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Economic Load Distribution Among Generating Plant Using Software Based on Articial Neural Network (ANN).

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Abstract

This paper presents an application system that provided the best load distribution for optimal power flow (OPF) with minimal fuel cost using artificial neural network (ANN). The idea was informed by the application of the principle of equal incremental cost rate for all the generators. The study also demonstrated a new computational model for the exponential function e which was introduced to the Tanh transfer function. A new version of Tanh function was therefore developed called the Tansigmod. It increased the speed of training of the feed forward network by a gain factor of about 3 units. To test the effectiveness of the proposed system, the case of a five bus network for Trans-Amadi gas turbine power station in Port Harcourt, Nigeria was demonstrated. Result obtained from the system show for example cost saving or Netsave monthly of about 108,520 Naira for a service load of 60MW supply. This benefit was derived from the system due to optimal distribution of load as against equal distribution of load. The application will assist the operators in the gas turbine power stations with the task of planning power generation economically.

Keywords: optimal power flow, artificial neural network, feed forward network, equal incremental cost rate, exponential function, Tansigmod, Netsave, optimal distribution, equal distribution..

Introduction

In managing an electricity generating industry, several decision making techniques, both technical and economical, are usually taken with the aim of either maximizing output or minimizing the cost of operation. The job is made even more difficult with rapid the increase in developmental technologies that massively utilizes large amount electrical energy resources. Planning, operation and control of the industry therefore become more complex, complicated and increasingly ever more challenging. To maintain efficiency and sustainability, best practices in economic distribution of load [2] are employed. The objective is to systematically seek the lowest cost of electricity production that will be consistent with electricity demand. To minimize cost, increase in the use of more efficient generating unit will be employed and at the same time this will address three major issues of concern - better fuel usage, reduce maintenance cost and reduced green house gas emission [3, 4, 5], that would result from less efficient generation.

In perspective, many solution techniques have been proposed and also available to solving economic load distribution problem with varied degree of successes have been reported in several literatures. Among the algorithmic solutions are Interior point (IP) algorithm [7], Simplex algorithm (SA), Quadratic programming (QP), and Dynamic programming (DP) [8]. Lagrange relaxation method (LRM) [9, 10], linear programming (LP), Non-linear programming (NLP) and Newton-based methods have also been reported. These methods provided solutions with iterations that converges slowly, have difficulty in detecting infeasibility, tendency to error due to linear approximation of non linear estimates and high computational complexity of solution due to large sparse linear system. As a result they arrive at sub optimal solutions or local minima. Currently proposed Artificial Intelligent methods based on heuristics and operational research presented by researchers have emerged with global optimum solution for power system economic load distribution. They include Expert system (ES), Ant Colony search (ACS) [11], Simulated annealing (SA) [12], Artificial Neural networks (ANN) [13, 14, 15, 16, 17], Fuzzy logic (FL) [18] and Genetic Algorithm (GA) [19]. Others are Meta heuristic methods such as

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Tabu search (TS) [20], Particle swarm optimization (PSO) [21] and Evolutionary programming (EP) [22]. Application of these methods depends on the researchers' area of interest as each method has its own advantages and disadvantages; and notably ANN has proved to be very efficient in solving complex problems because of its properties of robustness, fast computation, non linear modeling and learning ability.

In particular, the learning ability of ANNs enables it to take care of the following problems which completely elude mathematical solutions in economic load distribution:

- Use of knowledge bases to store human knowledge
- Operator judgment particularly in practical solutions
- Experience gained over a period of time
- Characterization by network uncertainty, load variations, etc.

ANNs are characterized by their connection pattern, learning algorithm and activation functions. In feed forward ANN, back propagation algorithm is usually employed as the learning algorithm with the sigmoid activation function. The sigmoid function contains the exponential function ***e*** which slows down the rate of training because of its value that runs through a trillion set of numbers. In this paper, we propose to solve economic load distribution among generating plants using ANN with a new activation function called the Tansigmod (modified tanh function). Tansigmod is a developed mathematical model that replaces the ***e*** in the sigmoid function and provides a faster rate of training and as we observed impacted positively on the accuracy of the result.

Problem statement

Providing electricity to service various load distributed in an area is fundamental and inevitable to daily living as well as the sustainability of industrial growth. The collapse of the industrial sector, small and medium scale businesses and economic standstill of any nation is traced to the inadequate and erratic state of the country's electricity market. Nigeria is considered as one of the energy rich countries in the world, with considerable quantity of natural gas reserve discovered especially in the Niger Delta with a distribution between associated gas with oil and natural gas. Currently, the figure is put at 256 trillion scf probable gas reserves, and 197 trillion scf proven gas reserves. About 7.1 billion scf are produced daily, out of which about 1.75 billion scf are flared and 3.4 billion scf are consumed every day [1, 24]. She is rated among the top oil producer in Africa, second in natural gas reserve yet when global electricity market trend is considered, Nigeria is far from realizing the expected target. The reason for the scarcity of the commodity is lack of proper management to harness the available resources [25] and inability of the managers to apply the principle of economic load distribution amongst the generating plants.

Problem formulation

The control of economic load distribution of a power system is determined by the power output of each power plant, power output of each generating unit, which will minimize the total cost of fuel used to serve the system load. Fuel cost is a major component in operating cost of a power system and its optimal use by the generating units forms the basis for economic load distribution. Each generating unit has minimum and maximum power output it can generate and to arrive at any, a variation in the fuel input is necessary. These properties of generators are defined by the input-output (I/O) curve. If the curve is quadratic, then the cost of fuel input for a generating unit is given by the equation:

$$I = a + bP + cP^2 + dP^3 + \ldots\ldots\ldots\ldots\ldots nP^r \ldots\ldots\ldots (1)$$

where I is the input(cost of fuel) and the output P (power produced by generator) with coefficients a, b, c to n.

If the input-output behavior of all the generating units of a power system is the same then they can be loaded economically equally, but in the ideal case, the behaviors are not the same. This implies that for the input cost of a particular generator, the power generated will be different.

The slopes of the input-output curve at various load-points of a generator give the incremental cost rate (IC). The criterion for economic distributing of load among generators is based on whether increasing the generation of one unit and decreasing the generation of the other by the same quantity results in increase or decrease in total cost. If Ri is the incremental rate, by differentiating the expression in equation 1 (stopping at the third power), we obtain the incremental rate characteristic (IRC) as:

$$Ri = \frac{dI}{dP} = b + 2c(P) + 3d(P^2) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Economic load distribution

The objective of economic load distribution is to schedule generation such that input (I) is minimum for the given total power P, subject to restriction that sum of $P_k = P$ is the total load received, where P_k is the output of unit k. Suppose

$$f\ (P_1,\ P_2,\ -------------P_k) = 0\ \ldots(3)$$

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And $\sum_{k=1}^{n} P_k - P = 0$ ....(4)

Then $\sum_{k=1}^{n} P_k = P$ ....(5)

If I represent the cost of input, the minimum input cost is realized when

$$\frac{dI_t}{dP_k} = 0 \ where\ I_t = \sum_{k=1}^{n} I_k$$

I_t = total input

Applying lagrangian type multiplier where

I = I_t - λf λ = lagrangian type of multiplier

$$\frac{dI}{dP_k} = \frac{dI_t}{dP_k} - \lambda \frac{df}{dP_k} = 0$$

But RHS

$$\frac{dI_t}{dP_k} - \frac{\lambda d}{dP_k}\left[\sum_{k=1}^{n} P_k - P\right] = 0$$

$$\frac{dI_t}{dP_k} - \lambda\ [1-0] = 0$$

$$\therefore \frac{dI_t}{dP_k} = \lambda \quad and \quad \frac{d}{dP_k}\left[\sum_{k=1}^{n} I_k\right] = \lambda$$

Hence

$$\frac{dI_t}{dP_k} = \lambda \ \text{..........................(6)}$$

The incremental cost of input to k^{th} unit in Naira per MW hour is equal to the incremental cost of the received power. The equation (6) may be rewritten as:

$$\frac{dI_1}{dP_1} = \frac{dI_2}{dP_2} = \frac{dI_2}{dP_3} ------ = \frac{dI_n}{dP_n} \text{ ....(7)}$$

If the incremental rate of k^{th} unit in written as R_{ik}, then

R_{i1} = R_{i2} = R_{i3} ------- R_{ik} = ---------- R_{in} = λ …………...(8)

Using symbol, C, for incremental production cost in Naira per MW hour then:

$$Ci_1 = Ci_2 = Ci_3 --- = Ci_k -- Cin = \lambda \text{......(9)}$$

λ - the lagrangian multiplier - is the incremental cost of received power in Naira/MW hour.

The neural network method

Precisely, the technique involved in ANN-based methods does not require explicit models to represent the complex relationship between the various factors that determine the problem [13, 15]. Only parametric data in respect of the problem (which may historical or online) are needed. ANN with its parallel architecture can approximate any continuous function due to its robustness, and fault tolerance capability [16].

In general, we consider the case of Trans Amadi power station, a five-bus power system network in a one line diagram as shown in Fig 1. The five-bus power system network consists of three generator buses (P_{G1}, P_{G2}, P_{G3}) and two load buses (P_{D3} and P_{D4}).

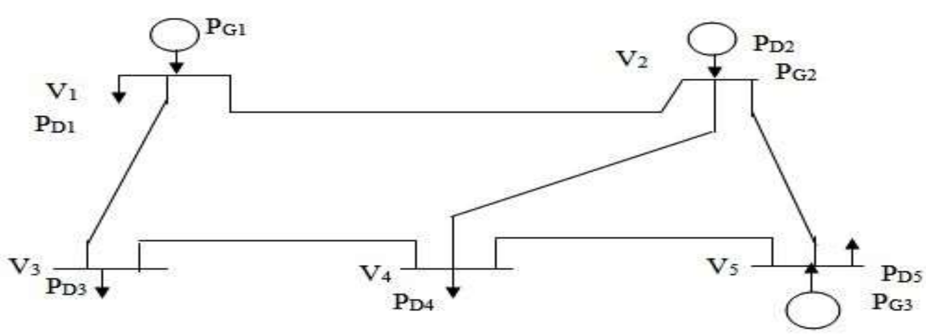

Fig 1: One-Line Diagram of a Five Bus System

For the task of performing economic load distribution for the model we begin with the specification of the neural network parameters (in this case historical) as follows:

Input parameter

C_s -- Cost of fuel (gas) in Naira/mmscf per day for all the generators.

Output Parameter

P_r --Total output power/load in MW per hour serviced by the generators per day.

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A neural model for the operation of the station generators is shown in Fig 2.The input parameters C1 to Cs are cost of fuel used by the three generators. The Pr is total output power produced by the combined three generators to service a load. This specification will propagate the input parameters (cost) through the network to the output. During this process the network learns (neural learning) with different inputs and the weight values are changed dynamically until their values are balanced (output equals target) or the error (MSE = d) is minimal or zero. The activation function is Tansigmod and the learning algorithm is back propagation.

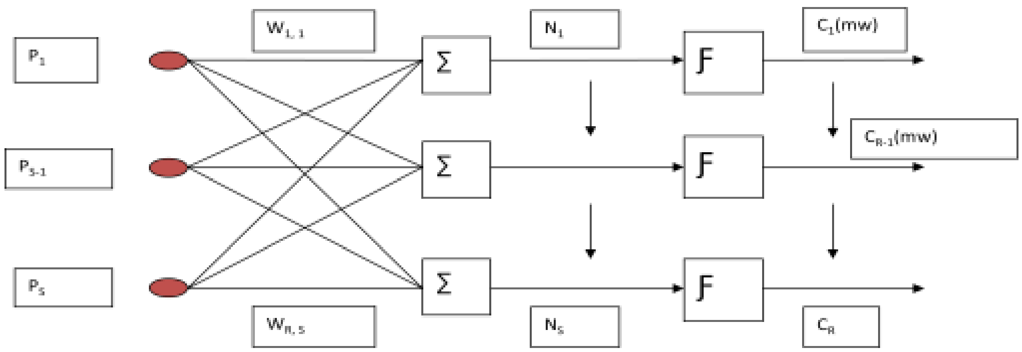

Fig 2 Network Diagram of ANN component

$P = F(W*C + b)$ Tansigmod = $(2/\ (1+ (((k-n)/(k-m))^{k}\ )^{-2x})) -1$

$$W = \begin{matrix} W_{1,1} & W_{1,2} & W_{1,S} \\ W_{2,1} & W_{2,2} & W_{2,S} \\ W_{R,1} & W_{R,2} & W_{R,S} \end{matrix}$$

w = weight Matrix
R = number of neuron in the layer.
F= tansigmoid type activation function.
b = bias
S = number of elements in the input vector.

Table 1 shows the historical data for the operation of the five-bus network. The table contains data of generator input cost as C1, C2, C3, while P1, P2, P3, are power generated data for P_{g1}, P_{g2}, and P_{g3} generators respectively for the five-bus network in fig 1. It is derived based on the fuel input and power output of the polynomial of equation (1).

Table 1: Sample of Output Power and Cost of Input in Naira Per Hour

P1 (MW)	P2 (MW)	P3 (MW)	C1 (#/hour)	C2 (#/hour)	C3 (#/hour)
24.1	24.1	24.1	598.7405	581.8886	503.3648
20.8	20.8	20.8	535.232	525.4784	461.8112
21.5	21.5	21.5	548.6125	537.335	470.48
22.3	22.3	22.3	563.9645	550.9574	480.4832
16.6	16.6	16.6	455.978	455.5736	411.4448
22.7	22.7	22.7	571.6645	557.7974	485.5232
22.9	22.9	22.9	575.5205	561.2246	488.0528
22.7	22.7	22.7	571.6645	557.7974	485.5232
25.3	25.3	25.3	622.1045	602.7254	518.9072
23.4	23.4	23.4	585.178	569.8136	494.4048
24.2	24.2	24.2	600.682	583.6184	504.6512
25.1	25.1	25.1	618.2005	599.2406	516.3008
23.6	23.6	23.6	589.048	573.2576	496.9568
22.4	22.4	22.4	565.888	552.6656	481.7408
22	22	22	558.2	545.84	476.72

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23.3	23.3	23.3	583.2445	568.0934	493.1312
17.3	17.3	17.3	469.0645	467.0774	419.6432
22	22	22	558.2	545.84	476.72
25.7	25.7	25.7	629.9245	609.7094	524.1392
22.7	22.7	22.7	571.6645	557.7974	485.5232
26.1	26.1	26.1	637.7605	616.7126	529.3968
26.2	26.2	26.2	639.722	618.4664	530.7152
24.3	24.3	24.3	602.6245	585.3494	505.9392
25.9	25.9	25.9	633.8405	613.2086	526.7648

Neural network architecture

The Network architecture usually describes the number of layers in a network, the number of neurons in each layer, each layer's transfer function, and how the layers are connected to each other. The best architecture depends on the type of problem to be represented by the network.

The architecture employed in the above neural model is multilayer feed forward network with one hidden layer. The performance function is MSE (mean square error). Network functions are determined by connections between elements. Learning for a particular function is by adjusting the values of the connections (weights) between elements. The Tansigmod activation function is given by:

Tansigmod = $(2/\ (1+\ (((k-n)/(k-m))^{k}\ )^{-2x}))\ -\ 1$…………………………(10)

The back propagation learning algorithm updates the network weights and biases in the direction in which the performance function decreases most rapidly – the negative of the gradient.

$\mathbf{x}_{k+1} = \mathbf{x}_k - \alpha_k \mathbf{g}_k$, $\mathbf{x}_k$ = vector of current W and b, $\mathbf{g}_k$ = current gradient α_k = learning rate.

Based on the data in table 1 the neural architecture for the five-bus network is shown in fig 3. The input and output parameters are also stated as for the neural model.

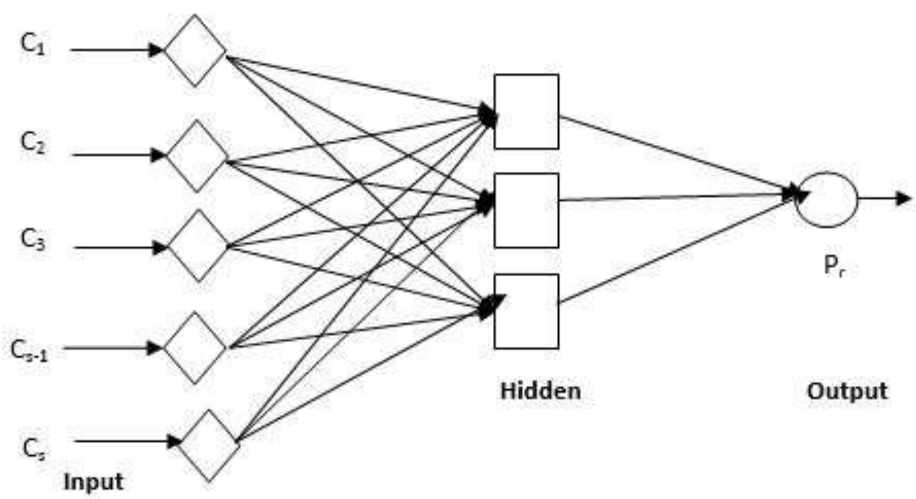

Fig. 3: Neural Architecture

Input Parameters for the Model:

- $C_{(s)}$ - Total fuel cost Consumed by the station per generator

Output Parameters for the Model:

- $P_{(r)}$ Total output power/Load demand

Results

Results obtained from the application are shown in table 2 for various load demands. Expectedly the difference between operating the station optimally as against equal distribution is clearly identified in the table as NetSave. The daily cost saving (NetSave) for each of the load demands per day is also shown. The table 2 also shows result of economic load scheduling (ELS) for various load demands. This provides operators with information on how to allocate loads for economic load operation.

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Table 2: Sample of Economic Distribution Cost from the Neural Network Per Load Demand

G/N EDL	L1	L2	L3	L4
Load	60.0001	70.0001	80.0001	90.0001
1	528.44	571.298	629.5553	715
2	525.6432	561.5709	608.5789	686
3	479.127	499.6541	521.0878	582
G/N ELO				
Load	60.0001	70.0001	80.0001	90.0001
1	271.0207	305.4121	331.6866	439.596
2	344.4445	444.0634	557.8328	625.845
3	767.0219	783.4681	795.6507	849.827
NetSave	3617.355	2389.903	1777.247	1625.568
ESL POW	Load1	Load2	Load3	Load4
Load	60.0001	70.0001	80.0001	90.0001
Gen1	0.19852	4.82787	10.32734	15.72
Gen2	17.25028	19.74504	22.07521	26.62
Gen3	39.46955	41.83981	44.53678	47.61

Key: EDL = Cost of Equal Distribution of load: L1, L2, L3, L4 = load demand: ELO = Cost of Economic load operation: ESL = Economic Scheduling of load per generator.

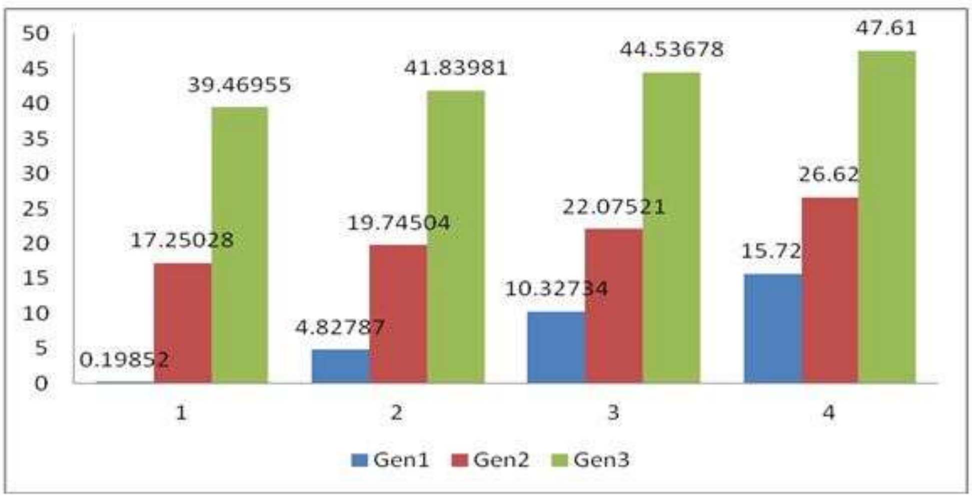

Fig. 4: Bar chart of the result

Discussions

In the analysis of Economic load division between the various units of a plant, it is expected that the available historical data on cost is absolutely correct. The implementation of the application program is based on data set for the test cases of table 1. The input cost function is derived from equation 1 with all coefficients positive. (The coefficients for input cost equations are obtained using Matlab Curve Fitting Toolbox). The software application was formulated using artificial neural network method and developed as an interactive application for operators at gas

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turbine generating (GTG) plant. The design uses a special object oriented methodology feature of MatLab called handle graphics technology (HGT). This approach provides menu-driven guides that would enable operators with little knowledge of computer to navigate through the application without difficulty. Each set of input parameter is stored in an excel file to avoid error while entering data. The optimum economy is achieved if every unit (i.e. P_{g1}, P_{g2}, and P_{g3}) operates at the same incremental cost (IC). At any point on the incremental cost, the three generators are operated optimally and fuel utilization is seen to be less. Neural output of simulation in plot and numerical values, daily cost saving and network performance plot derived from the application are shown in fig 5 and fig 6. The output of daily net saving per load demand when multiplied by 30 days will give the cost savings per month.

Conclusion

This paper presented an application tool designed to determine the best combination of power generating plant to produce electricity that services a demand load with less fuel cost. ANN is used to model cost of power generation while Object Oriented Methodology is used to model the GUI interfaces. Both models runs on a MatLab platform. It can be extended to include an embedded form. When interfaced with a sensor it can automatically control the switching of power plant for optimal operation. Robustness and fault tolerance are qualities of this approach over the lagrangian method. Simulation data from other stations tested on this application show no significant difference in result implying that the system can be deployed in a dissimilar geographical location.

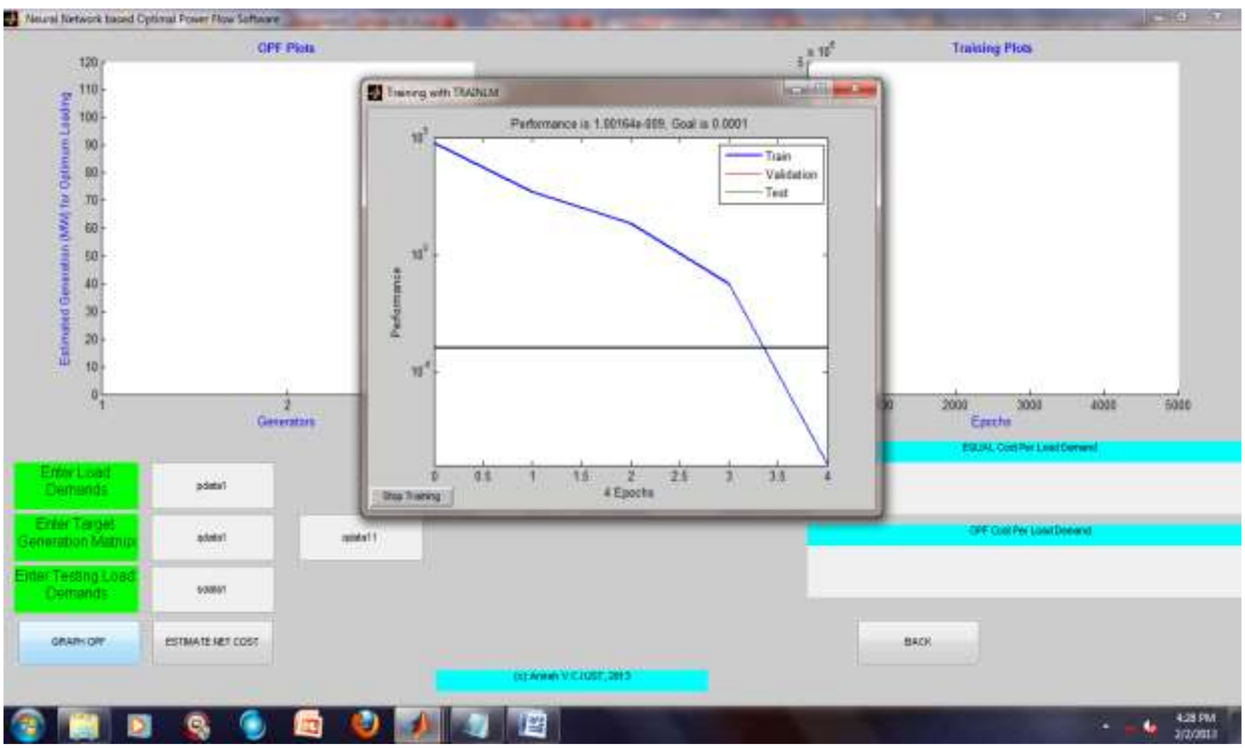

Fig. 5 Sample screen for the neural network ED with training plot inserted.

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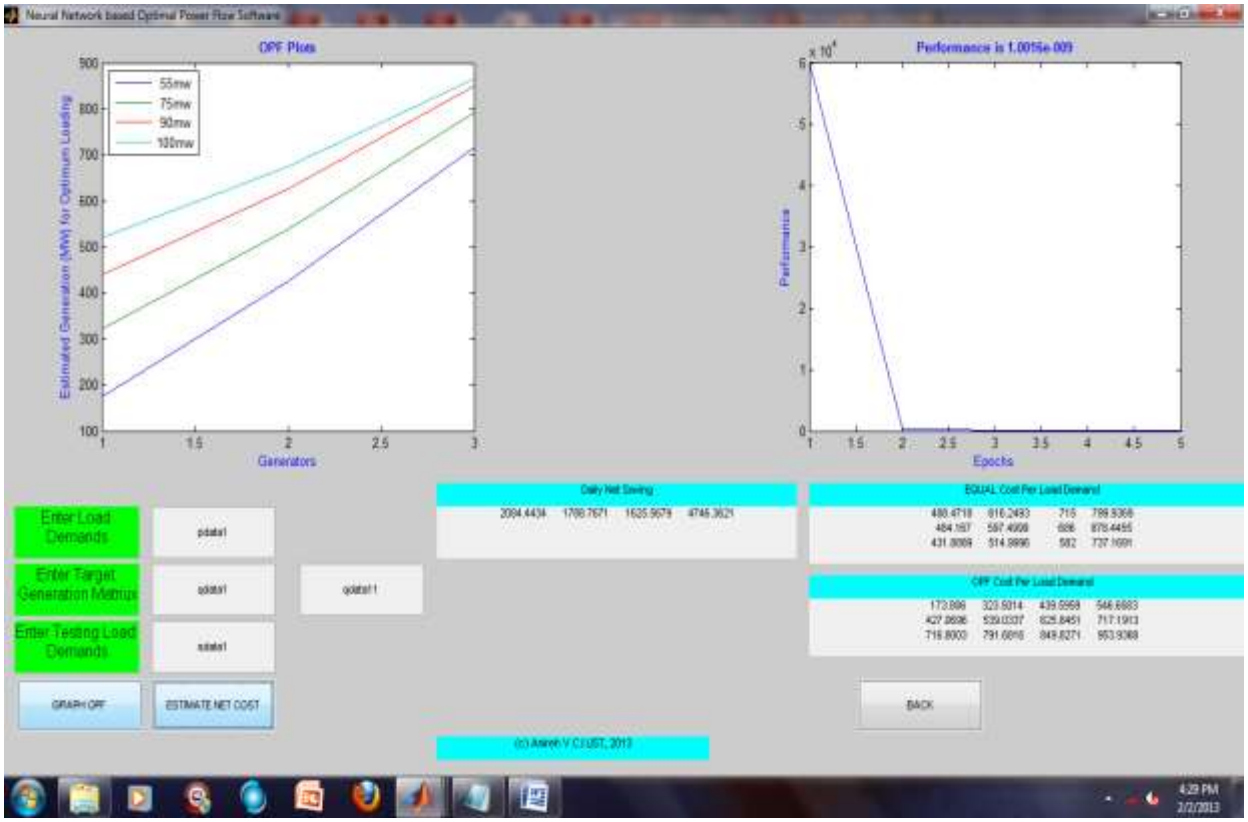

Fig. 6: Sample screen for the Neural network ED with output of simulation in plot and numerical values, daily cost saving and network performance plot.

References

1. Sambo A.S, "The Challenges of Sustainable Energy Development in Nigeria". Presentation to Nigerian Society of Engineers', Abuja, Nigeria, 2009.
2. Dongxiao N, Yanan W. "A novel social-environmental-economic dispatch model for thermal/wind power generation and application" International Journal of Innovative Computing, Information and Control ICIC International c 2013 ISSN 1349-4198 Volume 9, Number 7, July 2013.
3. Alrashidi M.A, Hawary M.E. "Impact of loading conditions on the emission economic dispatch". Proceedings of World Academy of Science, Engineering and Technology 2008;
4. Wang L, Chanan S. "Reserve constrained multiarea environmental/economic dispatch based on particle swarm optimization with local search". Engineering Application of Artificial Intelligence Science Direct 2008;
5. Liao G. "A novel evolutionary algorithm for dynamic economic dispatch with energy saving and emission reduction in power system integrated wind power", Energy, vol.36, pp.1018-1029, 2011.
6. Palma-dos-Reis, A., & Zahedi, F. M. "Designing personalized intelligent financial support systems". Decision Support System, 26(1), 31-47, 1999.
7. Martinez L. J, Lora T. A, & Santos R. J. "Short term hydrothermal coordination based on interior point nonlinear programing andgenetic Algorithm". IEEE Porto Power Tech Conference, 2001;
8. Shi CC, Chun HC, Fomg I-K, & Lah PB. "Hydroelectric generation scheduling with an effective differential dynamic programming algorithm". IEEE Transactions on Power System 1990;
9. Erion F., Silva E, & Laudia S. "Solving the unit commitment problem of hydropower plants via Lagrangian relaxation and sequential quadratic programming". Journal of Computational & Applied Mathematics 2005;
10. Tkayuki S, Kamu W. "Lagrangian relaxation method for price based unit

commitment Problem". Engineering Optimization Taylor Francis 2004;

11. Huang J.S. "Enhancement of hydroelectric Generation scheduling using ant colony system based optimization approaches". IEEE Transactions on Energy Conversion 2001;
12. Mantawy A, Abdel-Magid Y & Selim S. "A simulated annealing algorithm for unit commitment", IEEE Trans. Power Syst., vol.13, no.1, pp.197-204, 1998;
13. Naresh R, Sharma J. "Short term hydro scheduling using two phase neural network". International Journal of Electrical Power and Energy Systems 2002;
14. Liu D, Dong X & Shi P. "The optimization based on improved membrane algorithm for fuzzy RBF neural network control of ball-plate system", ICIC Express Letters, Part B: Applications, vol.3, no.5, pp.1259-1267, 2012.
15. Lopes, D. C. "Implementation of a Modular Neural Network in a Multiple Processor System on FPGA to Classify Electric Disturbance". In: Industrial Electronics, 2009. IECON '09. 35th Annual Conference of IEEE, Porto, Portugal;
16. Peixoto, H. M., Cruz, R. M. S., Guerreiro, A. M. G., Dória Neto, A. D. & D'Assunção, A. G. "A comparison of multilayer perceptrons training algorithms for the optimization of frequency selective surfaces", Proceedings of 8th International Information and Telecommunication Technologies Symposium, Florianópolis, SC, Brazil; 2009.
17. Peixoto, H. M., Guerreiro, A. M. G. & Dória Neto, A. D. "Image processing for eye detection and classification of the gaze direction", Proceedings of the 2009 International Joint Conference on Neural Networks, pp. 2475-2480, ISBN 978-1-4244-3553-1, Atlanta, GA, USA
18. Lee T.E, Su J.P & Yu K.W. "Fuzzy gain scheduled alpha-beta-gamma filter design based on particle swarm optimization method", ICIC Express Letters, vol.4, no.6 (B), pp.2305-2310, 2010.
19. Kazarlis S, Bakirtzis A & Petridis V. "A genetic algorithm solution to the unit commitment problem", IEEE Trans. Power Syst., vol.11, no.1, pp.83-92, 1996;
20. Lin W.M, Cheng F.S, & Tsay M.T. "An improved Tabu search for economic dispatch with multiple minima". IEEE Transaction on Power System 2002;
21. Jie X, Deyun X. "New Metropolis coefficients of particle swarm optimization". IEEE 2008;
22. Yang H. T, Yang P. C, & Huang C. L. "Evolutionary programming based economic dispatch for units with non smooth fuel cost function". IEEE Transaction on Power System 1996;
23. Gangadhar, K.A. "Electrical Power Systems". Khanna Publishers. Nai,Sarak, Delhi. India, 2006.
24. Sambo, A.S. "The Role of Energy in Achieving Millennium Development Goals (MDGs)" *National Engineering Tech. Conference (NETEC)*, 1 – 42, 2008.
25. Anireh V.I.E, Afa J.T. "Proper Energy Mix: A Solution to Stable Power Supply in Nigeria." *Academic Journal of Interdisciplinary Studies, MCSER Publishing, Rome-Italy. Vol 2 No 13, ISSN 2281-3993.*