An Approach for Metering Real-Time Reactive Power Consumption Using a Neural Network Approach

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Abstract– **The current research focus on spot pricing of electricity has led to development of complex spot pricing based electricity rate models. As research matures to implementation stages, approaches to meter the actual power consumption in real-time are required. In this work, we model a real-time reactive power metering approach based on neural networks. A spot pricing model which incorporates the shortcomings of power factor penalties is used to determine the reactive power rates at each bus. A carefully designed artificial neural network (ANN) is trained to recognize the complex optimal operating point of an all-thermal electricity generating utility. A real time rate is allocated to each bus for a given power system's loading pattern and the recall process is instantaneous. The proposed approach is tested using a spot pricing model on 5 and 14 bus electric power systems. Different loading levels are used at each bus.**
Keywords: Neural Networks, Electricity Metering, Spot Pricing

SYMBOLS USED

P_{Gi}/Q_{Gi}	Active/reactive power generation at bus i.
P_i/Q_i	Active/reactive power flow from bus i.
P_{ij}	Active power flow between buses i and j.
P_{Di}/Q_{Di}	Active/reactive power demand at bus i.
$\kappa_i, \beta_i, \gamma_i$	Generator cost coefficients at bus i.
F_i	Fuel cost function for generator at bus i.
Y	The network bus admittance matrix
Y_{ij}	The magnitude of the ij th element of Y.
θ_{ij}	The phase angle of the ij th element of Y.
V_i/δ_i	Voltage magnitude/phase angle at bus i.
N_B/N_G	Number of buses/generators in the system.
r_{qi}	The reactive power rate at bus i.
R_G	Set of all active power generating buses.
R_S	Set of all reactive power generating buses.
N_H	Number of neurons in the hidden layer.
u_i	Vector of ANN input patterns.
d_i	Vector of ANN desired output patterns.
α	ANN momentum term.

I INTRODUCTION

Research work on metering electric power has received a lot of attention lately. This is partly due to the development of a number of complex but desirable spot pricing algorithms [10] and partly due to advances in telecommunication systems used in electricity metering [7]. Significant research work has been done or proposed on communicating metering data and other information using different methods. Although some software [6] and expert systems [11] approaches have been used in metering and spot pricing respectively, the application of ANNs has not been fully explored. Our earlier contributions [2, 3] focus on the applications of ANN and fuzzy logic to spot pricing.

Like metering, research work on spot pricing [10] has been extensive for some time now. Recently, some complex rate structures have been proposed and/or developed [9]. The advantage of using the spot pricing model is that it eliminates the limitations of existing rate policies such as power factor penalties [1] and considers real-time power consumption by each consumer. In these new approaches, electricity rates are determined through rigorous nonlinear programming approaches [10]. As the design of electricity pricing policies gets more complicated, a lot of computational effort is required to solve them. Consequently the metering required to implement the rates method becomes an almost impossible task.

Since many utilities are gradually moving to spot pricing, there is a need to to explore new methods that can effectively handle this new approach. This study explores and presents a fast and accurate method of determining real-time electricity rates us-

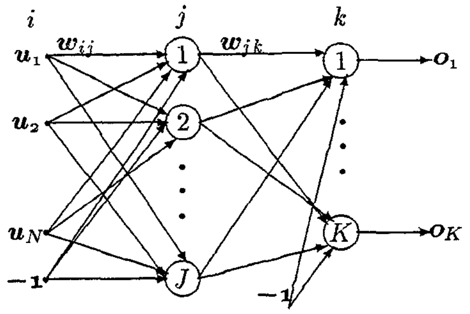

Figure 1: A two layer feed-forward neural network.

ing ANNs. The approach capitalizes on the superior computational abilities of ANNs and their ability to do some complex nonlinear mappings from the simple data patterns of a power systems network.

The utility, which in this case is responsible for selling power to consumers, collects data from the power systems network through its control center(s). The raw data is presented to a multi-output ANN which in turn determines the spot price for each consumer. These rates can then be communicated to each consumer in real-time.

Basically, the approach involves the training of a feed-forward ANN using the error backpropagation algorithm. The network is trained to recognize a complex mapping that characterizes the power system's operating point for a given data input pattern. When fully trained, the network determines the rate structures instantly without going through any iterative loops as in conventional methods.

II THE ANN

An ANN is a processing device designed to emulate the functioning of the human brain and its components. It is a meshed network of very simple processors (neurons) interconnected by unidirectional communication channels which carry numeric values (weights) as the strengths of the connections.

The ANN is *trained* by repeatedly adjusting the weights so that its output equals the desired output. In this work the error backpropagation algorithm is used in the training. The training involves the presentation of a set of input patterns $\boldsymbol{u}_i$ and a corresponding set of desired outputs $\boldsymbol{d}_i$. A set of small random numbers are selected as the initial weights w_{ij}. The sets of input and desired output training patterns are repeatedly presented to the network until a correct classification (characterized by network convergence) is achieved, [4]. Figure 1 shows a two layer feed forward ANN whose training algorithm is as given below [12].

For the *ith* pattern presented at the input, the output from the first hidden layer is

$$\boldsymbol{y}_i = \Gamma[\boldsymbol{V}\boldsymbol{u}_i] \tag{1}$$

and the output pattern from the output layer is

$$\boldsymbol{o}_i = \Gamma[\boldsymbol{W}\boldsymbol{y}_i] \tag{2}$$

Matrices $\boldsymbol{V}$ and $\boldsymbol{W}$ contain the weights for the input and output layers respectively. In this study the function Γ is a bipolar continuous [12] function function which defines the output from each node in a given layer for a given input pattern $\boldsymbol{u}_i$ as

$$o_i = f(net_i) \tag{3}$$

$$net_i = \begin{cases} \mathbf{V}\mathbf{u}_i \text{ in hidden layer} \\ \mathbf{W}\mathbf{y}_i \text{ in output layer} \end{cases} \tag{4}$$

The output pattern $\boldsymbol{o}_i$, for a given input pattern $\boldsymbol{u}_i$, is compared with the desired output $\boldsymbol{d}_i$ and the total error E at the output layer is computed as:

$$E = \frac{1}{2}\sum_{k=1}^{K}(d_k - o_k)^2 \tag{5}$$

This value is normally used as an indication of network convergence.

The error signal vectors (called delta) for the output and hidden layer are respectively given by

$$\Delta_{ok} = 0.5(d_k - o_k)(1 - o_k^2) \quad k = 1, \ldots, K \tag{6}$$

$$\Delta_{yj} = 0.5y_j(1 - y_j)\sum_{k=1}^{K}\Delta_{ok}w_{ik} \quad j = 1, \ldots, J \tag{7}$$

The weight adjustments which minimize the error function E by the steepest descent approach [4] is given by the following *delta learning rule*:

$$\begin{array}{l} w_{jk} \leftarrow w_{jk} + \eta\Delta_{ok}y_i \\ w_{ij} \leftarrow w_{ij} + \eta\Delta_{yj}u_i \end{array} \left\{ \begin{array}{l} i = 1, \ldots, N+1 \\ j = 1, \ldots, J \\ k = 1, \ldots, K \end{array} \right. \tag{8}$$

Updating of the weights is repeated in each training step until a convergence criterion is achieved. The learning rate parameter η is chosen to accelerate the convergence of the error back-propagation algorithm.

A momentum term can also be included to speed up convergence. This is achieved by adding a fraction of the previous weight change to the current weight change. Thus Equation 8 can be generalized to;

$$w(t+1) \leftarrow w(t) + \eta\Delta_{ok}(t)y_i(t) + \alpha\Delta_{ok}(t-1) \tag{9}$$

where t represents the iteration time.

III SPOT PRICING MODEL

In modelling electricity pricing, the objective is to set prices of active and reactive power for each consumer at a particular time interval equal to the marginal costs of supplying power to that consumer at that particular time interval. These marginal costs are determined through an operational-cost minimization OPF. Since the demand changes during each time interval, the spot pricing model considers these real-time electric power demands, determines the operational constraints, the power generated to meet the demand, the cost of meeting this demand and most importantly the real-time rates at which the utility charges its consumers for the provision of this power.

As already stated, power demand patterns are considered as they come in real-time. They are not known or estimated prior to the time interval under consideration. Thus, for the purpose of this study, the power prices are not known in advance- they only become known as power is consumed.

The OPF formulation is as follows:

$$min \left[\sum_{i \in R_G} F_i(P_{Gi}) \right] \tag{10}$$

Subject to:

$$PM_i = P_{Di} - P_{Gi} + P_i = 0 \quad i = 1, \ldots, N_B \tag{11}$$
$$QM_i = Q_{Di} - Q_{Gi} + Q_i = 0 \quad i = 1, \ldots, N_B \tag{12}$$
$$P_{Gimin} \leq \; P_{Gi} \; \leq P_{Gimax} \quad i \in R_G \tag{13}$$
$$Q_{Gimin} \leq \; Q_{Gi} \; \leq Q_{Gimax} \quad i \in R_G,\ R_S \tag{14}$$
$$V_{imin} \leq \; V_i \; \leq V_{imax} \quad i = 1, \ldots, N_B \tag{15}$$
$$P_{ijmin} \leq \; P_{ij} \; \leq P_{ijmax} \quad i, j = 1, \ldots, N_B \tag{16}$$

where

$$P_i = V_i \sum_{j=1}^{N_B} Y_{ij} V_j \cos(\delta_i - \delta_j - \theta_{ij}) \tag{17}$$

$$Q_i = V_i \sum_{j=1}^{N_B} Y_{ij} V_j \sin(\delta_i - \delta_j - \theta_{ij}) \tag{18}$$

$$P_{ij} = Y_{ij}(V_i^2 \cos\theta_{ij} - V_i V_j \cos(\delta_i - \delta_j - \theta_{ij})) \tag{19}$$

and the operating cost function F_i is

$$F_i(P_{Gi}) = \kappa_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2 \tag{20}$$

For detailed descriptions of the objective function and the constraints see [10].

The Lagrangian for the problem defined above is given by:

$$F_L(\mathbf{P_G}, \mathbf{Q_G}, \mathbf{V}, \delta) =$$

$$\sum_{i \in R_G} F_i(P_{Gi}) + \sum_{i=1}^{N_B} \lambda_{pi} PM_i + \sum_{i=1}^{N_B} \lambda_{qi} QM_i$$
$$+ \sum_{i}^{N_B} \mu_{1i}(P_{Gi} - P_{Gimin}) + \sum_{i}^{N_B} \mu_{2i}(P_{Gi} - P_{Gimax})$$
$$+ \sum_{i}^{N_B} \mu_{3i}(Q_{Gi} - Q_{Gimin}) + \sum_{j}^{N_B}\sum_{i}^{N_B} \rho_{ij}(P_{ij} - P_{ijmin})$$
$$+ \sum_{i}^{N_B} \mu_{4i}(Q_{Gi} - Q_{Gimax}) + \sum_{j}^{N_B}\sum_{i}^{N_B} \rho_{ij}(P_{ij} - P_{ijmax})$$
$$+ \sum_{i}^{N_B} \mu_{6i}(V_i - V_{min}) + \sum_{i}^{N_B} \mu_{7i}(V_i - V_{max}) \tag{21}$$

The rates are defined [1, 10] as

$$r_{qi} = \frac{\partial F_L}{\partial Q_{Di}} \tag{22}$$

In spite of the complexity of solving the above problem, a lot of work has been done to come up with the required solution to this problem, to improve on existing solution models and more recently, to improve the computational speed to the problem. While requiring a lot of computational effort, large scale optimization packages like MINOS [5] have been successfully used to solve the problem.

To apply the pricing model to the ANN, a set of variables which would correctly and unambiguously classify the system's operating point are selected as ANN input patterns. In this study only those parameters which are easily accessible, the utility has little or no direct control over and affect the system's operating point are chosen.

Thus the inputs to the ANN are selected as follows

$$u_i = P_{Di} \quad i = 1, \ldots, N_B \tag{23}$$
$$u_{N_B+i} = Q_{Di} \quad i = 1, \ldots, N_B \tag{24}$$

These parameters are selected because the other variables are all dependent on the levels of these parameters.

IV APPLICATION

The formulation described above was successfully implemented on the 5 and 14 bus electric power systems networks (see [8] for network parameters).

To generate the training set patterns, different randomly generated load levels were applied to the system. Using a nonlinear programming package (MINOS/AUGMENTED version 5.1) [5] on an HP 900/755 computer, the rates r_{qi} were determined.

Table 1: ANN application example

Case	Rate [Mbtu/MVArhr]							
	Bus 2		Bus 3		Bus 4		Bus 5	
	MINOS	ANN	MINOS	ANN	MINOS	ANN	MINOS	ANN
1	0.080	0.079	0.234	0.228	0.231	0.220	0.271	0.267
2	0.154	0.156	0.363	0.352	0.358	0.341	0.401	0.403
3	0.00	-0.002	0.110	0.107	0.103	0.100	0.125	0.120
4	0.00	0.006	0.093	0.101	0.083	0.090	0.089	0.091
5	0.00	-0.007	0.106	0.098	0.098	0.090	0.110	0.097

These are representations of spot price based reactive power rates. Voltage boundaries were taken to be 1.0 ± 0.1 *pu* and were all satisfied in the solution.

Next, a two layer ANNs was trained using small random numbers as initial weights with 250 training patterns. After convergence, the trained ANN was tested with 50 different load patterns (also randomly generated) that were not used during training. The same load patterns were solved for with MINOS as before. The two sets of results obtained were compared.

The results agreed very well with the expected figures. A sample test set obtained from the 50 test patterns in the 5 bus system are shown in Table 1. It can be seen that the results obtained from the ANN recall are in very good agreement with the MINOS results. A similar trend was obtained in results of the the 14 bus system. In the 5 bus system, the mean square error (MSE) was 5.6×10^{-4} and in the 14 bus case, it was found to be 3.8×10^{-4}. In both cases, the error may be further reduced by allowing for more training–which overall requires a lot of computational effort. Thus, depending on the precision required in an application, a trade off between computational effort and precision has to be effected. In this work the precision obtained was very good.

V CONCLUSIONS

This paper has shown how important neural networks can be in real-time metering of electric power. Although the training of the ANN is computationally demanding, the recall process is very fast and easy to use. Thus, the method is suitable for metering real-time pricing where speedy processing is important. It should be noted however, that the ANN needs retraining once the network topology changes since the data used during its training includes network constraints. For big power systems networks, training an ANN with a large output set may become cumbersome. So it may be attractive to train individual ANN meters for each bus.

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