ARTIFICIAL NEURAL NTETWOK BASED REAL-TIME ECONOMIC DIPATCH: APPLICATION TO MUSCAT GRID

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Abstract This paper presents the application of artificial neural networks (ANN) to real-time optimal generation dispatch of Muscat power grid. The developed ANN predicts the optimal MW output of each generating unit operated on economic dispatch under different hourly load demand. Numerical results on the test practical example show that the proposed ANN can efficiently and accurately predict the optimal output of generating units to supply the system load demand. The results have indicated strong agreement between ANN model prediction and off-line calculated values. These results have demonstrated that the ANN-based model developed in this work can predict the optimal MW output of generating units with high accuracy.

Index-Terms: Economic Dispatch, Optimization Techniques, ANN Model, Application.

1. INTRODUCTION

The main objective in the operation of any of today's complex electric power system is to meet the demand for power at lowest possible cost, while maintaining safe, clean standards of environmental impact [3,11,12]. The efficient and optimum economic operation of power generation systems has always occupied an important position in electric power industry. In an interconnected power system, the objective is to find the real power scheduling of each power generation plant on such a way as to minimize the operating cost. This means that the generator's real power is allowed to vary within certain limits so as to meet a particular load demand with minimum fuel cost. The economic dispatch of power generation is to operate the power system to supply all load demands and transmission losses at minimum cost.

The efficient and optimum economic operation and planning of electric power generation systems have occupied an important position in the electric utilities and industries [3]. Periodic changes in the basic fuel price levels serve to accelerate the problem and increase its economic significance. Economic dispatch models the electric power system (with one or more control areas) and dispatches the available generation resources to supply a given load for each control area in the most economic matter in real-time operation.[1,2,3]. The objective of economic dispatch is to minimize the total generation cost including fuel cost and operation / maintenance cost and network loss cost by meeting the operation constraints - system load demand - lower and upper economic limits of each generation units - network security constraints (maximum MW power flows of transmission lines).

Considerable efforts have been placed on the applications of Ann's to power systems. Several interesting applications of ANNs to power system problems have been published [1011], and it has been shown that ANNs have great potential in power system on-line and off-line applications. In this paper, an approach using an ANN is proposed to predict the voltage on mitigated pipelines built in power lines right-of-way after using the mitigation system. The multilayer feed forward ANN with the error back propagation training method [4,5] is employed. The input to the ANN is the system parameters (fault current, soil resistivity, and separation distance between power lines and pipelines) and the output is the mitigated pipeline voltage. The results reported in this paper present the predicted pipeline voltage subjected to inductive and conductive coupling from an overhead power transmission lines after applying the mitigation system.

In this paper, an approach using an ANN is proposed to predict the output of generating units in power plants of Muscat power grid. The multilayer feed forward ANN with the error back propagation training method [5,6,7] is employed. The input to the ANN is the system hourly MW demand and the output is the optimal MW output power of each generating units and the total production cost. . The trained ANN model is based on one reference computer model, from which several series simulations are created by varying one parameter at a time through a range of values.

2. SOLUTION OF ECONOMIC DISPATCH POBLEM

There are various optimization techniques [3] have been proposed for the solution of economic dispatch (E.D) problem of power generation units. Among these techniques is the gradient iterative method.

The problem of E.D is to determine the MW output for each generating unit such that the total fuel cost C_{total} as defined by

$$C_{total} = \sum_{i=1}^{N} C_i = \sum \alpha_i + \beta_i P_i + \gamma_i P_i^2 \quad (1)$$

is minimum subject to the constraint

$$P_D + P_{loss} = \sum_{i=1}^{N} P_i \quad (2)$$

Satisfying the inequality constraint as given as

$$P_{i,\max} \le P_i \le P_{i,\min}; \quad i = 1,2,....,N \quad (3)$$

and

$$P_{loss} = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j \quad (4)$$

The B-coefficient (loss coefficient) can be determined using the power-flow solution [15].

Lambda iterative method

The optimal value of P_i is obtained by equating the derivatives of *Lagrange* functions to zero.

$$\frac{\partial L}{\partial P_i} = 0 \;;\quad \frac{\partial L}{\partial \lambda} = 0 \quad (5)$$

where L is the *Lagrange* function given by

$$L = C_{total} + \lambda(P_D + P_{loss}) \quad (6)$$

Therefore the condition for optimal dispatch is

$$\frac{\partial C_i}{\partial P_i} + \lambda \frac{\partial P_{loss}}{\partial P_i} = \lambda \quad i = 1,2,...,N \quad (7)$$

Equation (7) can be arranged as

$$\frac{\partial C_i}{\partial P_i} L_i = \lambda; \quad i = 1,2,...,N \quad (8)$$

Where L_i is the penalty factor and is given by

$$L_i = \frac{1}{1 - \frac{\partial P_{loss}}{P_i}}$$

Equations (8) can be solved by iterative process using Lambda iterative method [3] as given as:

$$\Delta\lambda^{(K)} = \frac{\Delta P^{(k)}}{\left(\frac{df(\lambda)}{d\lambda}\right)^{(k)}} = \frac{\Delta P^{(k)}}{\sum \left(\frac{dp_i}{d\lambda}\right)^{(k)}} \quad (9)$$

Where

$$\sum_{i=1}^{N} \left(\frac{\partial P_i}{\partial \lambda}\right)^{(k)} = \sum_{i=1}^{N} \left(\frac{\gamma_i + B_{ii}\beta_i - 2\gamma_i \sum_{j \ne 1} B_{ij} P_j^{(k)}}{2\left(\gamma_i + \lambda^{(k)} B_{ii}\right)^2} \right)$$

and therefore

$$\lambda^{(k+1)} = \lambda^{(k)} + \Delta\lambda^{(K)} \quad (10)$$

where

$$\Delta P^{(k)} = P_D + P_{loss}^{(k)} - \sum_{i=1}^{N} P_i^{(k)} \quad (11)$$

The iterative process is continued until $\Delta P_i^{(k)}$ in equation (11) is less than specified accuracy ($\varepsilon = 10^{-5}$). A MATLAB program has been developed for this iterative method.

3. PRACTICAL CASE STUDY

A practical case study is considered in this work. The generating units namely RSL-GT1 to GT6, GHB-GT12 and GT13, WDJ-GT2 toGT7, MNH-GT2 are the units operating on economic dispatch. Table 1 shows the parameters of the fuel cost ($C_i = \alpha_i + \beta_i P_i + \gamma P_i^2$) of different gas turbine generators of power stations. The maximum and minimum output power of each unit is given in Table 2. Figure 1 shows the daily load curve for typical summer day. In this load curve, the maximum is 1569 MW and a base of 358 MW was selected. The economic dispatch has been applied for peak loads.

Table 1: Cost function parameters (α, β, γ) in MJ/h for the gas turbine generators

Generating Unit	α(MJ/h)	β(MJ/h)	γ(MJ/h)
BRK_PS GT1	91365	7591.73	49.65
BRK_PS GT2	91365	7591.73	49.65
GBR_PS GT1 – GT9	91365	7591.73	49.65
GBR_PS GT10	109879.9	7945.25	22.646
GBR_PS GT11	109879.9	7945.25	22.646
GBR_PS GT12	342004	6928.77	7.2
GBR_PS GT13	342004	6928.77	7.2
KML_PS GT1-GT3	91365	7591.73	49.65
MNH_PS GT1-GT3	114244	6685.36	41.52
MNH_PS GT4-GT5	91365	7591.73	49.65
RSL_PS GT1-GT6	325155.5	7206.72	9.66
RSL_PS GT7	91365	7591.73	49.65
RSL_PS GT8	91365	7591.73	49.65
WDJ_PS GT1	89101.6	7869.15	53.73

Table 2: Maximum and minim output power of generating unit during summer condition

POWER STATION	UNIT	SUMMER	
		Max(MW)	Min(MW)
RUSAIL	GT-1 to GT-6	84	35
	GT-7 &GT-8	95	30
GHUBRAH	GT-1 to GT-9	17.5	5

	GT-10 &GT-11	27	7
	GT-12 &GT-13	95	40
	ST-1 to ST-3	8.5	2
	ST-4	50	5
	ST-5 & ST-6	32	5
ALKAMIL	GT-1 to GT-3	95	10
BARKA	GT-1	117	25
	GT-2	117	25
	ST-1	222	25
MANAH	GT-1A	27	10
	GT-1B	27	10
	GT-1C	27	10
	GT-2A	95	40
	GT-2B	95	40

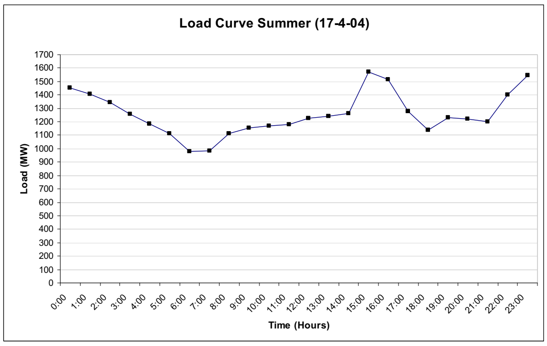

Fig. 1 Hourly load curve during summer condition

From the Fig. 1, the maximum is 1569 MW and a base of 358 MW was selected. The economic dispatch has been applied for peak loads.

4. ANN MODEL DEVELOPMENT

The first and the most critical step in developing an effective ANN model is input and output definition and data preparation. This includes identifying variables of interest, gathering the relevant data and inspecting them for possible errors, missing values, and outliers. Data accuracy is vital for the development of an efficient model that can provide accurate prediction. If incorrect or erroneous data are fed to the model, this will result in incorrect prediction. To develop an ANN model for the solution of economic dispatch problem, the variables: total MW power demand, optimal MW power generated by units supplying the load demand, and the total cost fuel cost data have been identified and have been obtained using the developed MATLAB program. Prior to conducting the network training operation using the backpropagation paradigm [5,6], training sets were obtained from the calculated optimal MW out put of generating units at different values of the hourly MW load demand. This data set covers different situations that could possibly take place. The ANN model is shown in Fig. 2.

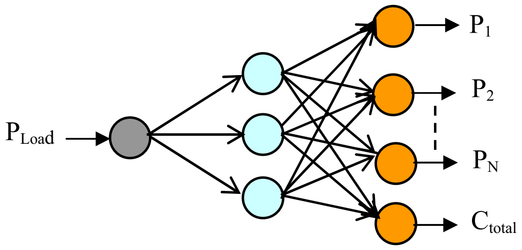

Fig. 2 Architecture of the Developed ANN Model

Once the ANN model architecture is defined, data are collected and fed to the model. The network is then trained to recognize the relationships between the input and output parameters. The Back-Propagation (BP) algorithm uses the supervised training technique. In this technique, the interlayer connection weights and the processing elements' thresholds are first initialized to small random values. The network is then presented with a set of training patterns, each consisting of an example of the problem to be solved (the input) and the desired solution to this problem (the output). These training patterns are presented repeatedly to the ANN model and the error between actual and predicted results is calculated. Weights are then adjusted by small amounts that are dictated by the General Delta Rule [7]. This adjustment is performed after each completed iteration whenever the network's Computed output is different from the desired output. This process continues until weights converge to the desired error level or the output reaches an acceptable level.

Prior to conducting the network training operation using the back propagation paradigm [4-7], training sets of different cases were obtained from the calculated data with different values of MW load demand. This data set covers different situations that could possibly take place. The training process was performed using the NeuroShell simulator [8]. After several adjustments to the network parameters, the network converged to a threshold of 0.00001 using 3 hidden nodes. The trained model prediction was in good agreement with the actual results producing R^2 value of 0.9978. This indicates that approximately 99.78% of the variation in the generation MW output power could be explained by the selected input variable and the data used for model development. Having trained the network successfully, the next step is to test the network in order to judge its performance and to determine whether the predicted results confirm with the actual results.

5. RESULTS AND DISCUSSIONS

The trained model is assumed to be successful if the model gives good results for the test set. Using the different cases allocated for the testing set, the model-input parameters (system MW load demand) was entered consecutively for each case and a prediction for the generators output was obtained. The results were then compared with the actual results of the cases in question. The statistical analysis of these results indicates that the R^2 value for the testing set was 0.9933. This high generalization capability indicates that the ANN model predicted with 99.3% accuracy. These results also demonstrate that the ANN-based model developed in this work can be used for future analysis. Figures 3-10 present a comparison between the actual and predicted MW output of generating units at different MW load demand. It is clear that there is good agreement between the actual and predicted results. Hence, the ANN-based model developed in this work can predict MW generators outputs.

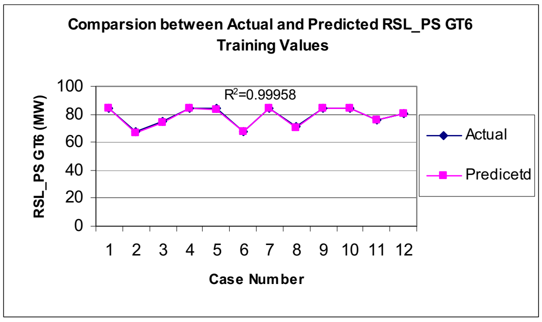

Fig. 3 Actual and ANN predicted MW of RSL-GT6

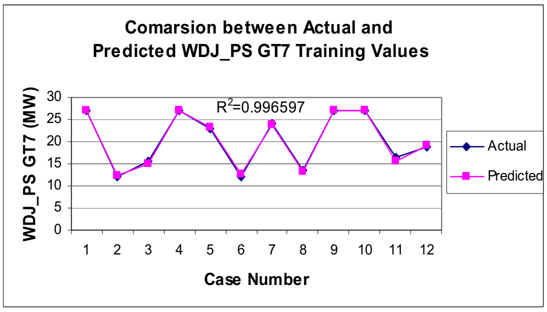

Fig. 4 Actual and ANN predicted MW of WDJ-GT7

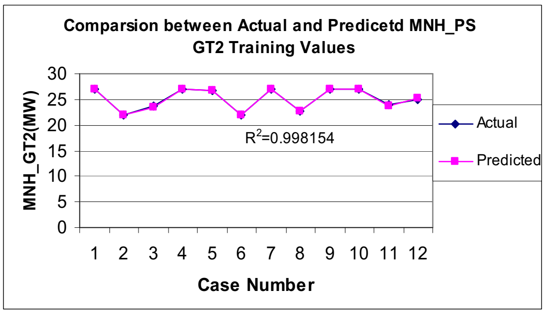

Fig. 5 Actual and ANN predicted MW of MNH-GT2

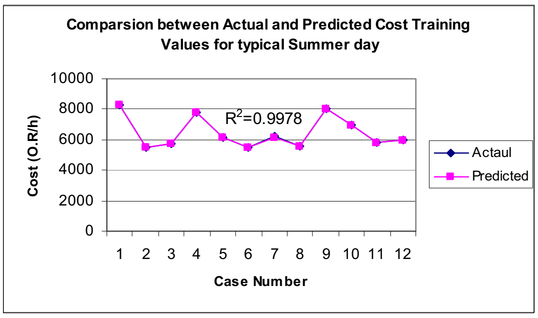

Fig 6.Actual and ANN predicted total Fuel cost

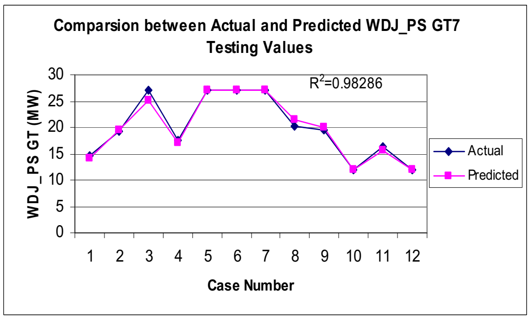

Fig.7 Actual and ANN predicted MW of WDJ-GT7

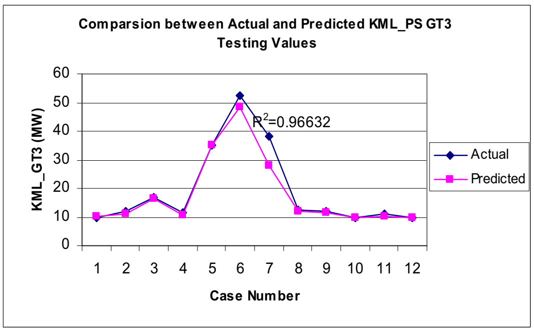

Fig. 8. Actual and ANN predicted MW of KML-GT3

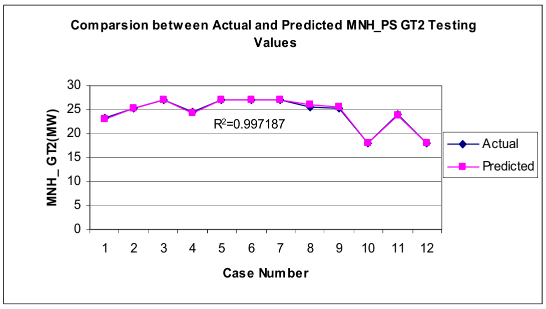

Fig. 9 Actual and ANN predicted MW of MNH-GT3

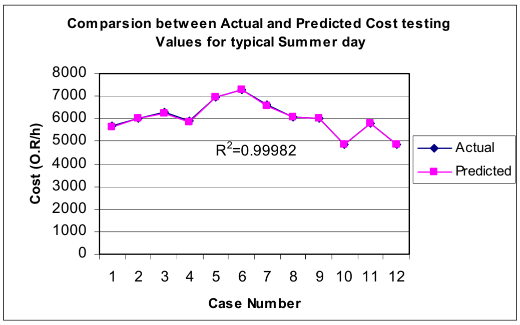

Fig. 10 Actual and ANN predicted total Fuel cost

6. CONCLUSIONS

An artificial neural network (ANN) model has been developed to solve the optimal dispatch problem of power plants of Muscat power grid. The ANN has been trained until a good agreement was achieved between actual and predicted values. Once the ANN is adequately trained, the network has been tested to insure that it can adequately predict the output power for each generating unit. The results presented in this paper have demonstrated that the developed ANN can predict the optimal MW output power generation which minimize the total fuel cost at a given hourly MW load demand. The ANN model has also been tested for several different scenarios and the results have showed a high agreement between actual and predicted generation values which prove the ability of the ANN to solve the problem of economic dispatch for a generation units in a power system.

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REFERENCES

1. X. S. Han, H. B. Gooi, and Daniel S. Kirschen ,"Dynamic Economic Dispatch: Feasible and Optimal Solutions", IEEE Transactions and Power Systems, Vol.16, No.1, February 2001.

2. L. M. Proenca, J. Luis Pinto, Manuel A. Matos, "Economic dispatch in isolated networks with renewable using evolutionary programming", IEEE Power Tech' 99 Conference, Budapest, Hungary, Aug 29-Sept 2, 1999.

3. Allen J. Wood and Bruce F. Wollenberg, Power Generation Operation and Control, John Wiley & Sons, New York, 1996.

4. Dan W. Patterson, Artificial Neural Networks: Theory and Application, Prentice Hall, Singapore, 1996.

5. J. Stanely, Introduction to Neural Networks, Third Edition, Sierra Madre, California Scientific Software,1990.

6. Rumelhart, D. E. and McClelland, J. L. Parallel Distribution Processing: Exploration in the Microstructure of Cognition, Vol. 1, Foundations, MIT Press, 1986.

7. Simpson, P. K., Artificial Neural Systems: Foundations, Paradigms, Applications, and Implementations, First Edition, Elmsford, NY, Pergamon Press, Inc., 1990.

8. NeurroShell™, Copyright © 1997-2004 Ward Systems Group, Inc.

9. Annual statistics book for MHEW 2002, 2004.

10. K. Ellithy, A. Al-Badi, S. Al-Alawi, "An Artificial Neural Network Model for Predicting Electromagnetic Interference Effects on Gas Pipelines Built in Power Line ROW", International Journal of Engineering Intelligent Systems, Vol. 17, No. 4, pp. 229-235, Dec 2004

11. S. M. Al-Alawi and K. A. Ellithy, "Tuning of SVC Damping Controllers Over a Wide Range of Load Models Using an Artificial Neural Network",. International Journal of Electric Power & Energy Systems. Vol. 22, Issue 6, pp. 405-420, June 2000.

12. B. B. Choudhry and S. Rahman, "A Review of recent advances in Economic Dispatch", Vol.5, N0. 4, 1990.

13. X. S. Han, H. B. Gooi and D.S. Kirschen, "Dynamic Economic Dispatch Visible and Solution", IEEE Transactions on power systems, Vol 16, No. 1, pp.22-28, Feb 2001.

14. D. W. Ross,"Dynamic Economic Dispatch", IEEE Power System Apparatus and System, Vol. PAS-99, pp. 2060-2068, 1980

15. Hadi Saadat, Power System Analysis, Second Edition, McGraw Hill, 2004.

16. W.G. Wood, "Spinning Reserve Constrained Static and Dynamic Economic Dispatch", IEEE Transactions Power Apparatus and System, Vol. Pass-101, No. 2, pp. 381-388, 1982.