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Anfis Based Prediction Model for Reduction of Failure Frequency in Captive Power Plant

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ABSTRACT

Boiler-Turbine unit is a complex multivariable system with high time variation, uncertainty and coupling. The improvement of its control quality is a key problem for automation improvement in thermal engineering. Adaptive Neuro-Fuzzy Inference System (ANFIS) is the neural network realization for Takagi and Sugeno fuzzy inference system. ANFIS can not only approach any linear and nonlinear function with any precision, but also quicken convergence speed, decrease errors, and lessen training data that are needed. The frequency of fluctuation of the water level in the drum may be significantly reduced by the ANFIS modeling of the water tube boiler water feed system to the drum. The ANFIS model applied for the boiler feed system in the Power plant will not only increases the efficiency of the system but shall considerably reduce the tripping of the power plant. The model so developed can be used for synthesis of digital control boiler system.

Keywords: Boiler- Turbine model, Power Plant,

INTRODUCTION

Boiler- Turbine system is an important integral part of thermal power plant. The dynamic performance of boiler will mainly determine the performance of power unit. A number of dynamic models which are used to predict the behavior of boilers can be found in literature [1]. These models are used for controller synthesis and real-time evaluation of controller performance. In general, an ordinary Water tube Boiler system, as shown in figure 1, the foremost difficulty is the fluctuation of water level in the Boiler drum. The boiler needs very accurate control and measurement for its efficient operation. On one hand, a sudden decrease in the water level may uncover boiler tubes, allowing them to become overheated and there are very high possibilities of damage. On the other hand, increase in this level may interfere with the process of separating moisture from steam within the Boiler drum, thus reducing boiler efficiency and carrying moisture into the process or turbine. Therefore, it would be an ideal condition if beforehand the opening of the pneumatic valves at scoop and at the feed control station can be predicted and transfer this signal to the controller of the valves. This will supply precise feed water according to the requirement of a unit of thermal power plant. This model reduces the tripping of a unit of thermal power plant due to fluctuation of the water level in the drum of the Boiler. In thermal power plant, Boiler tube failures are one of the important reasons for unexpected shut down of power plants. The major problem is due to frequent up and down of water level leading to excess or less water supply to the turbine. Due to this, tripping of the turbine takes place for the protection of turbine. The tripping logics are provided to save the unit from any abnormal condition in the boiler/turbine or generator. This tripping of the power plant leads to great loss of production of power and money, at the cost of saving the equipment life.

The other reasons are when either both induced fan or both forced draft fans will off other than the physical breakdown of spares and when furnaces pressure becomes very high .However, the 22% of the tripping of the Boiler is due to the high fluctuation of water level in the drum of the Boiler. The practice of tripping the generator breakers immediately would follow a boiler turbine tripping. To solve the above problem, conventional proportional integral (CPI) controller is used to control the pneumatic valve. However, even after the use of CPI controller, desired precision of drum level control is not achieved. A practically efficient and mathematically rigorous fuzzy proportional integral (Fuzzy PI) controller was proposed by H.Ying et.al in [2].The fuzzy controller is precisely equivalent to the nonfuzzy linear PI controller if linear defuzzification is employed. The fuzzy controller can control the time delay process model and nonlinear process model significantly better than the nonfuzzy linear PI controller or fuzzy method by Zadeh [3], is used. Here Malki et.al [4] inspired the better stability of fuzzy PI controller over conventional PI controller in nonlinear process. He had applied the stability principle in fuzzy PD controller. The Fuzzy PD controller enhances the self-tuning capability of the system. Chen. et.al. [5] has analyzed the stability of nonlinear fuzzy PI controller. The gain of the fuzzy PI controller change continuously with output of the process under control. Fuzzy proportional integral +derivative (Fuzzy PI+D) controller [6], and fuzzy proportional derivative integral (fuzzy PD+I) controller [7] also is inspired by the work of Ying et.el [8] for the better performance of ANFIS model over fuzzy PI controller.

The ANFIS model predicts the degree of opening of the pneumatic valves. To control the water level in the drum, one has to control the two pneumatic valves. One valve is located in the feed control station and another one is in the scoop. This scoop is the hydraulic coupling to control the Boiler feed pump. In this coupling, the transmission of power from driving shaft of the motor to drive shaft of the Boiler feed pump is happen by the help of fluid (generally oil). There is no mechanical connection between the two shafts. It consists of a radial pump impeller mounted on a driving shaft and a radial flow reaction turbine mounted on the driven shaft. Both the impeller and runner are identical in shape and they together form a casing which is completely enclosed and filled with oil and one separated oil tank is there. In the beginning, both the shafts are at the rest. When the driving shaft is rotated, the oil started moving from the inner radius to the outer radius of the pump impeller. The pressure energy and kinetic energy of the oil increases at the outer radius of the pump impeller. This oil of increased energy enters the runner of the reaction turbine at the outer radius of the turbine runner and flows inwardly to the inner radius of the turbine runner. The oil, while flowing through the runner transfers its energy to the blade of the runner and makes the runner rotates. The oil from the runner then flows back into the pump impeller, thus having a continuous circulation. A pneumatic valve controls the quantity of flow of oil inside the scoop. And, by this control of boiler feed pump happen. To predict the valve opening of valve of the feed control station, ANFIS take three inputs. That are steam flow from Boiler to the Turbine in tons per hour, feed water flow from Boiler feed pump to Boiler in tons per hour and water level in the drum of boiler in previous state. By seeing all these, ANFIS model predict the valve opening of feed control station as shown in figure 3. To control the feed water, scoop is there .This scoop is hydraulic coupling between Induction motor and Boiler feed pump. If more valves are open then less transmission of speed will take place. Hence flowing of feed water will reduce.

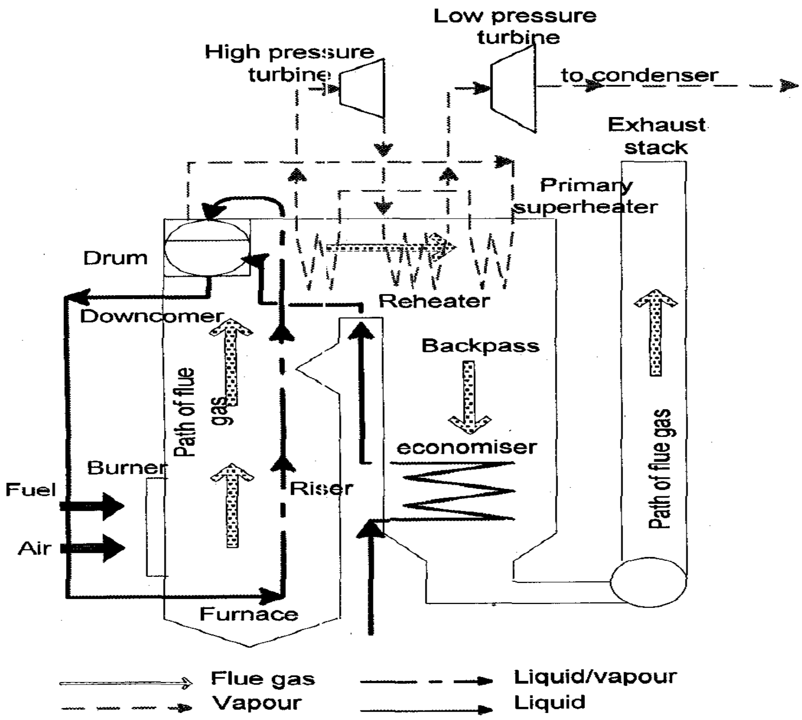


Figure 1.Thermal power plant

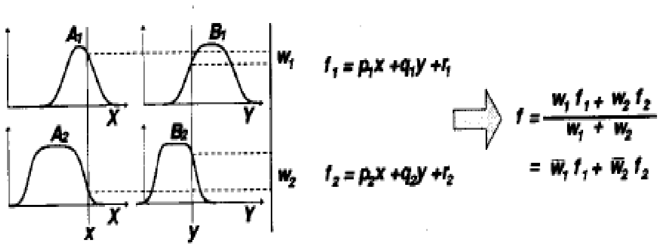
2 Adaptive neuron fuzzy inference systems (ANFIS)

This section introduces the basics of ANFlS network architecture and its hybrid learning rule. A detailed coverage of ANFlS can be found in [10], [I1], [12], [13]. Takagi and Sugeno proposed the T-S fuzzy model [14] in 1985. The Sugeno fuzzy model is a nonlinear model. It can aptly express the dynamic characteristic of complex systems. Furthermore, it is the fuzzy inference model that is in the common use. A typical fuzzy rule in a Sugeno fuzzy model has the format:

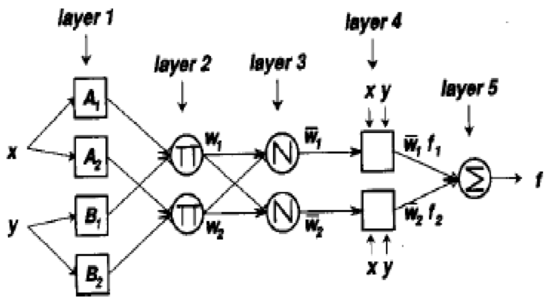
If x is A and y is B Then z=/(x,y),

Where A and B are fuzzy sets in the antecedent; z = f (x,y) is a crisp function in the consequent. Usually, f(x,y) is a polynomial in the input variable x and y ,but it can he any other function that can appropriately describe the output of the system within the fuzzy region specified by the antecedent of the rule. When f(x, y) is a first-order polynomial, we have the first-order Sugeno fuzzy model. Figure 2(a) and 2(b) show the first-order Sugeno fuzzy inference system. Consider a first-order Sugeno fuzzy inference system, which contains two rules.

Rule I: If x is A_1 and y is B_1, then $f_i = p_l x + q_1 y + r_l$,
Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 y + r_2$.



(a)



(b)

Figure 2(a). First-order Sugeno fuzzy model Figure 2(b). Corresponding ANFIS Architecture
In Figure 2(a), [x, y] is input vector. The firing strengths w_1 and w_2 are usually obtained as the product of the membership grades in the premise part. The output f is the weighted average of each rule's output. E1, and E2 are the ratio of each firing strength to the total of all firing strengths. In order to facilitate the learning of the Sugeno fuzzy model, it is convenient to put the fuzzy model into the framework of adaptive networks that can compute gradient vectors systematically. The resultant network architecture, called ANFIS, is shown in Figure 2(b). This adaptive network is a multilayer forward feed network. The square nodes need train the parameters. The parameters learning can adopt the gradient descent method. However, this method is generally slow and likely to become trapped in local minima. Here we propose a hybrid-learning algorithm [11], [12] that combines the gradient method and the least squares estimate to learn parameters.

Layer 1: Every node i in this layer is a square node with a node function

$$O_i^1 = \mu A_i(x)$$

Where x is the input to node i, and A, is the linguistic label (small , large, etc.) associated with this node function. In other words, 0_i^1 is the membership function of A, and it specifies the degree to which the given x satisfies the quantifier A_i. Usually we choose A (x) to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as

$$\mu A_i = \frac{1}{1+[(\frac{x-c_i}{a_i})^2]b_i}$$

Where $\{a_i, b_i, c_i\}$ is the parameter set. As the values of these parameters change, the bell-shaped functions vary accordingly, thus exhibiting various forms of membership functions on linguistic label A_i. In fact, any continuous and piecewise differentiable functions, such as commonly used trapezoidal or triangular-shaped membership functions, are also qualified candidates for node functions in this layer. Parameters in this layer are referred to as premise parameters.

Layer 2: Every node in this layer is a circle node labeled II which multiplies the incoming signals and sends the product out. For instance,

$$w_i = \mu A_i(x) \times \mu B_i(y), \text{ i=1,2 .}$$

Each node output represents the firing strength of a rule.

Layer 3: Every node in this layer is a circle node labeled N. The i^{th} node calculates the ratio of the i^{th} rule's firing strength to the sum of all rules firing strengths:

$$\overline{w} = \frac{w_i}{w_1 + w_2} \quad \text{, i=1, 2 .}$$

For convenience, outputs of this layer will be called normalized firing strengths.

Layer 4: Every node i in this layer is a square node with a node function

$$O_i^4 = \overline{w}\; f_i = \overline{w_i}\;\; (p_i x + q_i y + r_i)$$

Where $\overline{w_i}$ is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer will be referred to as consequent parameters

Layer 5: The single node in this layer is a circle node labeled C that computes the overall output as the summation of all incoming signals, i.e.,

$$O_1^5 = \sum f_i \overline{w_i} = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad =\text{overall output}$$

Thus we have constructed an adaptive network which is functionally equivalent to a type-3 fuzzy inference system. For type-1 fuzzy inference systems, the extension is quite straightforward and the type-1 ANFIS is shown in Figure 2, where the output of each rule is induced jointly by the output membership function and the firing strength. For type-2 fuzzy inference systems, if we replace the centroid defuzzification operator with a discrete version which calculates the approximate centroid of area, then type-3 ANFIS can still be constructed accordingly. However, it will be more complicated than its type-3 and type-1 versions and thus not worth the efforts to do so. The premise part of a rule delineates a fuzzy subspace, while the consequent part specifies the output within this fuzzy subspace.

From the proposed type-3 ANFIS architecture, it is observed that given the values of premise parameters, the overall output can be expressed as a linear combinations of the consequent parameters. More precisely, the output f in can be rewritten as

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2$$

$$= \begin{array}{l} (x\overline{w_1})p_1 + (y\overline{w_1})q_1 + (\overline{w_1})r_1 + \\ (x\overline{w_2})p_2 + (y\overline{w_2})q_2 + (\overline{w_2})r_2 \end{array}$$

3. ANFIS model for water fluctuation control

To predict the valve opening of valve of the feed control station, ANFIS take three inputs. That are steam flow from Boiler to the Turbine in tons per hour, feed water flow from Boiler feed pump to Boiler in tons per hour and water level in the drum of boiler in previous state. By seeing all these, ANFIS model predict the valve opening of feed control station as shown in figure 3. To control the feed water, fluid coupling is there. If less valve is open, less transmission of speed will take place. Hence flowing of feed water will reduce. The ANFIS model for this valve has one input and one output. The input is pressure difference of water between feed pump and Boiler. ANFIS model for this is shown in figure 12.

The real life data is obtained from a unit in the thermal power plant situated at the northern part of India, Whose operational parameter are observed during the period from 21st March 2007 to 24th March 2007 and is given in table 1` have the following parameters taken in between 21 march to 24 march 2007. During this period, the fluctuation of demand is varied too much due to maintenance and tripping of other units in the power plant.

BPNN (Back propagation neural network) method is chosen for the prediction of water level in Boiler drum. The values of connection weights between processing elements in the input and hidden layer and between the hidden layer and output layers are to be selected which minimize the differences between the network output and the measured input values. The data used included the steam pressure in the boiler, load of the power plant as a input and water level in the drum of boiler as a output of the model which is shown in figure 3.

Table 1

Serial no.	Operational parameters	Real life data
1	Load	120 MW
2	Rate evaporation capacity	345t/h
3	Drum operating pressure	148 bar
4	Superheated steam temperature	545^0C
5	Feed water temperature	242^0C
6	Water wall surface area	2916.4m^2
7	Water wall tube diameter	60 mm
8	Number of the water wall tube	748
9	Height of the water wall	45m
10	Downcomer diameter	426 mm
11	Diameter of the leading tube	159 mm
12	Drum diameter	1600 mm
13	Drum length	25 m
14	Normal water level of drum	0.625

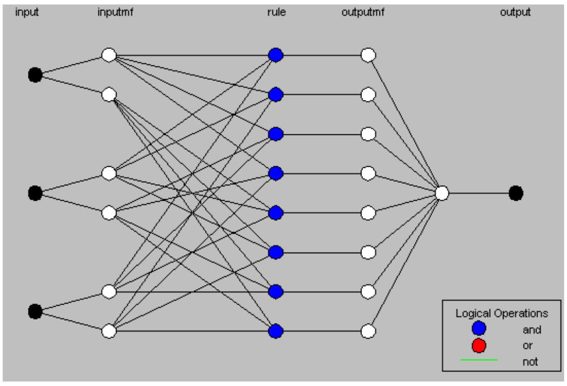
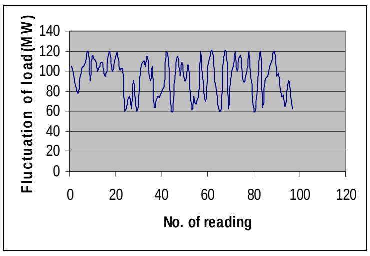
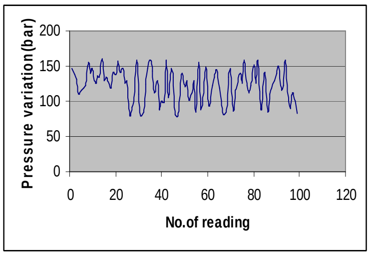


Figure 3 ANFIS architecture for the feed control station

For precise control of the water level in the Boiler drum, One has to control two pneumatic valves. Both valves are very important to control. One valve is control the flowing of oil in the fluid coupling and other one is to control the feed water in the Boiler. If more oil is flowing in the fluid coupling then Boiler feed pump will run with high speed and vice versa is also happened. This is the way to control water level in boiler drum considering the entire plant operation. To control the water level in the drum in precise way, one has to control other pneumatic valve in the feed control station. The extra or less water by controlling this valve will create high or low pressure between feed control station and Boiler feed pump. This pressure difference acts as a input for the pneumatic valve controller, which is used to controlled the flow of oil in the fluid coupling. This leads to control of Boiler feed pump. In this way, precise control of the water level in the drum of Boiler happen. In this work, there are two ANFIS model has made for controlling the water level in the drum one for pneumatic valve used in the feed control station as shown in figure 10 and other pneumatic valve used in the fluid coupling as shown in the figure 14. Figure 3 shows the ANFIS architecture for the feed control station of the power plant. This is used to control the feed water of the Boiler. In this model, there are three inputs and one output is there. The input parameters are steam flow from boiler to turbine, feed water flow in the boiler and the just previous state water level in the drum of the boiler. The output parameter is degree of opening of the pneumatic valve in the feed control station. This pneumatic valve will open from 0 to 100% based on our requirement. This valve regulates the excess water in the feed water system. Real life data pertaining to various at the plant site are collected for trains the ANFIS model as shown in the table 1.Trials are performed using two hidden layers with the number of neurons one hundred in each of hidden layer, three neurons in the input layer and one in the output layer. Each neuron is represented by one of the input parameter and output neuron is represented by the output parameter. Training the ANFIS is an important step for developing a useful network. The experimental data are used as the learning samples to train the ANFIS. Each time a pattern is presented to the network, the weights leading to an output node are modified slightly during learning in the direction required to produce a smaller error the next time the same pattern is presented. The amount of weight modification is called the learning rate. The successive weight is the previous weight and addition/subtraction of error with multiplication of learning rate. The addition or subtraction of the error depends upon whether error is positive or negative. The larger the learning rate, the larger the weight changes, and the faster the learning will proceed. Oscillation or no convergence can occur if the learning rate is too large. Here the learning rate is 0.9. So this means new weight is previous weight addition/subtraction of error in multiplication of 0.9.

Large learning rates often lead to oscillation of weight changes and learning never completes, or the model converges to a solution that is not optimum. One way to allow faster learning without oscillation is to make the weight change a function of the previous weight change to provide a smoothing effect. The momentum factor determines the proportion of the last weight change that is added into the new weight change. Here momentum factor is taken as 0.8. As neurons pass values from one layer of the network to the next layer in back propagation networks, the values are modified by a weight value in the link that represents connection strengths between the neurons. Here weight is 0.8.





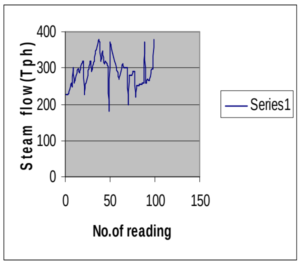
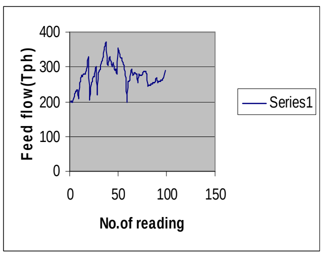
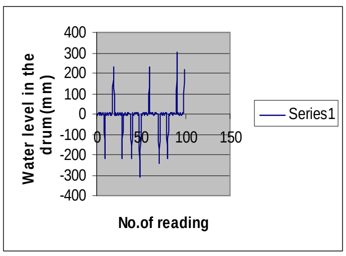


Fig.4Variations of load in MW Fig.5.Variation of pressure inside drum Fig.6.Variation of steam flow





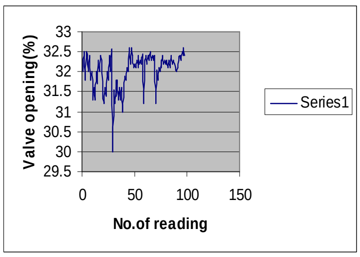


Fig.7 Variation in feed flow fig.8 Variation in water level Fig. 9 Variation in opening of feed valve

Here, the abscissa of the above all figures are number of consecutive readings with respect to change in requirement of power plant taken in a unit of thermal power plant. In figure 4, shows the fluction of load of a particular unit of thermal power plant . This shows about variation in demand of power in the captive power plant The high fluctuations of load is also due to of the tripping of the Boiler of a unit of power plant. The scale of power generation is taken in MW. Figure 5 shows the variation of pressure inside the drum of the Boiler. The pressure increases as the load of generation increases. At the time of tripping also large variation in pressure take place. The scale of pressure is in bar. Figure 6 shows the variation of steam flow from Boiler to the Turbine. The measurement of this is done in the tons of steam flowing per hour. The temperature and pressure of this steam is very high. Figure 7 clearly shows the variation of feed water flows in the Boiler. The measurement of this is done in the tons of water flow per hour. This water is coming from the Boiler feed pump. Figure 8 shows the variation of water level in the drum of the Boiler. The dimension of this is to taken in the mm. These fluctuations are controlled by the help of scoop and feed control station. Figure 9 shows the variation of opening of the pneumatic valve in the feed water control loop. This valve is pneumatic controlled valve. This can be open either 10% or 90% .This is all depend upon our requirement. The opening and closing of this valve is responsible of the fluctuations water level in the drum of Boiler.

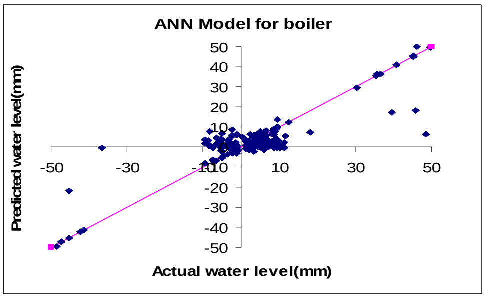


Fig. 10 The ANFIS for the feed control station

The training will stop when the 0.975 correlation coefficient for model of feed control station as shown in the Fig.10. The ordinate of this figure is the predicted opening of the valve and the abscissa of this graph is actual opening of the valve. The total of 10000 epochs is needed to achieve the correct weight. One has selected these parameters depending upon our requirement. The inhibitory and excitatory effect of the weight factors is straightforward which makes the transfer function quite advantageous. So the sigmoid transfer function (logistic) is chosen for the neurons in the all layers. The software is used to train ANFIS model with the above mention parameter give a c-program, which based on our model. When one give the input parameters in this program then this will gives output parameter. This will enable one to transfer the information related to predicted valve opening to the valve controller and feed water level will controlled. Hence tripping due to high/low water level in the drum will easily be avoided.

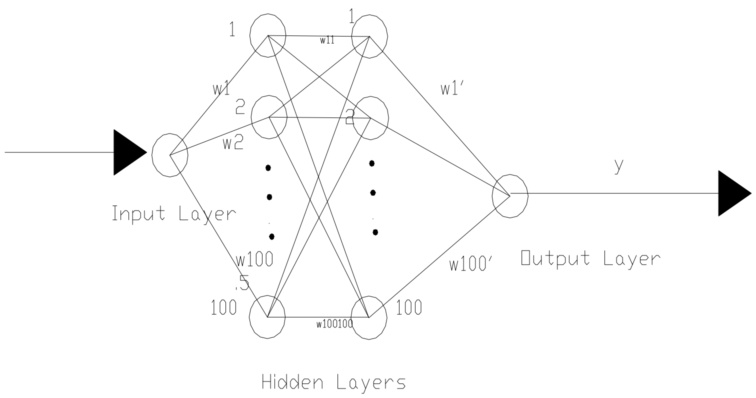
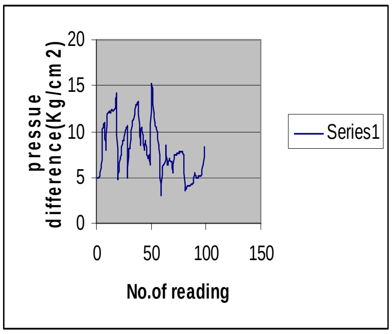


Figure 11 The ANFIS architecture for the fluid coupling

Figure 11 shows the ANFIS architecture for the fluid coupling of the power plant. This is use to control the speed of the Boiler feed pump. In this model, there is one input and one output is there. The input parameter is pressure difference between pressure at Boiler and pressure at the Boiler feed pump and output parameter is degree of opening of the pneumatic valve in the fluid coupling. This valve controls the flow of oil in the fluid coupling. If flow of oil in the fluid coupling is more then Boiler feed pump will run in high speeds and vice versa. Sample data is to be shown in table 1. Trials are performed using two hidden layers with the number of neurons one hundred in each of hidden layer, two neurons in the input layer and one in the output layer. Training the ANFIS is an important step for developing a useful network. The experimental data are used as the learning samples to train the ANFIS. According to our requirement based on ANFIS model, the learning rate, momentum factor and initial weight are taken as .9, .8and .8 respectively.



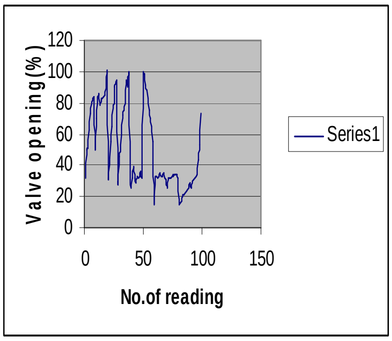


Fig. 12 Variation of the pressure difference Fig.13 Variation of opening of the valve

Figure 12 show the variations of the pressure difference between near Boiler and near Boiler feed pump. The unit is taken in mmwc. Figure 13 shows the ANFIS model for the feed control station. Here abscissa is the actual value and ordinate is the predicted value.

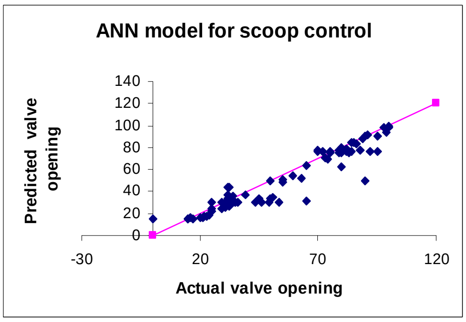


Fig. 14 ANFIS model for fluid coupling

The training will stop when the 0.875 correlation coefficient for model of fluid coupling as shown in the Fig.14. The ordinate of this figure is the predicted opening of the valve and the abscissa of this graph is actual opening of the valve. . The total of 10000 epochs is needed to achieve the correct weight. One has selected these parameters depending upon our requirement. The inhibitory and excitatory effect of the weight factors is straightforward which makes the transfer function quite advantageous. So the sigmoid transfer function (logistic) is chosen for the neurons in the all layers. The software is used to train ANFIS model with the above mention parameter give a c-program, which based on our model. When one give the input parameters in this program then this will gives output parameter. This will enable one to transfer the information related to predicted valve opening to the valve controller and oil flowing in the for fluid coupling will controlled. Hence tripping due to high/low water level in the drum will easily be avoided.

RESULT AND DISCUSSION

The collected data for the minimization of the failure frequency are obtained from a power plant situated in the northern site of India with in the period of the 14^{th} April to 24^{th} April 2007.

In this work, proportional gain (Kp) =6 and integral gain (Ki) =5 are taken. The gains are applied both in fuzzy proportional integral (FPI) controller and conventional proportional integral (CPI) controller. Both controllers have used the step function as an input. Their settling time is one second. Figure (5.6) shows the curve of step function in blue color, curve of CPI controller in red color and curve of FPI controller in green color. CPI controller shows maximum overshoot 1.6 and undershoot 0.4. As the time increases, the steady state error decreases. However, the FPI controller starts from 0.5 unit of output and settles in one second. It has no overshoot and very small undershoots .It shows very small steady state error. The delay time for conventional proportional integral (CPI) controller is 0.05 second and the delay time for fuzzy proportional integral (FPI) controller is 0 second. The rise time for conventional proportional integral (CPI) controller is 0.1 second and the rise time for fuzzy proportional integral (FPI) controller is 0.55 second. The peak time for conventional proportional integral (CPI) controller is 0.15 second.

The ANN modelling has been done for the control of feed control station and the regulation of pump through fluid coupling. For the feed control station, after so many trials the convergence criteria has been achieved. In first trials, the learning rate, momentum factor, initial weight for three layer back propagation neural network (BPNN) are taken 0.1,0.1and ,0.1. After 1500 iterations, the coefficient of correlation 0.518 is achieved. Next trial is done for 5586 iterations and keeping all other parameter same which improves correlation coefficient by 0.541. However, the convergence criteria has not been achieved. Finally the learning rate, momentum factor, initial weight for back propagation neural network (BPNN) for four layers are taken 0.9, 0.8, and 0.8. After 10000 iterations, the coefficient of correlation 0.975 is achieved. For the regulation of pump, similarly after so many trials of the ANN model, the desired convergence criteria has been achieved. In first trials, the learning rate, momentum factor, initial weight for three layers BPNN are taken 0.1, 0.1, and 0.1. After 559 iterations, the coefficient of correlation 0.9634 is achieved. The next trial is done for 1039 iterations and keeping all other parameter same, 0.9631 correlation coefficient is achieved. The scope of improvement may be there, so another trial is attempted. Finally the learning factor, momentum factor, initial weight for three layers BPNN for four layer are taken 0.9, 0.8, and 0.8. After 10000 iterations, the coefficient of correlation 0.9684 is achieved . Both ANN model 1&2 help in reducing fluctuation of water level in the Boiler drum. Applying this model to the boiler feed system in the Power plant will not only increases the efficiency of the system but also reduce considerably the failure frequency of the boiler that usually occurs due to sudden fluctuations of the load

Basically the ANFIS is a linear model with very nice properties. The main idea of ANFIS is to construct a hyper plane as the decision surface in such a way that the margin of separation between positive and negative examples is maximized. This model achieves this desirable property by following a principled approach rooted in the statistical learning theory. Using the Matlab ANFIS code the network is trained and trained network gives results within 1% of error which shows the superiority of ANFIS over ANN for better predication of water level in the boiler drum. . ANFIS proved its superiority over ANN and Fuzzy PI controller in controlling the feed control station where it gives 0.315 % of error whereas ANN gives a 2.5% of error. In the regulation of the boiler feed pump too, ANFIS obtained the minimum error of 0.90 % as compared to ANN that could offer 3.66% of error.

CONCLUSION

Various control methodologies namely, the Fuzzy PI controller, Artificial neural network (ANN) and Adaptive Neuro Fuzzy inference system (ANFIS) are used to describe a systematic approach to predict the water level in the drum of boiler. The real time data required for the implementation of these methodologies was obtained from a captive power plant located in the eastern part of the India. A comparative study of the error for Fuzzy PI controller, ANN and ANFIS are done in an absolute scale. The fuzzy PI controller showed lesser precision in comparison with ANN and ANFIS. The fuzzy PI controller showed a 10.4% error in the feed control station system and 10.8 % error in the control valve of the fluid coupling. ANFIS proved its superiority over ANN and Fuzzy PI controller in controlling the feed control station where it gives 0.315 % of error whereas ANN gives a 2.5% of error. In the regulation of the boiler feed pump too, ANFIS obtained the minimum error of 0.9 % as compared to ANN that could offer 3.66% of error.

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