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Short Term Load Forecasting using a Neural Network trained by A Hybrid Artificial Immune System

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***Abstract*— Short term load forecasting is very essential to the operation of electricity companies. It enhances the energy-efficient and reliable operation of power system. Artificial Neural Networks are employed for non-linear short term load forecasting owing to their powerful non-linear mapping capabilities. These are generally trained through back-propagation, genetic algorithm (GA), particle swarm optimization (PSO) and artificial immune system (AIS). All these algorithms have specific benefits in terms of accuracy, speed of convergence and historical data requirement for training. In this paper a hybrid AIS is proposed, which is a combination of back-propagation with AIS to get faster convergence, lesser historical data requirement for training with a little compromise in accuracy.**

***Index Terms*—Short term load forecasting, genetic algorithm, particle swarm optimization and artificial immune system.**

I. INTRODUCTION

Short term load forecasting is a time series prediction problem. It analyzes the pattern of future electrical load. The information is very crucial to determine hydro-thermal generation mixture, to allot transmission corridor, to decrease over all loss of grid, and to increase operational efficiency.

The load is decomposed into two components. One is weather dependent, and the other is weather independent. Each component is usually modeled separately and the sum of these two gives the total load forecast. The behavior of these two controls the total load pattern. The behavior of weather independent load is mostly represented by Fourier series or trend profiles in terms of the time functions. The weather sensitive portion of the load is arbitrarily extracted and modeled by a predetermined functional relationship with weather variables.

Feed forward neural net structures like multi layer perceptron, functional link, wavelet, recurrent or feedback structures like Hopfield, Elman, Multi Feedback [1] & hybrid structures using fuzzy neural networks have been widely proposed for non-stationary forecasting applications and have seen to provide very high degree of predictive accuracy. But many of those papers have been tested on Macky-Glass series or some other smooth differentiable functions rather than actual load data. Actual load

data putforths many challenges to design a predictive neural net structure Prominent of those challenges are, data pre-processing, input parameter selection, type of neural net structure selection, computational complexity and training algorithm. Computational complexity is dependent on the structural complexity and training algorithm. This factor becomes important for real time implementation of algorithms in power generation and transmission equipment.

Moreover, evolutionary and behavioral random search algorithms such as genetic algorithm (GA) [2–4], particle swarm optimization (PSO) [5, 6], etc. have previously been implemented for different problems. Infact, genetic algorithms, based on the theory of genetic evolution, due to their parallel search techniques, have attracted much attention in the past, and were successfully implemented to a variety of electrical engineering problems. GA has been deployed to forecast short term load with various modifications over the years. In spite of its successful implementation, GA does posses some weaknesses leading to longer computation time and less guaranteed convergence, particularly in case of epistatic objective function containing highly correlated parameters [7, 8]. Moreover, premature convergence of GA is accompanied by a very high probability of entrapment into the local optimum. In order to alleviate the aforementioned difficulties, this paper proposes a new approach, to forecast short term load, inspired by the characteristics of immune system. Immune system (IS) is a very intricate biological system which accounts for resistance of a living body against harmful foreign entities. Artificial immune system (AIS) imitates the immunological ideas to develop some techniques used in various areas of research [9]. It works on the principle of pattern recognition (distinguishing antibody and antigen) and clonal selection principle, whereby clonal selection algorithm (invariably called as AIS) is implemented to accomplish learning and memory acquisition tasks. In IS, receptors present on the antibodies are responsible for antibody–antigen interaction. In these interactions, different antibodies have different affinity towards an antigen and the binding strength is directly proportional to this affinity [10]. AIS effectively exploit these interactions and the corresponding affinity by suitably mapping it to fitness (objective function) evaluation. These ideas are further emulated and thereby harnessed into earning, memory and associative retrieval to solve the prediction problems.

In conventional AIS, the fitness function is calculated on basis of the final network error, which is used to update the weights and biases. In back propagation algorithm error contribution of all the neurons is taken into consideration for updation of corresponding weights and biases of neurons. This paper proposes a hybrid Artificial Immune System (AIS) algorithm for predicting short term load. This method has a better convergence, and accuracy than conventional AIS, GA, PSO and ANFIS.

Following this introduction the remaining paper is organized as under. Section 2 provides overview of artificial immune system, while Section 3 analyzes the proposed Hybrid AIS algorithm. Section 4 highlights the system model for load forecast. The experimental results are presented in Section 5 and Section 6 provides the concluding remarks.

II. ARTIFICIAL IMMUNE SYSTEM APPROACH

In this section, some concepts and technical terms necessary for the development of our model is introduced [11].Generally speaking the main function of the immune system is to limit the damage to the host organism exposed to foreign harmful substances (e.g. bacteria and viruses). These harmful substances are identified by molecules called antigens. The antigens are responsible for triggering an immune response, which consists of secretion of antibodies by B-cells to participate in the recognition and destruction of theses invading antigens. The B-cells are monospecific, that is they have a single type of receptor, thus, no distinction between he B-cell and its receptor is considered in this work. These biological principles of clone generation, proliferation and maturation are modeled into an algorithm termed the clonal selection algorithm (CLONALG).

In [12] de Castro and Von Zuben focused on the clonal selection principle and affinity maturation process of the adaptive immune response in order to develop an algorithm suitable to perform tasks such as machine learning, pattern recognition, and optimization. Their algorithm was evaluated in a simple binary character recognition problem, multimodal optimization tasks and a combinatorial optimization problem; more specifically the traveling salesman problem (TSP). The main immune aspects taken into account to develop the algorithm, named CLONALG, were: selection and cloning of the most stimulated cells proportionally to their antigenic affinity; death of non-stimulated cells; affinity maturation and selection of cells proportionally to their antigenic affinity; and generation and maintenance of diversity. The algorithm CLONALG works as follows:

1. Generate a set of N candidate solutions (antibody repertoire) in a shape-space to be defined by the problem under study.
2. Select n_1 highest affinity cells in relation to the antigen set to be recognized or to the function being optimized.
3. Clone (generate identical copies of) these n selected cells. The number of copies is proportional to their affinities: the higher the affinity, the larger the clone size (number of offspring).
4. Mutate with high rates (hyper mutation) these n selected cells with a rate inversely proportional to their affinities the higher the affinity, the smaller the mutation rate.
5. Re-select n_2 highest affinity mutated clones to compose the new repertoire.
6. Replace some low affinity cells by new ones.
7. Repeat steps 2 to 6 until a given stopping criterion is met.

The authors characterized CLONALG as an evolutionary like algorithm with the main features of population based search guided by the mechanisms of reproduction, genetic variation and selection. It is important to note however, that though CLONALG is a type of evolutionary algorithm, it was developed using inspiration from the immune system. In contrast, the standard evolutionary algorithms were devised inspired by the neo-Darwinian theory of evolution. Thus, in the former case (CLONALG) the evolutionary theory is used to explain how the algorithm behaves, and in the latter case (EAs) the evolutionary theory was used to create the algorithm. There are however, some important differences between CLONALG and a GA for example. CLONALG performs not only affinity proportionate selection, but also affinity proportional mutation, and there is no crossover. Similarity does exist however, in the fact that both algorithms encode the individuals of the population. When compared with the evolution strategies, for example, again, differences exist between the algorithms. Evolution strategies work with real-valued encoding, while CLONALG works with binary representation, and the affinity proportional mutation in CLONALG is not controlled by Gaussian distributions. Therefore, no matter which type of evolutionary algorithm is compared with

CLONALG, there are always enough differences between them, in terms of inspiration and computation that justify the proposal of CLONALG as an evolutionary algorithm inspired by immunology.

III. PROPOSED HYBRID ARTIFICIAL IMMUNE SYSTEM APPROACH

In order to reduce the computational cost, increase convergence speed, and reduce less historical load input, the hybrid AIS algorithm is proposed in this paper. The AIS is implemented to Short term Load Forecasting problem utilizing the following four main features. Firstly, a pool of immune cells or antibodies is generated. This is followed by cloning or copying of the parents. Then, maturation of these clones takes place which is analogous to hyper mutation. Thereafter, the antibody–antigen interaction is evaluated followed by the elimination of self reacting immune cells or lymphocytes, i.e., individuals with low affinities or fitness values. In conventional neural network structures Artificial Immune System is used to minimize the final error but in this proposed method the error contributed by each neuron is calculated through back propagation from the Jacobian matrix. So, instead of having one fitness function for all the antibodies, we have as many number of fitness functions as number of neurons. In turn the cloning and hyper mutation of the antibodies, representing the weights and biases are dependent on the error contributed by the particular neuron.

A population of antibodies is initialized using binary strings each encoding weights and biases of the neural network. Affinity is calculated via fitness or objective values. Fitness is calculated as:

$$\mathrm{fitness}^{j}(\mathrm{k}) = 1/\left(1+\mathrm{e}(\mathrm{t})^{2}\right) \qquad \ldots (1)$$

where e refers to one epoch error at time t. Error is calculated as:

$$e(t) = y(t) - d(t) \qquad \ldots (2)$$

Where $y(t)$ is the forecasted output and $d(t)$ is the desired output at time t. Each of the antibodies from the initial pool is copied into a number of clones to generate a temporary population of clones. Number of clones of each antibody is calculated as:

$$N * \left(fitness^{j}(k) \Big/ \sum_{i=1}^{N} fitness^{j}(i) \right) \qquad \ldots (3)$$

where N is the number of antibodies of same type. $fitness(k)$ is the fitness function value of k^{th} antibody related to j^{th} neuron. This population of clones is made to undergo maturation process through hyper mutation mechanism. The hyper mutation is carried out via affinity based hyper mutation rate. Larger hyper mutation rate is set for lower affinity clones and vice versa. That is, the probability of hyper mutation of each clone is inversely to its affinity. In this case number of bits to be mutated is calculated as:

$$M * \left(\max\left(fitness^{j}\right) - fitness^{j}(k) \Big/ \max\left(fitness^{j}\right) - \min\left(fitness^{j}\right) \right) \qquad \ldots (4)$$

A new population of the same size as initial population of the antibodies is selected from the mutated clones and this completes the first iteration. In the next iteration, this fresh population is made to undergo cloning and hyper-mutation as discussed above and likewise.

IV. INPUT & OUTPUT FOR THE HYBRID AIS MODEL

In our analysis, the ANN model uses nine inputs including load at hour ‘hr-1’ , ‘hr-2’, ‘hr-3’ of same day, ‘hr’, ‘hr-1’, ‘hr-2’ of previous day, & ‘hr’, ‘hr-1’, ‘hr-2’ of same day of previous week. Only one output node is used representing a 24-hour ahead load forecast at hour ‘hr’ in the lead time.

The reason behind taking the specific inputs are as follows: It takes into consideration the hour of the day effect to map hourly load variation.

Day of the week is taken into account to map weekly pattern of industrial and commercial load pattern on week days and weekends. Seasonal variation is gradual so previous day load pattern as an explicit input takes care of seasonal mapping.

V. SIMULATION RESULTS

The acceptable criteria for a particular model is based upon the (i) minimum average percentage error (MAPE), (ii) number of hours in which it gives negative MAPE,

(iii) time taken by the model to get trained. The acceptable criteria (i) & (iii) are self explanatory. The second criteria signifies the under estimation of required load. Under estimation of load may stress the generation units.

The Mean average percentage error (i.e. MAPE) in case of MLP-BP was found to be 3.5543 % with logsig activation function, 17 nos. of hidden neurons, learning rate of 0.1, & Guyen-Widrow parameter initialization as shown in Figure.1.

In case of GA-MLP the best result was found to be, MAPE of 3.1943 %, with 4 nos. hidden neurons, and tansig activation function. This is shown in Figure.2.

In case of PSO-MLP the best result was found to be, MAPE of 4.2118 %, with 4 nos. hidden neurons and logsig activation function as shown in Figure.3.

In case of the conventional AIS-MLP, the best result was found to be, MAPE of 5.2756 %, with 4 nos. hidden neurons and logsig activation function. The performance curve for this is shown in Figure.4.

In case of the proposed Hybrid AIS-MLP, the best result was found to be, MAPE of 4.2036 %, with 4 nos. hidden neurons and tanh activation function as shown in Figure.5.

As it is observed, the proposed Hybrid AIS algorithm trained neural network gives better accuracy than conventional AIS trained neural network. This training approach requires a leaner network than back-propagation (BP) to reach at the almost same level of accuracy. GA & PSO trained networks require 150 iterations & 36 data sets, where as hybrid-AIS require hardly 6 iterations & 21 data sets to converge to the same extent.

Network	MAPE in %
BP-MLP	3.5543
GA-MLP	3.1934
PSO-MLP	4.2118
AIS-MLP	5.2756
Hybrid AIS-MLP	4.2036

Table 1. MAPE comparisons

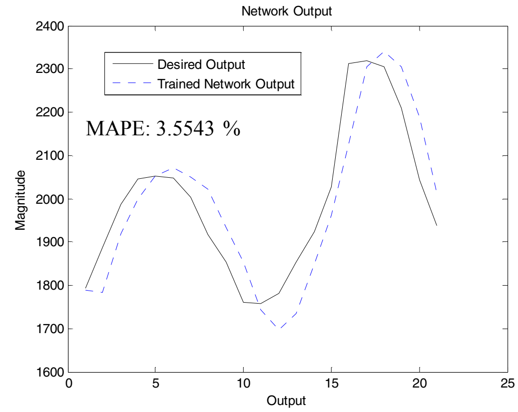

Figure 1. Performance of BP – MLPNN

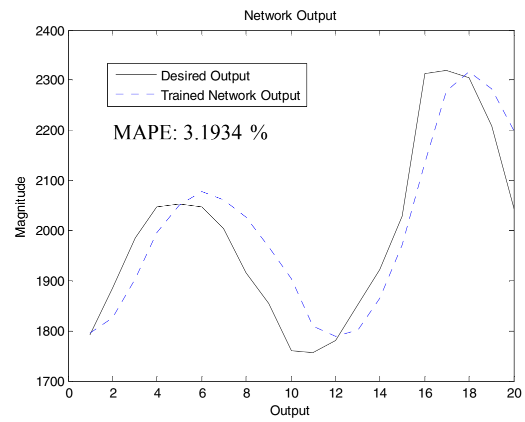

Figure 2. Performance of GA – MLPNN

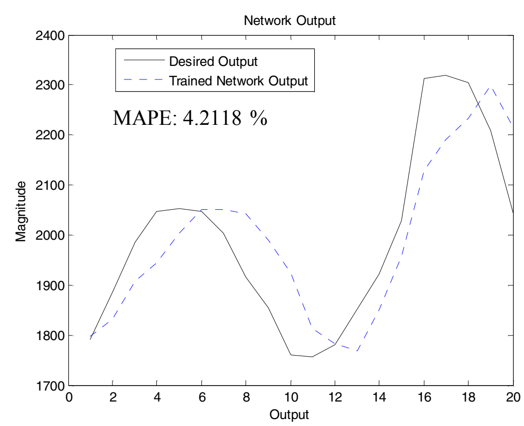

Figure 3. Performance of PSO – MLPNN

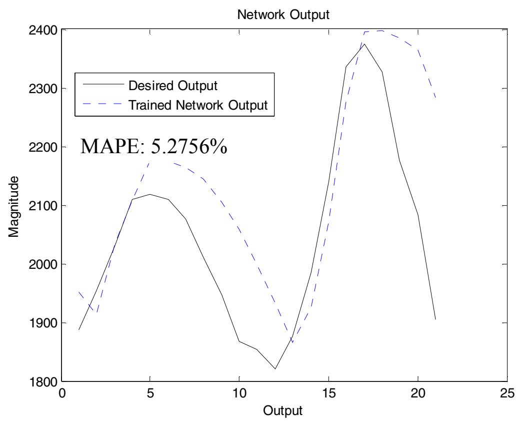

Figure 4. Performance of AIS - MLPNN

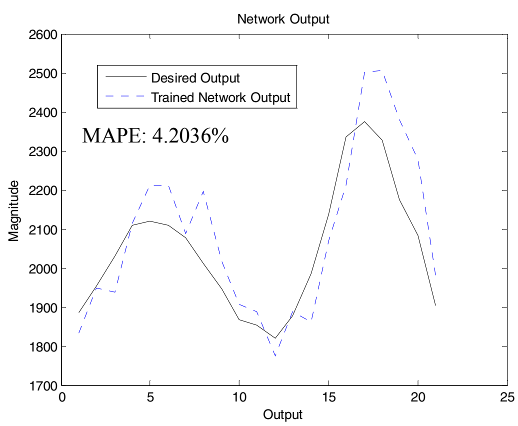

Figure 5. Performance of Hybrid AIS - MLPNN

VI. CONCLUSION

The paper has employed AIS Algorithm on the short term load forecasting. As it is observed, the proposed Hybrid AIS algorithm trained neural network gives better accuracy than conventional AIS trained neural network. This training approach requires a leaner network than back-propagation (BP) to reach at the almost same level of accuracy. GA & PSO trained networks require 150 iterations & 36 data sets, where as hybrid-AIS require hardly 6 iterations & 21 data sets to converge to the same extent. The proposed approach has produced results comparable or better than those generated by other algorithms and the solutions obtained have superior solution quality and good convergence characteristics. From this limited comparative study, it can be concluded that the proposed hybrid artificial immune system algorithm can be effectively used for training neural networks for short term load forecasting.

VII. REFERENCES

[1] A. Savran, Multifeeback-layer Neural Network, IEEE Trans. Neural Networks Vol. 18 No. 2, (2007) 373-384.

[2] J. H. Holland, *Adaptation in Natural and Artificial Systems*, Ann Arbor, MI: Univ. Michigan Press, 1975.

[3] D. T. Pham and D. Karaboga, *Intelligent Optimization Techniques, Genetic Algorithms, Tabu Search, Simulated Annealing and Neural Networks,* New York: Springer-Verlag, 2000.

[4] L. Davis, "*Handbook of Genetic Algorithms",* New York: Van Nostrand Reinhold, 1991.

[5] R. C. Eberhert and J. Kennedy, "A new optimizer using particle swarm theory", *Proceeding of the Sixth International Symposium on Micro Machine and Human Science*, page 39-43,, Nagoya, Japan, 1995, IEEE Service Center, Piscataway, Nj.

[6] J.B. Park, K.S. Lee, J.R. Shin, K.Y. Lee, A particle swarm optimization for economic dispatch with non-smooth cost function, IEEE Trans. Power Syst. 20 (20) (2005) 34–42.

[7] D.B. Fogel, Evolutionary Computation: Toward a New Philosophy of Machine Intelligence, second ed., IEEE Press, Piscataway, NJ, 2000.

[8] R.C. Eberhart, Y. Shi, Comparison between genetic algorithms and particle swarm optimization, in: Proc. IEEE Int. Conf. Evol. Comput., May, 1998, pp. 611–616.

[9] L. N. de Castro, F. J. Von Zuben, Artificial Immune Systems: Part II—A Survey of Applications. FEEC/Univ. Campinas, Campinas, Brazil.

[10] L.N. de Castro, F.J. Zuben, Learning and optimization using through the clonal selection principle, IEEE Trans. Power Syst. 6 (3) (2002) 239–251.

[11] A.S.Perelson and G. Weisbuch "Affinity maturation and learning in Immune Networks" in *Molecular Evolution in rugged landscapes*, pp. 189-205, ed. A Perelson and S. Kauffman, Addison Wesley, (1991).

[12] de Castro, L. N. & Von Zuben, F. J. (2000), "The Clonal Selection Algorithm with Engineering Applications", (full version, pre-print), In Proceedings of GECCO'00, Workshop on Artificial Immune Systems and Their Applications, pp. 36-37.