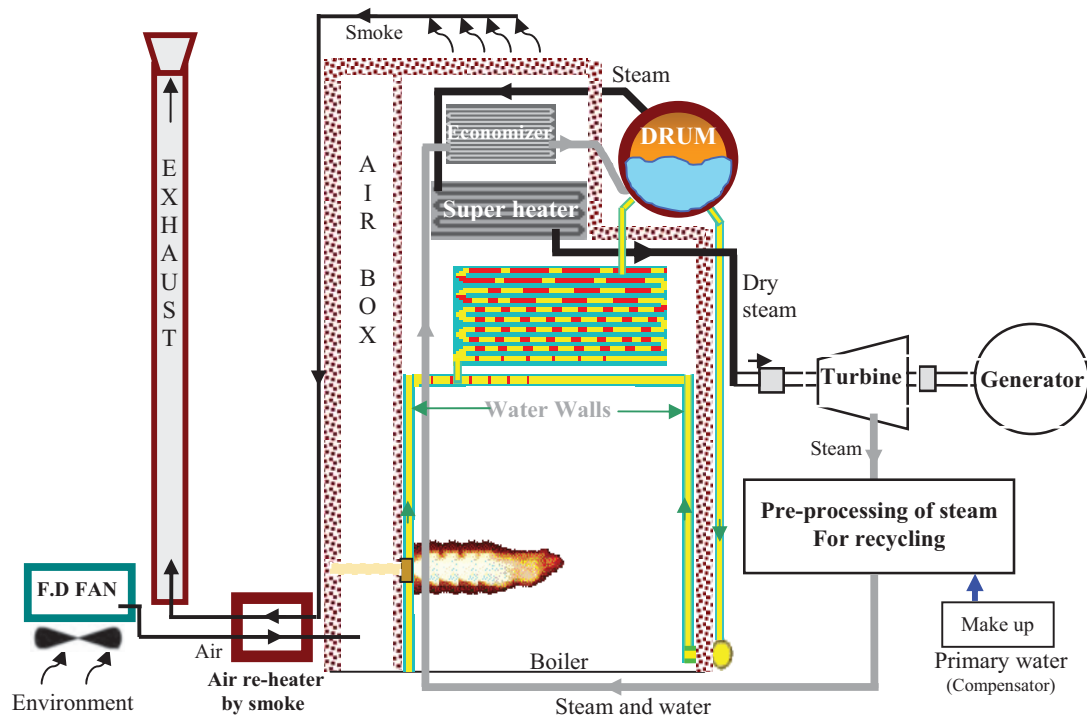


Fig. 1. Schematic viewpoint of a steam boiler in power plant.

Step 1: In this step, after recognition of effective parameters on problem, the required data are selected to build the data set of the simulation. These data are recorded for six months of a year in boiler unit of a power plant. The most important point in this step is the attention to data selection; because these selections must be match with condition of the type of ANN. In fact these selections must be compatible with used feed-forward back-propagation networks as inputs.

Step 2: Data mining is impossible without data pre-processing. This step consists of data reduction, data elimination, data normalization and data clustering. Data reduction is imperative for efficiently manipulating the massive quantity of data. On data reduction an average method is be used [1]. In fact, each 24 hours of a day, is divided to three parts. Each of these parts is about 8 hours and the same recorded data are reduced to average data for each 8 hours. But for the data elimination, the data are preprocessed to remove noise and missing values, to correct errors. Next, all of data are normalized using (1):

$$x'_i = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \quad (1)$$

Finally these data are prepared for clustering. Clustering process divides a database into different groups. The goal of clustering is to find groups that are very different from each other, and whose members are very similar to each other. Some of the common algorithms used to perform clustering include Kohonen feature maps and K-means [13]. After more computational efforts, we detect three types of cluster. In

fact it is better to use these data based on these types of cluster:

Cluster A: This group is included of data on normal operating condition of unit.

Cluster B<sub>1</sub>: This group is included of data under immediate fault condition.

Cluster B<sub>2</sub>: This group is included of data under dependent fault condition for future.

In the boiler's burner system some of rare events cause of defect on components that result kind of faults immediately. Such as: mechanical defect on sequence, high decrease on pressure or temperature of fuel. But some of defect may affect on other components that cause to reduce the efficiency of boiler. So a dependent fault occurs in the future operating cycles. For example: leakage on pneumatic valve or dirty photocell.

Step 3: In this step two types of neural networks are used for learning the behavior of model. Based on the clustering in previous step; in order to detection and prediction of faults, two types of networks are used for training process. The first network is used for training of B<sub>1</sub> cluster (for immediately faults) and the second is used for training of B<sub>2</sub> cluster (for dependent faults).

Step 4: In this step some practical data are used for evaluating networks. But for more interpretation, some rule bases is assumed. Details of this step are presented in the section IV.B.

#### A. Used networks for training of model

The most successful implementations of neural networks involve very careful data learning, recognition and prediction. For instance, neural nets require that all variables be numeric. Use of ANN reduces the need for the complex modelization associated with quantitative model-based approaches, since they are inherently immune to noise and capable of extrapolating beyond their training scope. ANN can be used to process the database with satisfactory results even in their most simple forms, i.e. feed-forward Back-propagation networks using standard training algorithms. As shown in Fig. 3, the used network is included of four hidden layer. Sigmoid activation functions are used for these layers and for the output layer, a linear activation function is applied [13].

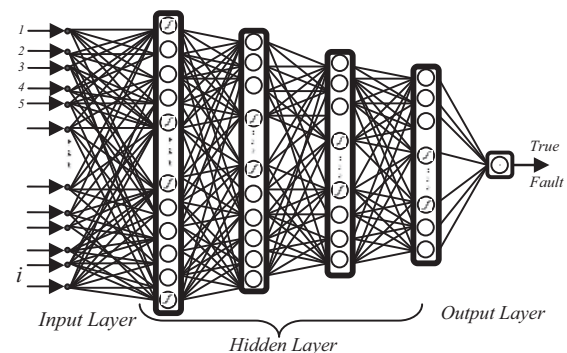


Fig. 3. Structure of used network.

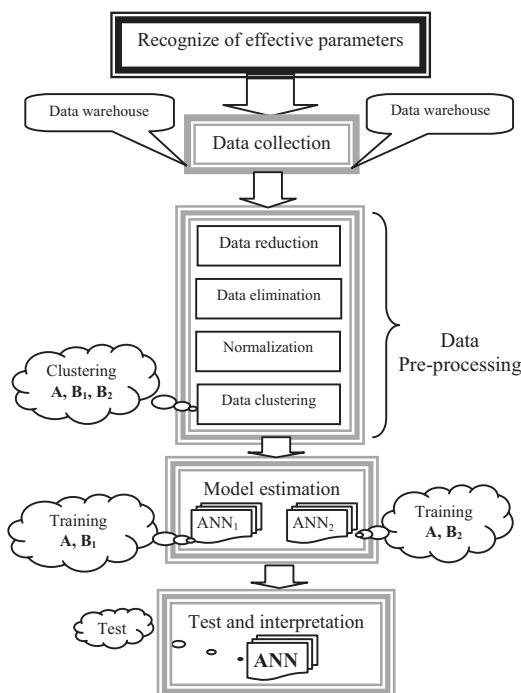


Fig. 2. Flowchart of the proposed method.

### A.1. proposed network for fault detection:

In order to detection of immediate faults, all of the prepared data of each operating cycle (for each 8 hour) is used as input of the network that is shown in Fig. 4. This network includes of four hidden layer and the number of neurons in each layer is 27, 23, 17 and 17, respectively. The number of input data of each operating cycle in this step is 20 and the Gradient descent with momentum and adaptive learning rate back-propagation method is used for training [13]. Results of this simulation are presented in section IV.

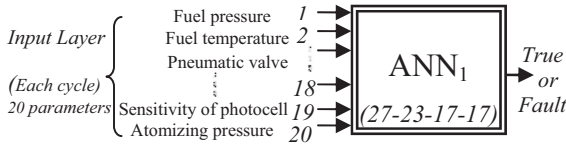


Fig. 4. Schematic figure of training process in fault detection.

### A.2. proposed network for fault prediction:

In this section, in order to prediction of faults, the data of each two continual cycle (each cycle include of 8 hours) are used as input of network. This process is shown in Fig. 5. So the number of input for this network is 40 and the Scaled conjugate gradient back-propagation method is used for training of this large network [14].

Minimization is a local iterative process in which an approximation to the function, in a neighborhood of the current point in the weight space, is minimized.

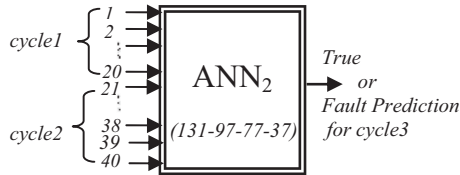


Fig. 5. Schematic figure of training process in fault prediction.

Most of the optimization methods used to minimize functions is based on the same strategy. The Scaled Conjugate Gradient (SCG) algorithm [14] denotes the quadratic approximation to the error  $E$  in a neighborhood of a point  $w$  by:

$$E_{qw}(y) = E(w) + E'(w)^T \cdot y + \frac{1}{2} y^T \cdot E''(w) \cdot y \quad (2)$$

In order to determine the minimum to  $E_{qw}(y)$  the critical points for  $E_{qw}(y)$  must be found. The critical points are the solution to the linear system defined by Moller in [15].

$$E_{qw}(y) = E(w) + E'(w)^T \cdot y + \frac{1}{2} y^T \cdot E''(w) \cdot y \quad (3)$$

SCG belongs to the class of Conjugate Gradient Methods, which show super-linear convergence on most problems. By using a step size scaling mechanism SCG avoids a time consuming line-search per learning iteration, which makes the algorithm faster than other second order algorithms. And also we got better results than with other training methods and neural networks tested, as standard back-propagation and cascade neural network.

## IV. SIMULATION RESULTS

In this section, to verify the performance of proposed methods, two studies have been done. The first one is based on fault detection in recent operational cycle and the second study is based on prediction of faults for each next cycle. The simulations are done using MATLAB platform and the system parameters are given in [12]. Note that each parameters that are defined in section II, must be work in acceptable operational range. So when the values of each parameter violates from this range, a type of fault may be occurs. For each case, to demonstrate effectiveness of the proposed method, the Root Mean Square Error (*RMSE*) is calculated by:

$$RMSE = \sqrt{\frac{1}{Q} \sum_{k=1}^Q e(k)^2} = \sqrt{\frac{1}{Q} \sum_{k=1}^Q (output_{desired}(k) - output_{ANN}(k))^2} \quad (4)$$

### A. Case 1: fault detection

In this section, based on the information of section III, the network is trained. Next, the results of testing network are presents in Figs. 6-7 and Table I. Note that, the desired outputs for training of networks are 0 and 9. In fact, the 0 value is used for each fault and the 9 value is used for the correct condition of boiler.

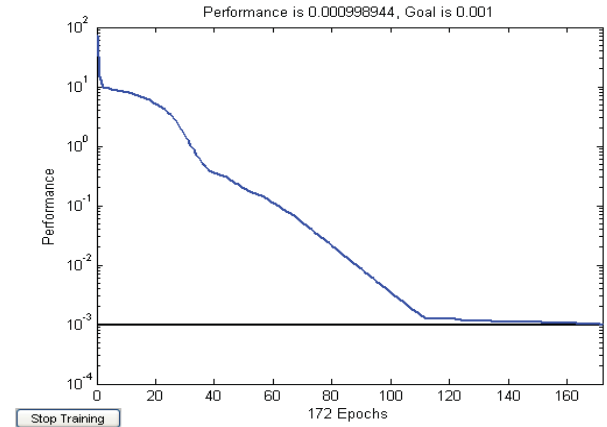


Fig. 6. Total square error in learning process for case 1.

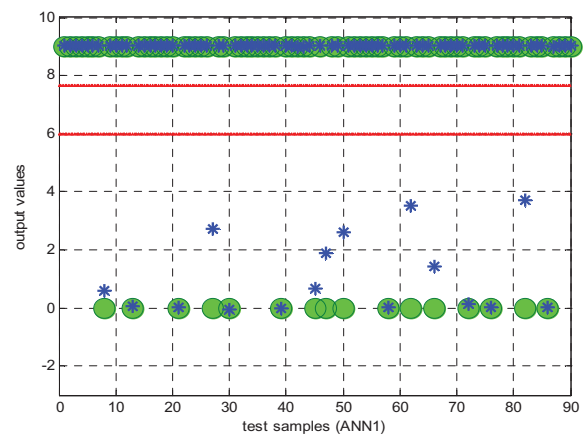


Fig. 7. Spread of results for case 1. (0=fault and 9=true), circle: real values and star: by ANN.

TABLE I  
SIMULATION RESULTS IN CASE I.

Detection of faults in boiler of power plant:				
Q	Actual		Estimated by ANN <sub>1</sub>	
	Value	Type	Value	Type
1	9	T	9.01689	T
2	9	T	9.01711	T
3	9	T	9.01727	T
4	9	T	9.01695	T
5	9	T	9.01621	T
6	9	T	9.01954	T
7	9	T	9.01622	T
8	0	F	0.57386	F
9	9	T	9.01662	T
10	9	T	9.01612	T
11	9	T	9.01612	T
12	9	T	9.01612	T
13	0	F	0.04484	F
14	9	T	9.01703	T
15	9	T	9.01711	T
16	9	T	9.01593	T
17	9	T	9.01702	T
18	9	T	9.01741	T
19	9	T	9.01274	T
20	9	T	9.01594	T
21	0	F	0.02825	F
22	9	T	9.02359	T
23	9	T	9.01786	T
24	9	T	9.01893	T
25	9	T	9.01809	T
26	9	T	9.01707	T
27	0	F	2.73384	F
28	9	T	9.01824	T
29	9	T	9.01801	T
30	0	F	-0.03741	F
31	9	T	9.02092	T
32	9	T	9.02174	T
33	9	T	9.02017	T
34	9	T	9.02187	T
35	9	T	9.02034	T
36	9	T	9.01872	T
37	9	T	9.01758	T
38	9	T	9.01542	T
39	0	F	-0.0235	F
40	9	T	9.01515	T
41	9	T	9.02416	T
42	9	T	8.99343	T
43	9	T	9.00591	T
44	9	T	9.01332	T
45	0	F	0.67475	F
46	9	T	9.01794	T
47	0	F	1.88953	F
48	9	T	9.01631	T
49	9	T	9.01647	T
50	0	F	2.61215	F
51	9	T	9.01601	T
52	9	T	9.01564	T
53	9	T	9.01605	T
54	9	T	9.01631	T
55	9	T	9.01539	T
56	9	T	9.01606	T
57	9	T	9.01646	T
58	0	F	0.01429	F
59	9	T	9.01753	T
60	9	T	9.01768	T
61	9	T	9.01695	T
62	0	F	3.50646	F
63	9	T	9.01687	T
64	9	T	9.01708	T

65	9	T	9.01705	T
66	0	F	1.42728	F
67	9	T	9.01753	T
68	9	T	9.01685	T
69	9	T	9.01606	T
70	9	T	9.01608	T
71	9	T	9.01635	T
72	0	F	0.13446	F
73	9	T	9.01758	T
74	9	T	9.01694	T
75	9	T	9.01755	T
76	0	F	0.03024	F
77	9	T	9.01822	T
78	9	T	9.01847	T
79	9	T	9.01895	T
80	9	T	9.01671	T
81	9	T	9.01819	T
82	0	F	3.69621	F
83	9	T	9.01511	T
84	9	T	9.01774	T
85	9	T	9.01684	T
86	0	F	0.01797	F
87	9	T	9.00726	T
88	9	T	9.01911	T
89	9	T	9.01558	T
90	9	T	9.01907	T

RMSE for test data = 0.72028

### B. Case 2: fault prediction

In this case, based on the information in section III for fault prediction in future cycle, another simulation is done. But for more interpretation, some rule bases is assumed:

IF  $output_{ANN_2} \geq 7.65$  THEN True

IF  $6 < output_{ANN_2} < 7.65$  THEN Low Fault

IF  $output_{ANN_2} < 6$  THEN Fault

In fact, when the estimated outputs of ANN are more than 7.65, the system condition is correct but for the range between 6 and 7.65 the system has a weak condition. Note that with using this method, on the weak conditions in correct operation, the "ALARM!" message is shown by this method. The results of this case are shown in Figs. 8-9 and Table II. As shown in Fig. 8, training is done after 132 iterations and base on the Table II the RMSE error for the test of network is 1.937. The Fig. 9 is shown that the proposed method has a good ability for prediction of faults.

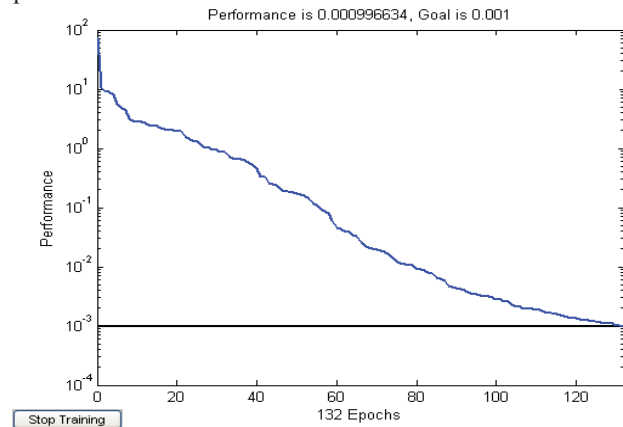


Fig. 8. Total square error in learning process for case 2.



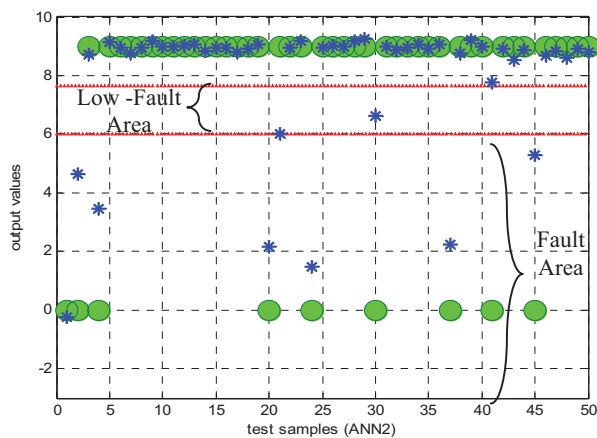


Fig. 9. Spread of results for case 2. (0=fault and 9=true), circle: real values and star: by ANN.

Table II  
Simulation results in case2

Prediction of faults in boiler of power plant for cycle3					
Q	Actual		Estimated by ANN <sub>2</sub>		Special conditions
	Type	Value	Type	Value	
1	0	F	-0.2516	F	
2	0	F	4.65226	F	
3	9	T	8.71301	T	
4	0	F	3.46164	F	
5	9	T	9.12915	T	
6	9	T	8.94026	T	
7	9	T	8.77536	T	
8	9	T	8.93434	T	
9	9	T	9.19301	T	
10	9	T	9.00692	T	
11	9	T	8.99122	T	
12	9	T	9.02821	T	
13	9	T	9.05585	T	
14	9	T	8.83632	T	
15	9	T	8.94814	T	
16	9	T	8.95193	T	
17	9	T	8.78775	T	
18	9	T	8.91896	T	
19	9	T	9.07083	T	
20	0	F	2.16537	F	
21	9	T	6.02234	LF	ALARM!
22	9	T	8.94545	T	
23	9	T	9.16216	T	
24	0	F	1.46196	F	
25	9	T	8.9687	T	
26	9	T	9.04089	T	
27	9	T	8.99504	T	
28	9	T	9.18021	T	
29	9	T	9.24411	T	
30	0	F	6.62173	LF	
31	9	T	9.00618	T	
32	9	T	8.88644	T	
33	9	T	8.94144	T	
34	9	T	9.04851	T	
35	9	T	8.92663	T	
36	9	T	9.05668	T	
37	0	F	2.25373	F	
38	9	T	8.75883	T	
39	9	T	9.20276	T	
40	9	T	9.00319	T	
41	0	F	7.77193	T	ERROR!
42	9	T	8.93082	T	

43	9	T	8.54697	T	
44	9	T	8.8579	T	
45	0	F	5.27837	F	
46	9	T	8.68787	T	
47	9	T	8.84905	T	
48	9	T	8.60396	T	
49	9	T	8.91004	T	
50	9	T	8.78987	T	

## V. CONCLUSION

In this paper, in order to detection and prediction of faults on boiler's burner system of a power plant, a new method is proposed with a practical viewpoint. In this research an intelligence data mining approach using artificial neural networks is presented. The knowledge extracted by this data mining algorithm is an important component of an intelligent alarm system. Furthermore, using this method is more valuable for further study in this field. The following conclusions can be drawn about the proposed method:

- 1- Preparing of data and proposing three useful types of inputs for this simulation, using clustering idea.
- 2- Propose an effective approach on fault detection and prediction in boiler; include data processing using intelligence data mining method.
- 3- This research is proposed a new method with so good ability for improving the security of operating system. Based on the results in section IV.B, with using this method, on the weak condition in correct operation, the ALARM message is shown by this method (Table II).

## REFERENCES

- [1] U.M. Fayyad, G. Piatetsky-Shapiro, P. Smyth, *From data mining to knowledge discovery: an overview*, in: *Advances in Knowledge Discovery and Data Mining*, AAAI/MIT Press, Cambridge, MA, 1996.
- [2] J.R. Quinlan, C4.5: *Programs for Machine learning*, Morgan aufmann, San Mateo, CA, 1993.
- [3] Z. Pawlak, *Rough Sets: Theoretical Aspects of Reasoning About Data*, Kluwer Academic Publisher, Dordrecht, Boston, London, 1991.
- [4] H. Mizuno, M. Kosaka, H. Yajima, Application of Neural Network to Technical Analysis of Stock Market Prediction. [www.oco.ro/ici/revosta/soc98\\_2/art03.html](http://www.oco.ro/ici/revosta/soc98_2/art03.html), 1998 (Retrieved 8.9.2004).
- [5] P. Langley, H. Simon, Application of machine learning and rule induction, in: *Communications on ACM*, vol. 38, 1995, pp. 55–64.
- [6] K. Veropoulos, *Machine learning approaches to medical decision making*, PhD thesis, Bristol University, 2002.
- [7] Y. Chuang, M. Hsu, Analysis of insurance packages by using data mining technology, *Proceedings of the International Conference on Systematics, Cybernetics and Informatics*, Florida, CDROM, 2004.
- [8] M.M. Lavallo and G. R. Ortiz, "Obtaining expert system rules using data mining tools from a power generation database", *Expert Systems with Applications*, vol. 14, pp. 37–42, 1983.
- [9] M. Sforza, "Data mining in a power company customer database", *Electric Power Systems Research*, vol. 55, pp. 201–209, 2000.
- [10] C.C. Chang, T.Y.P. Chang, Y.G. Xu, M.L. Wang, Structural damage detection using an iterative neural network, *Journal of Intelligent Material Systems and Structures*, vol. 11, pp. 32–42, 2000.
- [11] K. Worden, A.J. Lane, Damage identification using support vector machines, *Smart Materials and Structures*, vol. 10, pp.540–547, 2001.
- [12] PBC Company, "Operating instruction manual", Iranshar Power Plant, Iran, 1991.
- [13] Haykins, *Neural networks-a comprehensive foundation*, New York: Macmillan College Publishing Co.; 1994.
- [14] MathWoks, Inc., Matlab. *Neural Networks Toolbox*, V.7.2
- [15] Moller, "A Scaled Conjugate Gradient Algorithm for Fast Supervised Learning", *Neural Networks*, vol.6, no. 4, pp.525–533, 1993.