Development of Genetic Algorithm based Neural Network model for parameter estimation of Fast Breeder Reactor Subsystem

Subhra Rani Patra, R. Jehadeesan, S. Rajeswari, S. A.V. Satya Murty, M. Sai Baba

Abstract— This work provides the construction of Genetic Algorithm based Neural Network for parameter estimation of Fast Breeder Test Reactor (FBTR) Subsystem. The parameter estimated here is temperature of Intermediate Heat Exchanger of Fast Breeder Test Reactor. Genetic Algorithm based Neural Network is a global search algorithm having less probability of being trapped in local minimum problem as compared to Standard Back Propagation algorithm which is a local search algorithm. The various development stages of Genetic Algorithm based Neural Network such as the preparation of the training set, weight extraction from the genetic population, training of the neural network and validation phase etc have been described in detail.

Keywords—Genetic Algorithm based Neural Network, Fast Breeder Test Reactor, Intermediate Heat Exchanger, Multi layer Perceptron

I. INTRODUCTION

For efficient and quick learning, the weight optimization of Back Propagation neural network has been carried out using Genetic Algorithm. Genetic Algorithms (GA) are adaptive search and optimization techniques, mimicking the principles of natural evolution. Genetic Algorithms have been proposed as one of the potential candidates for optimization of weight parameters of neural network. Conventionally, Standard Back Propagation network performing gradient descent learning algorithms have encountered difficulties of getting struck in local minima problem. Whereas Genetic Algorithm does not guarantee a global minimum solution, however it can locate the neighborhood of optimum solution much quicker than conventional strategies and provide encouraging results. This lessens the large number iterations needed for training the standard back propagation network too. Genetic Algorithms encodes the parameters of neural network as string of properties of the network, i.e. chromosomes. A large population of chromosomes representing many possible parameters sets is generated and crossover, mutation and reproduction are then performed in order to arrive at the best fit optimized parameters.

Genetic Algorithms work with population of individual strings, each representing a possible solution to the problem considered. Each string is assigned a fitness value accessing how good the solution is, to that particular problem. The string having high fitness values, participate in reproduction yielding new strings by cross breeding. The least fit individuals are discarded out. A whole new set of population, containing characteristics which are better than their ancestors, are generated by selecting the high fit individuals. Progressing in this way, after many generations, the entire population inheriting the best characteristics is formed. If the Genetic Algorithm is well implemented, the most promising areas of search space are explored, with the population having fitness values increasing towards the global optimum. A population is said to have converged if 95% of the individuals constituting the population share the same fitness value [1, 2]. The Fig.1 represents the flow chart representation of the Genetic Algorithm based Feed Forward Neural Network.

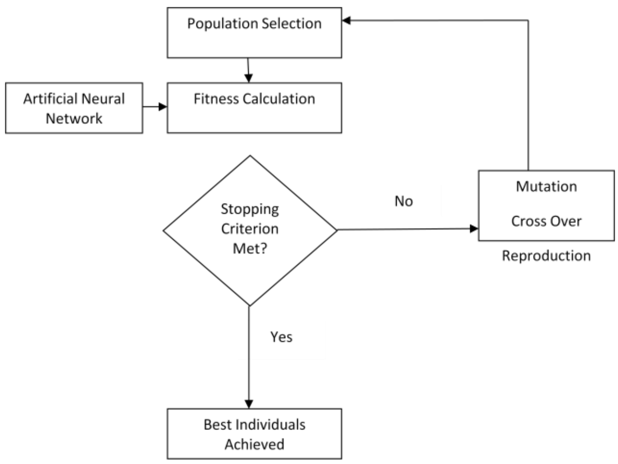


Fig.1 Hybrid Genetic Algorithm for weight optimization of Artificial Neural Network

The objective of this modeling is to evaluate primary and secondary sodium outlet temperatures for given mass flow rate in shell & tube side and respective inlet (primary and secondary) temperatures. The temperature prediction for severe unbalanced primary and secondary flow is performed using Nodal Heat Balance (NHB) method. Later it is modified with the help of Quadratic Upstream Interpolation for Convective Kinetics (QUICK) scheme and from QUICK code the required input data is generated for Artificial Neural Network modeling. The multilayer feed forward network model is observed to be best suited for parameter estimation in Intermediate Heat Exchanger.

Manuscript received September 02, 2012.

Subhra Rani Patra, Computer Division, EIRSG, Indira Gandhi Center for Atomic Research, Kalpakkam-603102, Tamil Nadu, India.

R. Jehadeesan, Scientific Officer/F, at IGCAR, DAE, Kalpakkam, India.

S. Rajeswari is Head of CSS, Computer Division, EIG,IGCAR, DAE, Kalpakkam, India.

A comparison study of two different algorithms, back propagation and Genetic Algorithm based Neural Network is carried out which showed that Genetic Algorithm based Neural Network showed faster convergence with less number of iterations.

II. DESCRIPTION OF FBTR

The FBTR is a loop type, sodium cooled reactor which consists of primary sodium circuit, secondary sodium circuit and steam water system. Heat generated in the reactor is transferred from primary sodium circuit to secondary sodium circuit through Intermediate Heat Exchangers. Hence it is very crucial subsystem whose parameter prediction is of utmost importance in a reactor. From secondary sodium circuit, with the help of once through steam generators, heat is transferred to steam water system comprising of turbine generator which in turn produces electricity. In this paper the behavior of Intermediate Heat Exchanger (IHX) parameters are examined. The IHX subsystem is explained below.

A. Intermediate Heat Exchanger

The Intermediate Heat Exchanger is a vertical, counter flow, shell and tube heat exchanger that transfers heat from active primary sodium to inactive secondary sodium. Primary sodium flows on the shell side and secondary sodium flows on the tube side. It is housed in a fixed vessel with its double envelope. In the reference fast reactor system there are two Intermediate Heat Exchangers in primary circuit, one in each looping[3]. The schematic of IHX is shown in Fig.2.

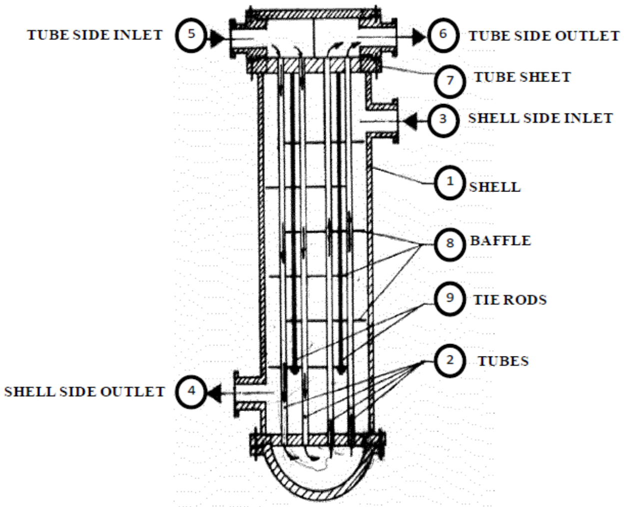


Fig.2 Schematic of sodium-sodium Heat Exchanger of Fast Reactor

When reactor is in operation the control rods are taken out partially so that the neutrons generated can actively participate in the fission reaction which generates heat. The primary sodium will take heat from the radiated core and then will move in upward direction (because of low density property of sodium). Then it will reach up to IHX and enters in radial manner the shell side of IHX at the top. The primary sodium flows vertically downwards and comes out radially at the bottom to the cold pool. The secondary sodium flows upwards inside the tubes. Heat is then transferred from primary sodium to secondary sodium which in turn goes to the steam generator to produce superheated steam. This steam rotates the turbine to generate electricity.

B. Quadratic Upstream Interpolation for Convective Kinetics Scheme Simulation

The QUICK scheme is a higher order up winding numerical scheme which takes care of strong convective flow. It uses a three point upstream weighted quadratic interpolation for cell face values. The cell face values of fluxes are always calculated by quadratic interpolation between two upstream nodes and one downstream node. Since the scheme is based on a quadratic function its accuracy in terms of Taylor series truncation error is third order on a uniform mesh,[4]. It is an explicit scheme which uses discretization method which puts values in terms of nodes. The nodes themselves are treated as ordered or discrete values. With the help of QUICK scheme primary and secondary outlet and inlet temperatures have been evaluated for given mass flow rates of sodium-sodium Heat exchanger in shell and tube side. The outlet temperature of primary and secondary sodium can be estimated using linear interpolation of QUICK scheme and is given in equation 1a and 1b.

$$(T_p)_{out} = 1.5(T_p)_k - 0.5(T_p)_{k-1} \qquad 1(a)$$

$$(T_s)_{out} = 1.5(T_s)_1 - 0.5(T_s)_2 \qquad 1(b)$$

Here T_p and T_s are primary and secondary sodium out-let temperatures in $^{\circ}$C. The required temperature and flow values of sodium-sodium Heat Exchanger have been generated by running the QUICK code and is used for training the ANN model.

III. TRAINING OF THE NETWORK

The training of present network has been accomplished using the Genetic Algorithm based Neural Network (GANN) to predict the temperature parameters of Intermediate Heat Exchanger of FBTR [5, 6]. In order to estimate these two parameters the input parameters taken into consideration are Primary Inlet Temperature, Primary Flow, Secondary Inlet Temperature and Secondary Flow. The input and output dataset for training the neural network has been generated using Quadratic Upstream Interpolation for Convective Kinetics scheme. Since the data is of wide range, it has to be scaled down between zero to one which is also known as normalization. The normalization formula is given by equation 2.

$$d_{norm} = \frac{d}{d_{\max}} \qquad (2)$$

Where d_{norm} the normalized value of the input and d is the input parameter value and $d_{\max}$ is the maximum value of the respective parameters. The normalized data is used for training and testing of the network.

Conventionally, A Back Propagation Network determines its weights based on a gradient search technique and hence runs the risk of encountering the local minimum problem [7]. On the other hand, Genetic Algorithm based Neural Network was found to be good at generating reasonably acceptable solutions with less number of iterations. The key idea was to hybridize Genetic Algorithm and Neural Network for weight optimization. Genetic algorithms use a direct analogy of natural behavior work with a population of individual strings, each representing a possible solution to the problem considered [8-11].

In the present work, the genetic algorithm has been modeled with 12 genes which represent the potential solutions to the problem and the genes are joined together to form a string, referred to as a chromosome. The various stages of genetic algorithm based neural network (GANN) model such as population generation, fitness function calculation, mutation, crossover and reproduction are discussed at length for better understanding of the algorithm. The back propagation network is having the configuration of 4-2-2 representing 4 input layers, 2 hidden layers and 2 output layers. The number of weights that are to be determined are (4+2)*2=12. With each weight being real number and the number of digits in individual gene or the gene length to be 5, the string length of the chromosome is 12*5=60. This chromosome string represents the weight matrices of the input-hidden and hidden-output layers, in a linear form. An initial population of p chromosomes are randomly generated where p representing the population size. The weights from the individual chromosome are extracted using a weight formula and the fitness function is calculated using FITGEN algorithm given below [2].

A. Weight extraction

Suppose $X_1, X_2,....X_d,...., X_L$ represent a chromosome and $X_{kd+1}, X_{kd+2},....X_{(k+1)d}$ represent the k_{th} gene $(k \geq 0)$ in the chromosome. The weight can be calculated by the equation

$$W_k = \begin{cases} +M, & if \quad 5 \leq Xkd+1 \leq 9 \\ -M, & if \quad 0 \leq Xkd+1 \leq 5 \end{cases} \tag{3}$$

Where, $$M = \frac{X_{kd} + 210^{d-2} + X_{kd+3}10^{d-3} + X_{(k+1)d}}{10^{d-2}} \tag{4}$$

B. Algorithm FITGEN

{

Let $\bar{I}_i, \bar{T}_i \quad i = 1,2,..., N$; where $\bar{I}_i = (I_{1i}, I_{2i},....I_{li})$ and $\bar{T}_i = (T_{1i}, T_{2i},....T_{ni})$ represent the input–output pairs of the problem to be solved by Back Propagation Network with a configuration $l-m-n$ (l being input neurons, m hidden neurons and n output neurons). For each chromosome C_i, $i = 1,2,..., p$ belonging to the current population P_i, whose size is p

{

Extract weights W_i, from C_i, Keeping W_i, as a fixed weight setting, train the Back Propagation Network for the N input instances; calculate error E_i for each of the input instances using the formula,

$$E_i = \sum_j (T_{ji} - O_{ji})^2 \tag{5}$$

Where, O_{ji} is the output vector calculated by Back Propagation Network; Find the root mean square E of the errors E_i, $i = 1,2,..., N$; $j = 1,2,..., N$;

i.e $$E = \sqrt{\frac{\sum_i E_i}{N}} \tag{6}$$

Calculate the fitness value F_i for each of the individual string of the population as

$$F_i = \frac{1}{E} \tag{7}$$

}

Output F_i for each C_i, $i = 1,2,..., p$;

}

C. GA based weight determination algorithm

{

$i \leftarrow 0$;

Generate the initial population P_i of real-coded chromosomes C_i^J each representing a weight set for the Back Propagation Network;

While the current population P_i has not converged

{

Generate fitness values F_i^J for each $C_i^J \in P_i$ using the Algorithm FITGEN; Get the mating pool ready by terminating worst fit individuals and duplicating high fit individuals; Using the cross over mechanism, reproduce offspring from the parent chromosomes;

$i \leftarrow i+1$;

Call the current population P_i; Calculate fitness values F_i^J for each $C_i^J \in P_i$;

}

Extract weights from P_i to be used by the Back Propagation Network;

}

IV. RESULTS AND DISCUSSION

The network has been trained with 92 training samples using both Standard Back Propagation algorithm and Genetic Algorithm based Back Propagation algorithm. The input and the corresponding learning output have been presented to the network till it learnt the desired relationship. The training data have been normalized to be in the binary form for speedy training of the network. About 90% of the data has been used in the training set and the rest of the data has been used for validation of the network model. In the Genetic algorithm based network, a population is said to be converged when 95% of the individuals constituting the population share the same fitness value [2]. The present network achieved this criterion after 210 iterations with satisfactory results in comparison to 50000 iterations required when trained with Standard Back Propagation Algorithm. The network is validated using nine test samples and the graph is plotted.

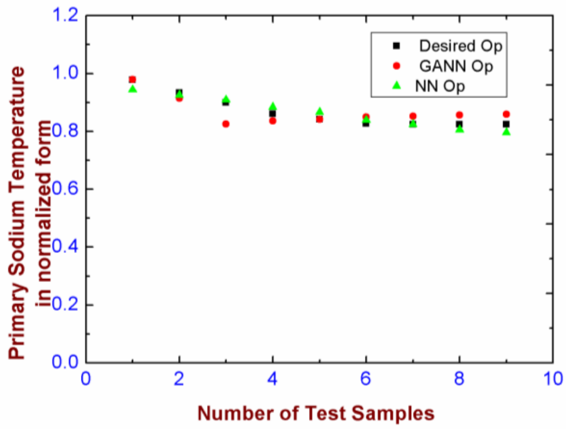


Fig3. Regression analysis for Testing samples of Primary Outlet Temperature in normalized form

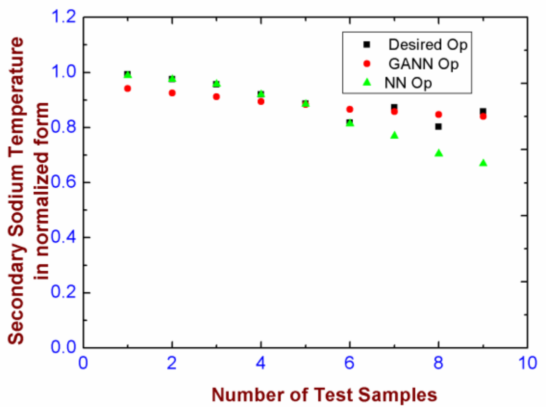
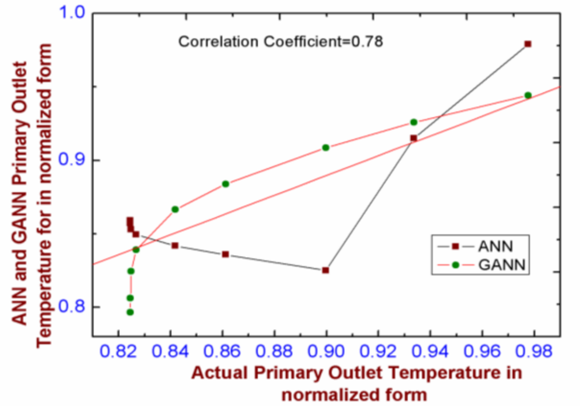


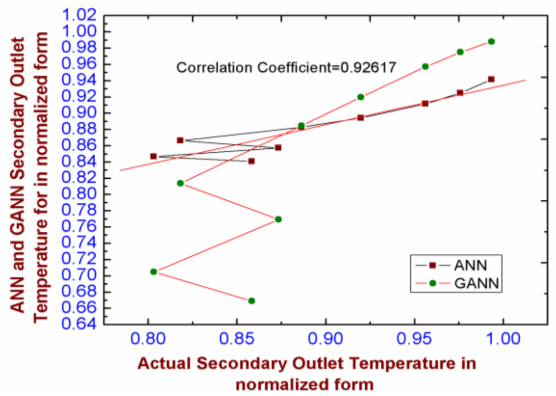
Fig4. Regression analysis for Testing samples of Secondary outlet temperature in normalized form

The trained neural network should be validated for future utilization in practical applications. The above Fig.3 and Fig. 4 depict the results obtained from Genetic Algorithm Based Neural Network.

It can be observed that Neural Network based on Genetic algorithm was used to generate reasonably acceptable results with less number of iterations. Thus a lot of time can be saved using this model without sacrificing the appreciable computational accuracy. The difference limit between the desired and actual output is set as ± 0.1 which is coming well within the permissible limit. In Fig.5, it is shown that the correlation coefficient value is 0.78 and 0.92617 for primary outlet temperature and secondary outlet temperature respectively which is reasonably acceptable.



(a)



(b)

Fig.5 Scatter plot between Actual and Artificial Neural Network Predicted values for (a) primary outlet temperature in normalized form (b) secondary outlet temperature in normalized form

V. CONCLUSION

A Genetic Algorithm based neural network was developed for parameter estimation of Nuclear Reactor Subsystem. The network was implemented to predict Primary and Secondary Sodium temperatures of Intermediate Heat Exchanger of Fast Breeder Test Reactor. The hybrid Genetic Algorithm was used for weight optimization to enhance the convergence speed. Various stages of development of Genetic Algorithm based Neural Network were discussed at length. The network was both trained with Back Propagation algorithm and Genetic Algorithm based Neural Network. From the results it could be concluded that Genetic Algorithm based Neural Network is a useful method for prediction of parameters in Nuclear Reactor Subsystems with less number of iterations compared to Back Propagation algorithm providing acceptably good generalization ability and faster convergence. This has been proved to be a quite straight forward approach to improve upon the capability of parameter estimation using Neural Network.

ACKNOWLEDGMENT

The authors would like to acknowledge Director Sri S.C Chetal for providing immense support to carry out the research work.

REFERENCES

1. Rajasekaran S., Vijayalakshmi Pai G. A., *PHI learning Pvt. Ltd*, 2008, pp. 305-327
2. Rao H., Ghorpade V.G., Mukherjee A., Genetic algorithm based weight determination for back propagation networks, *Proceedings of Trends in Computing, Tata McGraw-Hill*, 1996, pp. 73-80
3. Internal report on "Primary Sodium Main Circuit System Manual", Report No. FBTR/FRG/32000-DN-S-RS-06
4. Internal report on "Heat Exchangers", FRG/FBTR/TM
5. Erdogan E., Gecknli M., *Annals of Nuclear Energy*, Vol. 30, 2003,pp. 35-53
6. Ahmed A.A., Alfishawy N.A., Albrdini M.A., Mahmoud I.I., *Nature and Science*, Vol. 5, 2011,pp. 64-74
7. Burse K., Manoria M., Kirar V. P. S., *World Academy of Science, Engineering and Technology*, Vol. 72, 2010
8. Gupta J. N.D., Sexton R. S., *Omega*, Vol. 27, 1999,pp. 679-684
9. Montana D. J., Davis L., *Proceedings of the 11th international joint conference on Artificial intelligence*, Vol. 1, 1989, pp. 762-767
10. Montana D. J., *John Wiley & Sons*, 1995,pp. 85-104
11. Ileana I., Rotar C., Incze A., *Proceedings of the International Conference on Theory and Applications Mathematical and Informatics*, Thessaloniki, Greece, 2004, pp. 223-24

AUTHORS PROFILE

Subhra rani patra has completed her Masters in Electronics from Berhampur University. She was pursuing her PhD. at IGCAR, DAE, Kaplakkam and recently submitted her thesis. Her research area includes Artificial Neural Network and Soft Computing, Neuro Computing. She has 2 international Journal Publications to her credit. .At persent she is working as a post doctorate fellow at ISI,Bangalore, India.

R. Jehadeesan is a Scientific Officer/F, at IGCAR, DAE, Kalpakkam, India. He has done B.tech and M.S. in Computer Science. His research interest includes software engineering, artificial intelligence.

S.Rajeswari is Head of CSS, Computer Division, EIG,IGCAR, DAE, Kalpakkam, India. She has done her B.tech in Electrical and Electronics Engineering. Her research interest includes data mining, grid computing and artificial intelligence.