Cooperative Co-evolutionary Approach to Electricity Load and Price Forecasting in Deregulated Electricity Markets

Ali Karsaz, Habib Rajabi Mashhadi and R. Eshraghnia

***Abstract*-- Many electric power systems around the world have introduced deregulated markets where suppliers of electricity can freely compete. Deregulation of the electric power industry worldwide raises many challenging issues. Under this environment there will be new tasks to be solved. In the traditional and also new structure of the power industry, accurate short and long term load forecasting have been crucial to the efficient and economic operation of the system. However in the environment of a deregulated power market, various decisions require accurate knowledge of future spot prices for electricity. To buy or sell physical electricity, to offer a transaction to the market, or to analyze security of the network are examples of transactions that can rationally be made only with an idea of future electricity prices. Therefore, forecasting of the Market Clearing Price (MCP) is becoming increasingly relevant to different market players and system operator.**

This paper introduces a new forecasting method that forecasts the next-day electricity price and the electricity load based on Cooperative Co-evolutionary (Co-Co) approach. The proposed method is applied to predict the MCP and the load in a real power market. The results of the new method show significant improvement in the load and price forecasting process.

***Index Terms*-- Price forecasting, Load forecasting, Deregulation, Electric power markets, Artificial neural networks, Cooperative Co-evolutionary.**

I. INTRODUCTION

Electricity utility industries of many countries are undergoing a fundamental transformation from regulated and monopolistic to deregulated and competitive industry. The economic restructuring is bringing new problems to solve, especially in area of operation and planning of power systems. From a supplier's viewpoint, forecasting the electricity price is a major issue in the bidding process. The price forecasting plays an important role for all of market players and system operator who is responsible for reliability and security of the system. With this recent effort by many governments in development of open and deregulated power markets, research in forecasting methods is getting renewed attention [1-3].

Classical methods and intelligent methods in prediction such as Time-series methods and artificial neural networks can be used to predict the MCP. Application of time-series prediction can be found in the areas of economic and business planning, weather forecasting, signal processing, control, electrical load forecasting and recently in electricity price forecasting [1].

Neural networks have been widely used in many forecasting problems, including load and market clearing price predictions for power systems. The applications of neural network techniques to the system load forecasting were explored extensively in [4,5]. A modular General Regression Neural Network (GRNN) is used to predict the next day's 24 hour spot price or marginal price [6]. The GRNN was originally developed in statistics literature by Donal Specht [7].

Based on analysis of the time series corresponding to the market clearing price and the electrical system load and also computing of the autocorrelation coefficients of these series, the following factors can be considered as input variables for price and load forecasting:

1) Available historical price and load
2) System operating conditions
3) weather conditions and temperature values
4) Fuel Prices
5) Hour, weekday, season indices
6) Holidays, weekend days

It is found that the MCP time series in the electricity market behaves as a chaotic process with special properties. Fig.1 illustrates the hourly MCP values and hourly load values over two weeks, namely 1-14 May 2004 in New England power market.

Based on this figure, it can be found:

- The daily load curves have similar patterns.
- The daily MCP curves are various and fluctuating.

A. Karsaz is currently Ph.D. student in the Department of Electrical Engineering, Ferdowsi University, Mashhad Iran (e:mail: al_ka73@stu-mail.um.ac.ir)
H. R. Mashhadi is with the Department of Electrical Engineering, Ferdowsi University, Mashhad Iran (e:mail: h_mashhadi@um.ac.ir).
R. Eshraghnia is with the Departement of Electrical Ferdowsi University, Mashhad Iran (email: roozbeh_eshraghnia@yahoo.com)

0-7803-9525-5/06/$20.00 ©2006 IEEE.

- There exit some abrupt changes in the MCP curves.
- The MCP and load values are low at late night.

The MCP values usually reach their peaks at around 9 AM and 20 PM.

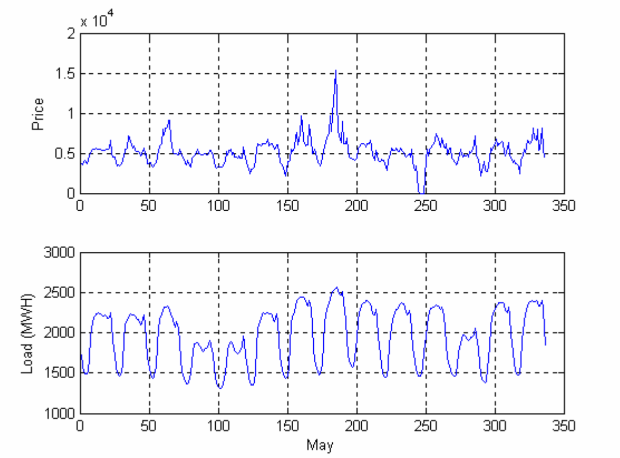

Fig. 1. MCP and Load Values in1-14 May 2004 in New England power market

The rest of this paper is organized as follows. The Cooperative Co-evolutionary basic idea which used to build our forecast model is briefly introduced in section II. Section III introduces the classical and intelligent forecasting methods which applied to predict system load and the MCP. The training and implementation of the proposed method are discussed in section IV. The results of the proposed method and other methodologies are compared in section V. Section VI provides some relevant conclusions.

II. COOPERATIVE CO-EVOLUTIONARY DEFINITION

Cooperative co-evolution [8] is an extension of traditional Evolutionary Computation. This approach involves multiple subpopulations, each dealing with a different set of the parameters of the problem under analysis. Some of the key aspects to bear in mind when developing a cooperative co-evolutionary procedure are as follows:

1. Decomposition of the problem – This task consists of determining the optimum number of subcomponents, as well as the role of each one. Obviously, it would depend on the problem under analysis.
2. Credit allocation– A value is allocated to each individual according to its contribution to the final solution.
3. Population Diversity – In cooperative co-evolutionary strategy, maintaining diversity in the population is very important and fitness sharing [8] or niche techniques [9] can be employed for this purpose.

The subcomponent credit allocation is determined through multi-objective cooperative co-evolutionary techniques, which measures factors such as their efficiency and complexity. Some papers that apply cooperative co-evolution to design neural networks are expressed in [10,15,17]. This paper deals with two different subspaces, namely Load prediction subspace and price subspace.

III. FORECASTING METHODS

There are several methods for load and price forecasting. They have been classified into following categories:

A. *Regression Model*

One approach to predict the market behaviors is regression. The basic idea is to use the historical prices and other information such as load, load forecast, temperatures, etc. to predict the MCP supposed that, $x_1, x_2, \cdots, x_p$ $(p > 1)$ are independent random variables. The output of the linear regression model y is obtained as: $y = b_0 + b_1 x_1 + \cdots + b_p x_p + \varepsilon$ where $N(0, \sigma^2)$ denote the usual Gauss Distribution, $b_0, b_1, \cdots, b_p$ are unknown constants, ε is a random variable with Gauss distribution, i.e. $\varepsilon \equiv N(0, \sigma^2)$ [3]. The most important task here is to choose the input variables, $x_1, x_2, \cdots, x_p$, so as to achieve best price forecasting. We can use the "Lscurefit" command of Matlab to apply this forecasting model.

B. *BP Neural Networks Structure*

A well-established nonlinear regression method is artificial neural network. Multi-layer Preceptron (MLP) feed-forward neural networks are used widely, usually called BP (back propagation) networks. The back propagation mechanism is used for training of these networks. There are several papers on determination neural networks structures (number of hidden layers and their corresponding weights) [14][18]. It has been proved that almost any finite dimensional vector function defined on a compact set can approximated to any specified accuracy by a MLP network if there are enough data, number of hidden layer units and enough computational resources [13].

C. *Neural Networks with Genetic Algorithms*

In BP, the global minimum may not be obtained and only a set of nearly optimal weighting coefficients can be found. To find global optimal solution corresponding to the weighting coefficients, Genetic Algorithm (GA) applied to solve the problem [12]. In this method, weights and biases are defined as a string in GA population and fitness of each individual defined as follow:

$$fitness = \frac{1}{\sqrt{\sum_{p=1}^{P} \left\| t_p - Y_p \right\|^2}}$$

for given data set $X_p, t_p, i = 1,2,....,P$ where X_p is the input vector of p-th sample, t_p is the target output of p-th sample and Y_p is the network output vector [12][13].

D. Recurrent Neural Networks structure

The recurrent neural network (RNN) has been used to forecast the locational marginal price (LMP) [19]. In RNN, a neuron's output is conducted as a feedback to its input. Fig 2 illustrates the RNN structure. In this paper, the RNN is utilized to train the correlations between the LMP values and the system conditions. Three RNN were presented for forecasting the LMP on weekdays, Saturdays and Sundays.

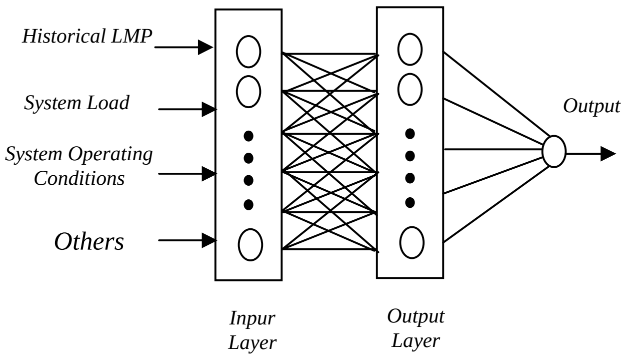

Fig. 2. The RNN for forecasting LMPs

E. Generalized Regression neural networks

Generalized regression neural networks are a kind of radial basis network that is often used for function approximation. GRNNs can be designed very quickly by using "Newgrnn" command of Matlab. In this approach, a modular General Regression Neural Network based on nonlinear regression theory for function approximation is used to predict the next hour spot price. GRNN is a 3-layer network that has an input layer, hidden layer consisting of at least one node for each presented pattern and an output layer [6,7]. The transfer function for this paradigm consists of a parameter called a smoothing factor, instead of a learning rate and momentum. This smoothing factor provides the same service as the learning rate and momentum in determining how tightly the data will match the predictions or fit the curve.

F. Fuzzy-Neural approach

The spot price forecasting in this approach is based on two components as shown in figure (3), [6]. The first component is the load forecasting component based on the fuzzy inference method and the second component is the spot price prediction component based on an artificial neural network. Using data analysis, it is evident that the daily load curve shows a definite pattern based on the season of the year, day of the week and temperature as shown in figure (3).

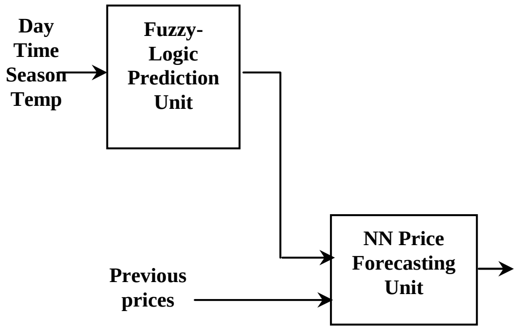

Fig. 3. Fuzzy –neural system for the price prediction

IV. THE PROPOSED CO- CO METHOD

This paper introduces a new methodology using Co-Co to predict efficiently the price and load. Figure (4) shows two spaces for this prediction process.

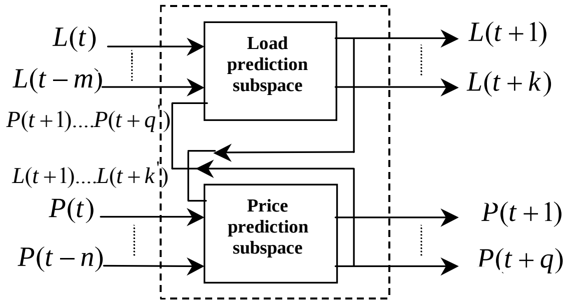

Fig. 4. Proposed method for the price and load prediction

q' *: Inputs of load prediction subspace from price prediction subspace*

k' *: Inputs of price prediction subspace from load prediction subspace*

The proposed spot price and load forecasting method is based on two components. The first component is the load forecasting component and uses *GRNN* structure and the second component is spot price predicting component **based on an artificial neural network.**

In the presented Co-Co algorithm, each subsystem evolves with last updated inputs as shown in figure (4). Number of inputs in each subspace is determined by computing of the correlation coefficients and the autocorrelation coefficients that discuss later.

V. RESULTS

The data of New England electricity market in February and March 2004 is used as a testing data set [20].

Table I. illustrates the autocorrelation coefficients for both price and load time series and also correlation coefficients between Price-Load for different lag step of time. The desired forecasting horizon for both price and load time series is considered seven hours, i.e. k and q are equal 7 (q=7, k=7). The proper values for the other parameters, m, k', n, q', should be selected based on correlation analysis. Using illustrated results in the table I., proper values for these parameters will be: $n = 3, k' = 3$, $m = 4, q' = 3$. In fact the parameters selected so that their correlation values of corresponding quantities be lager than 0.5. As the table shows, the autocorrelation coefficients of the Load are larger than their corresponding price values. Therefore, it is expected the load forecasting results be more accurate than the price forecasting.

TABLE I
THE CORRELATION COEFFICIENTS BETWEEN PRICE AND LOAD
SAMPLES

	Zero step	One step	Two step	Three step	Four step	Five step	Six step	Seven step
Price-Price	0.85	0.79	0.63	0.54	0.51	0.45	041	0.36
Price-Load	0.71	0.69	0.57	0.41	0.25	0.09	0.03	0.01
Load-Load	0.87	0.78	0.72	0.60	0.55	0.45	0.42	0.35

A sample of 800 points from the above explained data set

was used in this study for both load and MCP time series. The first 600 points of data are used as training data and the rest 200 points used as the test set to validate method. The obtained results of the proposed method and other methodologies are compared at the table II based on following performance indices:

- The mean absolute error (MAE)
- The mean absolute percent error (MAPE)
- The standard deviation of error (STD or σ)

These criteria are defined mathematically as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|x_i - \hat{x}_i\right| = \frac{1}{N}\sum_{i=1}^{N}\left|e_i\right| \tag{1}$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{\left|x_i - \hat{x}_i\right|}{x_i} \tag{2}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[e_i - \bar{e}_i]^2} \tag{3}$$

where x_i and $\hat{x}_i$ are the actual (load or price) and forecasted data respectively, and N is number of the forecasted data .

As table II shows the forecasting process has been done using five different ANN structures. The first and second methods use a MLP structure. However, in computing of weighting coefficients two different methods are applied. The first network uses BP mechanism but the weighting coefficients of the second network are computed using genetic algorithm. The third network is designed based on fuzzy-neural approach. GRNN structure is another method which selected for the comparison of the results and evaluating of the proposed method. The training and test data sets are the same for all methods. The values of performance indices which defined in this section for each method illustrated in table II. These values are computed based on all points in both training and test sets (800 points). Figure (5) shows the predicted and desired values of the price for one step prediction. The difference is only apparent on finer scale (Figure 6). Also, figure (7) shows the predicted and desired values of load for one step prediction based on the proposed method.

When proposed method compared with other methods, significant improvement can be observed in all performance indices. In the other word forecasting results show that this approach is more accurate than conventional techniques which introduced before.

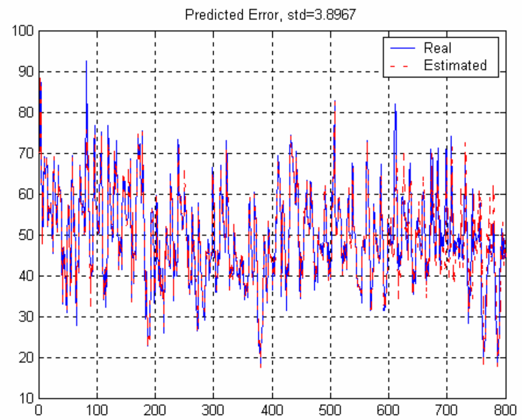

Fig. 5. Proposed method simulation results, price forecastin

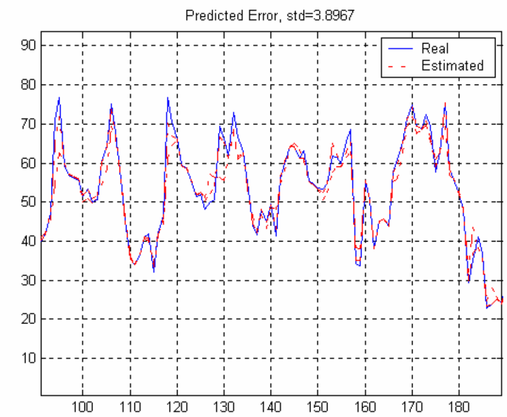

Fig. 6. Proposed method simulation results, price forecasting (finer scale)

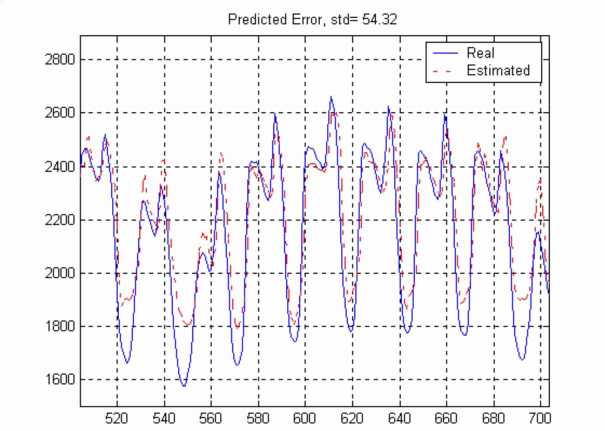

Fig. 7*. Proposed method simulation results, load forecasting (one step prediction)*

TABLE II
COMPARING ERROR VALUES BETWEEN DIFFERENT METHODS

	Method	*Specification*	*Price forecasting*			*Load forecasting*		
			STD ($)	*MAE ($)*	*MAPE (%)*	*STD (MW)*	*MAE (MW)*	*MAPE (%)*
1	MLP-BP	*2 – layer* Neuron - Layer1 = 10 Neuron - Layer2 = 7	5.38	4.20	9.01	69.75	56.50	2.60
2	MLP-GA	*2 – layer* Neuron - Layer1 = 10 Neuron - Layer2 = 7 generation - number = 2000;	5.18	4.1	7.01	68.75	47.50	2.30
3	Fuzzy-Neural	Fuzzy Logic for Load Prediction GRNN for Price Prediction spread - number = 0.1	4.68	3.51	6.01	67.75	44.50	2.20
4	GRNN	spread - number = 0.1	4.15	2.65	5.73	65.10	38.46	1.98
5	CO-CO	*2 subspaces for each*: Neuron - Layer1 = 10 Neuron - Layer2 = 7 spread - number = 0.1	3.89	2.04	4.47	54.32	24.58	1.29

VI. CONCLUTIONS

In this paper a new methodology using Cooperative Co-evolutionary (Co-Co) introduced to determine the weighting coefficients of the neural networks. The structure of the network designed based on correlation between the price and load time series. To show the applicability of the proposed method the actual data are used from the deregulated market. This approach is able to efficiently forecast the MCPs, & load in comparison with the other methods. The new method has shown to be able to improve the results in about 5-25% at confident interval 95% than the other algorithms.

VII. REFERENCES

[1] N. J. Francisco, C. Javier, and et al, “Forecasting next-day electricity prices by time series models.” *IEEE Transactions on Power Systems.* Vol. 17, No 2, pp. 342-348, May 2002.

[2] D. C. Sansom, and T. K. Saha, “Neural Networks for forecasting electricity pool price in a deregulated electricity supply industry.” *AUPEC/EECON 99*, Darwin, Australia, 1999.

[3] D. H. Sonhuai, and Zhijian. “Design on spot price forecasting and mutation alarm system In electricity market.” *Power Systems and Communications Infrastructures for the Future,* Beijing, 2002.

[4] D. C. Park, M.A., El-Sharkawi, R. J. Marks II, ‘Electric Load Forecasting Using an Artificial Neural Network.’ *IEEE Transaction on Power Systems,* Vol. 6, No. 2, May 1991, pp. 442-449.

[5] T. M. Peng, N. F. Hubele, and G. G. Karady, ”Advancement in the application of Neural Networks for short-term load forecasting ,” *IEEE Transactions on Power Systems,* Vol. 7, pp. 250-257, 1992.

[6] L. Vanaja, C. Fung and T. Gedeon, “A fuzzy-neural approach to electricity load and spotprice forecasting in a deregulated electricity market,” School of Information Technology, Murdoch University, South Street, AUSTARIA

[7] D. F. Specht, ”A general regression neural network.” *IEEE Transactions on NeuralNnetworks*, pp. 568-576, 1991.

[8] X. Yao, “A review of evolutionary artificial Neural Networks,” *International J. Intelligent Systems,* vol. 8, pp. 549-567, 1989.

[9] D. Beasly, R. Martin. “A sequential niche technique for multimodel function operation,” in conf. *Evolutionary Computation, 1993, vol.* 1. pp. 101-125.

[10] D. Golberg, and J. Richardson, “Genetic Algorithm with Sharing for Multimodel Function Optimization,” in *Proc. 2th International Conf. Genetic Algorithm,* 1993, pp. 41-49.

[11] N. Garcia, and C. J. Hervas, “Multi-objective cooperative coevolution of artificial Neural Networks,” *Neural Networks,* vol. 15, pp. 1259-1278, 2002.

[12] D. Whiteley, “Applying genetic algorithm to Neural Networks learning,” in *Proc. Conference of the socity of Artificial Intyelligence and Simulation of Behavior,* Sussex, England, 1986, pp. 320-331.

[13] M. R. Akbarzadeh, and Ms. Trabi., “Genetic searching in finding perceptron optimum weights and structure,” *in Proc. 11th Iranian Conference of Electrical Engineering,* 2003, vol. 1, pp. 234-230.

[14] K. Peng, and C. Wen, “An algorithm to determine Neural Network hidden layer size and weight coefficients,” *in Proc. IEEE Symposition on Intelligent Control*, 2000.

[15] A. Berlanga, and A. Sanchis, “A general learning co-evolution method to generalize autonomous robot navigation behavior,” SCA-LAB, Universidad, 30, Madrid, SPAIN, 2000 IEEE.

[16] F. G. Xiaochong, X. R. Cao, and A. P. Papalexopoulos, “Forecasting power market clearing price and quantity using a Neural Network method, pp. 2183-2188, *IEEE 2000.*

[17] J. Gonzalez, J. Ortega, H. Pomares,F. Fernandez, and A Diaz, “Multiobjective evolutionary opyimizition of size, shape and position parameters of radial basis function networks for function approximation,” *IEEE Transaction on Neural Network,* Vol. 14, No. 6, pp. 1478-1495, 2003.

[18] S. Haykin, *Neural Network: A Comprehensive Foundation,* prentice Hall, New Jersey, 1999.

[19] Y. Y. Hong, “Locational marginal price forecasting in deregulated electric markets using a recurrent Neural Network”, *In Proc. 2001IEEE 2001.*

[20] http://www.iso-ne.com/smd/operations_reports/

VIII. BIOGRAPHIES

Ali Karsaz received the B.S. degree in Electrical Engineering from the Amirkabir University of Technology, Tehran, Iran, in 1999. He Obtained his M.Sc. degree in Electrical Engineering in 2004 form Ferdowsi University of Mashhad. He is currently as a Ph.D. student in Control Engineering at the Ferdowsi University of Mashhad, Mashhad, Iran. His interest area is Artificial Neural Networks, Stochastic Modeling and Estimation, System Identification, Time Series Analysis and prediction, Inertial Navigation Systems.

Habib Rajabi Mashhadi obtained his B. Sc. and M. Sc. degrees with honor from the Ferdowsi University of Mashhad, Mashhad, Iran, in 1990, and 1994 respectively both in electrical engineering and his PhD from the Department of Electrical and Computer Engineering of Tehran University in 2002. He is now with department of Electrical Engineering, Ferdowsi University, Mashhad Iran. His research interests are Power System Operation &planning, power market and Biological Computation.

Roozbeh Eshraghnia was born in Tehran, Iran, on May 31, 1979. He studied Power Engineering in Yazd University at 2001. He graduated from Master of power engineering in Ferdowsi university of Mashhad, Iran at January 2006. His research interests include analysis of power market and power system operation.