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Full Length Research Paper

Comparison of time series methods and neural network in energy cost forecasting

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Different method sets for energy cost forecasting, based on neural networks and fuzzy-neural composition networks were used for several kinds of time series models and methods based on intelligence system. In this paper, performance and result of several kinds of time series models in energy cost forecasting in synchronic energy markets, were first studied; then in continuance, a trained neural network by Levenberg-Marquardt algorithm, was used for energy cost forecasting in the day-ahead electricity market of Spain and California during one week.

Key words: Energy cost, cost forecasting, time series, neural network.

INTRODUCTION

Electricity market created a better aim that is more cheaper with the need of consumers. The number of premium for this market can be mentioned as follow (Ott, 2003):

1. Provide right of choice for consumers.
2. Provide suitable bed sake giving service.
3. Challenge efficiency of electricity goods in variant levels and determine suitable cost for consumers.
4. Selection of existent capitals in private, and conduction of it for the sake of the public, does not need huge state investment.
5. Increase the quality of given goods, with due consideration of the existing contest.

Nowadays, energy cost forecasting is a necessary order, especially in synchronic electricity markets for producer and consumers. One of the devices which are used for energy cost forecasting is time series methods. In recent years, the kind of forecasting method is given and suggested based on artificial intelligence techniques and neural network by researchers. In this paper, we pay attention to the study of the existing methods and product results in energy cost forecasting in suggested markets.

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THE KINDS OF ENERGY MARKETS

Kinds of electricity markets comprise advance market of day-hour ahead electricity market, real time electricity market or equilibrium market, ancillary service market and transmission market. Among these, attention is paid to description trial and equilibrium markets.

Day ahead electricity market

In this market, all participants (such as generators and charge) should give cost suggestions after every work hour, the next day. After the closed suggestion period, the operator accounts for the other 24 h schematization based on given suggestions from two persons and the given schematizations based on at least cost, SCUC (security constraint unit commitment) and ED (economic dispatch) for every hour of the next day. During this process, he settles most of the market costs performed for every hour of that day.

It is essential to mention here that in this process, the operator spots necessary settlement related to the programme and imperative executives of the entire participants in the market.

Hour ahead electricity market

This market uses the day ahead market programme to resolve deviances. For very equality, it is used more than the day ahead market.

Real-time electricity market

In order to be sure of the performance of the power system, production and consumption of electricity power should be in equilibrium with the real time together, but real time values of charge, production and transfer system can be different from the ahead market programme. In other words, real time energy market is based on the accurate condition of real time beneficiary, but for the security of the equilibrium, there is need to create real time market and settlement cost of market accounts based on system beneficiary wee conditions. In this market, all inclinations of ahead market are covered, then all units that participate in the day-ahead programme, having many capacities, provide for every other unit that has been prepared by the battalion capacity, given the self suggestions made by participants in this market. Moreover, in that settlement cost, every 5 min account for the security constraint and economic dispatch distribution in real time performance condition. However, the importance of cost forecasting in this market is shown by the exact statement of cost which helps in determining further, the exact guidance of cost suggestion. As such, if a cost suggestion is more closer to the market settlement cost, it will lead to more income for GENCO.

Problems of energy cost forecasting

The most sensible energy cost property is instability. Instability is the amount of energy cost change in a certain period and it often accounts for the percent of exposition and standard annual inclination percent of daily cost changes. Some factors, which play a role in energy cost instability consist of:

1. Fuel cost instability;
2. Non pragmatism dispatch;
3. Changes in production of water electricity;
4. Non pragmatism production for events and non scheduled existence;
5. Conduction density;
6. Behavior of participants in the market, based on forecasting cost (Amjadi et al., 2006).

With due attention to the given properties, it is clear that forecasting is very hard and has an obscurant wee cost.

EXISTENT METHODS FOR ENERGY COST FORECASTING

Now, variant techniques are set for energy cost forecasting, in that the difference model of time series, used before for oil and gas cost forecasting, is used to dispatch short time forecasting in power system. Nowadays, it is used for short time forecasting. From this, reference can be made to ARIMA (Auto regressive integrated moving average) and GARCH (General auto regressive conditional heteroskedastic) (Nogales et al., 2006). In recent years, other kinds of forecasting methods based on artificial intelligence techniques and neural networks are given and suggested by researchers.

Energy cost forecasting by time series methods

In general, every cost forecasting, based on the performed variant time series stages, take precision for all existent methods. These stages are as follow:

a) Pattern recognition: In this stage, we try to select the time series properties of energy cost, which consist of first and second torques, namely mean functions, variance, auto covariance and self correlation of the best pattern.
b) Calculation of the unknown parameters model: In this stage, after model selection and spotted processes, two main duties for time series behavior are discussed:

(i) Determination of the process stage in the model.
(ii) Determination of the model parameters, that is, which method was used to obtain stamina.

By these two parts, we can determine the prime model for processor; in other words, we had a model to time series of energy cost.
c) Pattern recognition (study and pattern suitable recognition): In this stage, using methods like the analysis elegance model, a study was done to check if the main hypothesis of the model was set about it or not? While the hypothesis is set, we are going to stage d, after which we would return to stage b.
d) Forecasting: In this stage, cost forecasting model is the case of view in time (Nogales et al., 2002). In continuance, it studies and analyzes cost forecasting results by ARIMA and GARCH models.

Energy cost forecasting by ARIMA time series model

As mentioned in energy cost forecasting by time series methods, ARIMA is generally faced by stages (a) to (d) too. At first, the exact study of time series properties was selected. These time series properties of energy cost can refer to high data frequency (energy cost), average variance and several seasons. This has reference to the reality that cost, in every moment, has a correlation to cost value in days and past weeks.

ε_t or error term is the difference between real cost and forecasting cost and it includes white-noise property or is spotted as a strict accident process. Functions of ϕ and θ have the following forms:

$$\theta(B)W_t = \phi(B)\varepsilon_t \tag{1}$$

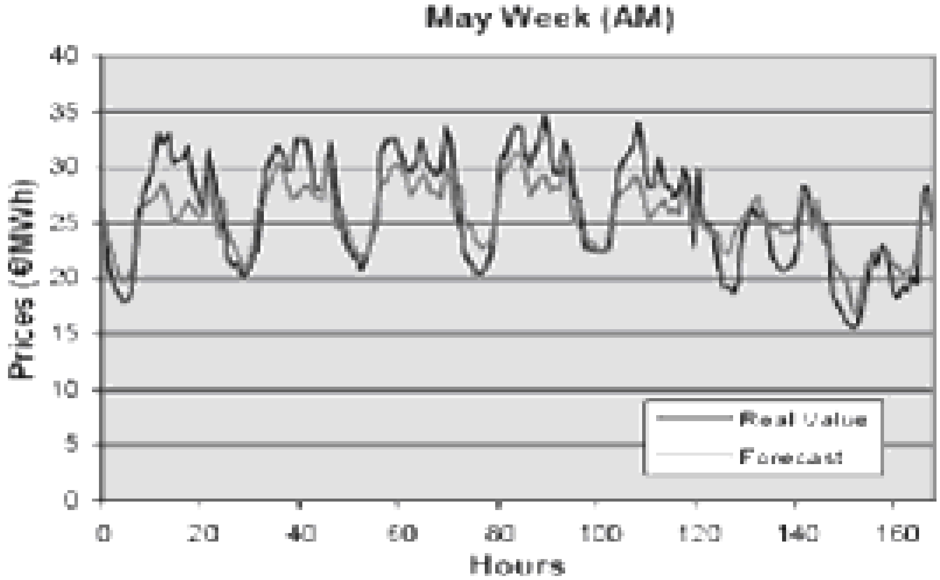

Figure 1. End week forecasting results (25 to 31 May) for Spain market.

Where $\theta(B)$ and $\phi(B)$ are several sentences stage of q and p relatively, and W_t (P_t) is the cost time series.

$$\theta(B) = 1 - \sum_{j=1}^{p} \alpha_j B^J \tag{2}$$

$$\phi(B) = 1 - \sum_{j=1}^{q} \beta_j B^J \tag{3}$$

p is the autoregressive process stage that relates the energy cost to the former costs, while q is the remote average process stage that modules the error term. A changeable condition for q stage remote average process is explained by using B forth performance. B forth performance performs on time indicator and turn it back on J unit. However, value α_j starts the process and value β_j reverses it.

With due attention to the selection process model, logarithm conversions or leach methods may be used to access the average variance and a more equal variance.

NUMERAL RESULTS ARIMA MODEL

During this time, cost forecasting results by ARIMA model came with day-ahead cost forecasting in day-ahead electricity market of Spain and California (Conejo et al., 2005). After the description process, the final model for the spain market in 2000, is seen according to the sub form as follows:

$$\begin{aligned}
&(1-\phi_1 B^1 - \phi_2 B^2 - \phi_3 B^3 - \phi_4 B^4 - \phi_5 B^5)\\
&(1-\phi_{23} B^{23} - \phi_{24} B^{24} - \phi_{47} B^{47} - \phi_{48} B^{48} - \phi_{72} B^{72} -\\
&\phi_{96} B^{96} - \phi_{120} B^{120} - \phi_{144} B^{144})(1-\phi_{168} B^{168} - \phi_{336} B^{336} -\\
&\phi_{504} B^{504}) \log \quad p_t = c + (1-\theta_1 B^1 - \theta_2 B^2)(1-\theta_{24} B^{24})\\
&(1-\theta_{168} B^{168} - \theta_{336} B^{336} - \theta_{504} B^{504})\varepsilon_t
\end{aligned} \tag{4}$$

Of course, in the same year, California market of this model is of the sub form:

$$\begin{aligned}
&(1-\phi_1 B^1 - \phi_2 B)(1-\phi_{23} B^{23} - \phi_{24} B^{24} - \phi_{47} B^{47} -\\
&\phi_{48} B^{48} - \phi_{72} B^{72} - \phi_{96} B^{96} - \phi_{120} B^{120} - \phi_{144} B^{144})\\
&(1-\phi_{167} B^{167} - \phi_{168} B^{168} - \phi_{169} B^{169} - \phi_{192} B^{192})\\
&(1-B)(1-B^{24})(1-B^{168}) \log \quad p_t = c + (1-\theta_1 B^1 - \theta_2 B^2)\\
&(1-\theta_{24} B^{24} - \theta_{48} B^{48} - \theta_{72} B^{72} - \theta_{96} B^{96})(1-\theta_{24} B^{24})\\
&(1-\theta_{168} B^{168} - \theta_{336} B^{336} - \theta_{504} B^{504})\varepsilon_t
\end{aligned} \tag{5}$$

In Spain, the market is spotted 2 weeks before forecasting, and then, real observation data are used for these two weeks to study the exact market that is valid among them. Figures 1 and 2 show number results of ARIMA model for May and August selection week in Spain market.

In California market, which includes short vibrations, only one week is selected for forecasting. Of course, for the model's input data in this market, the costs data of first January to second April were used. Figure 3 draws forecasting related to April's selection week for California market and real costs related to this week.

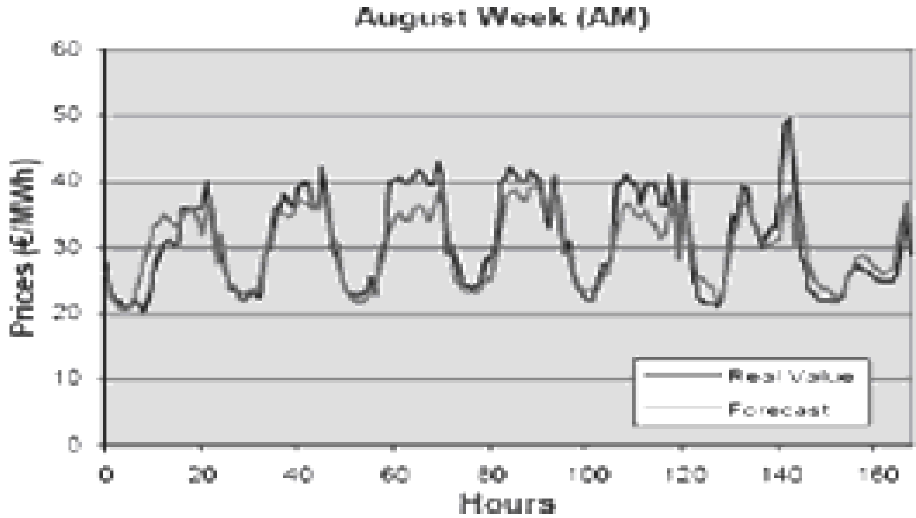

Figure 2. Last week forecasting results (25 to 31 August) for Spain market.

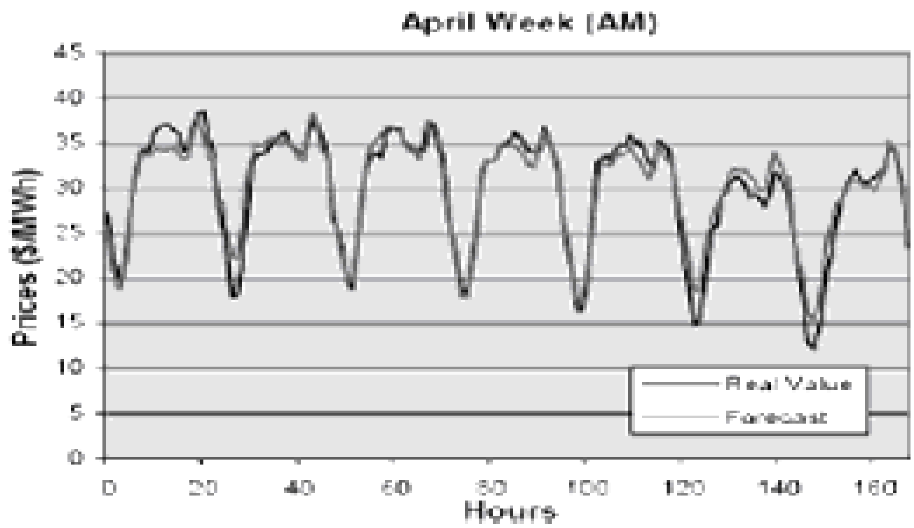

Figure 3. Forecasting results between weeks of April months (3 to 10) for California market.

Advantage of ARIMA model

1. Schedule based on time series analysis.
2. Lift by index changes in accuracy functions of very high model.
3. It can use the index changes in months that are too cost dependence on water powerhouse.
4. To enjoy the aster of accuracy model and high accuracy for hard mathematics.
5. Enjoy flexible structures for forecasting.
6. It is capable of a schedule by the general program such as MATLAB.
7. Necessary time for performance of this method by computer and software MATLAB is very low.

Energy Cost Forecasting by GARCH time series model

Instability in markets can lead to sudden jumps in cost, for example, in 2000, it led to the suitable behavior of California electricity market and a vital review.

GARCH model is the solution for this instability problem, especially in high instability market.

This model helped in accounting for the class coefficients of ARIMA model by molding markets instability and spotting it in this model, with a kind of guideless cost

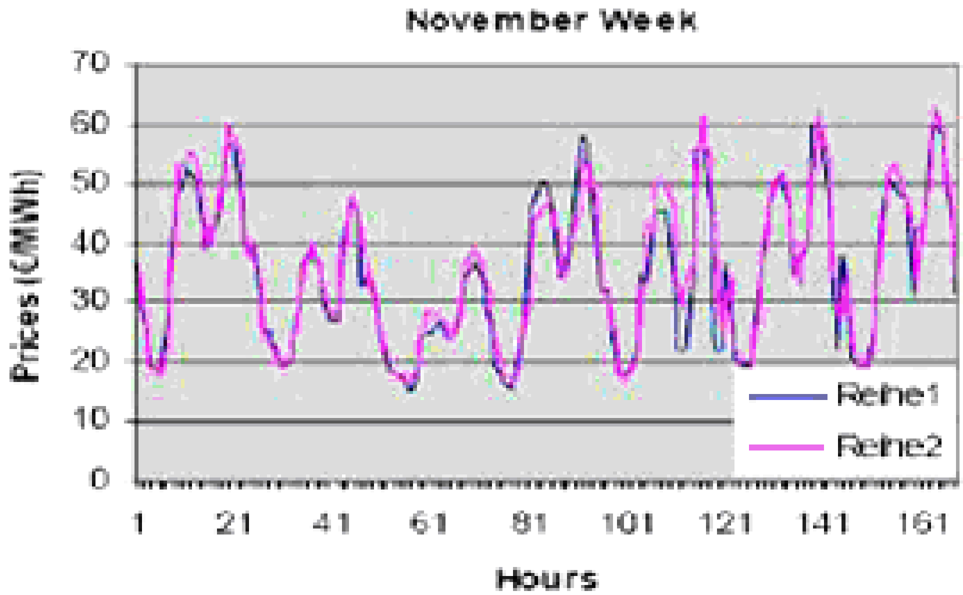

Figure 4. Forecasting results of the second week of November for Spain market.

that was better and suitably forecasted by the given energy, which was bought or sold. However, it was suggested that this caused giants trade and more charges for both exchange and stability behavior of energy cost series too. This variance model modules cost series like an auto regressive process of the former error terms. The general formula of GARCH model for cost dates is defined as follows:

$$\theta(B)W_t = \phi(B)\xi_t \quad (6)$$

Unlike the previous method of ε_t, error term should be an imitation of white-noise behavior. In this model, ξ_t error term does not have zero mean and its variance is not stable. The main structure of module GARCH consists of previous stages such as other patterns (Garcia et al., 2005).

NUMERAL RESULTS

In this section, cost forecasting results in Spain and California market by GARCH model is given. These models, after estimating the parameters by the former data and model process variance, are as follow:

Spain market:

$$P_t = c + (\theta_1 B + \theta_2 B^2 + \theta_3 B^3 + \theta_{24} B^{24} + \theta_{48} B^{48} + \theta_{120} B^{120} + \theta_{144} B^{144} + \theta_{168} B^{168})P_t + \xi_t \quad (7)$$

California market:

$$P_t = c + (\theta_1 B + \theta_2 B^2 + \theta_3 B^3 + \theta_{24} B^{24} + \theta_{47} B^{47} + \theta_{48} B^{48} + \theta_{120} B^{120} + \theta_{144} B^{144} + \theta_{167} B^{167} + \theta_{168} B^{168} + \theta_{169} B^{169} + \theta_{192} B^{192})P_t + \xi_t \quad (8)$$

Several seasons' effects can be observed in these markets clearly. In Figure 4, the second week forecasting result of November is the highest request period shown synchronically in while in Figure 5, it is the pointer selection week of April for California market. Generally, it induces the results of the model, which is logical, but the error from it is extreme with 10%.

Advantages of GARCH model

1. Markets, with more cost and high jump, devoid of stability, have better accuracy in comparison to others.
2. It needs short dates and uses short sampling.
3. In model relationship becomes shorter of degree and volume of shorter calculations.
4. Most error degrees are 10%.
5. The implementation time for it is done by a computer and very low software MATLAB with limited desirability.

Energy cost forecasting by methods based on neural network

In forecasting, the neural network used against the highly discussed methods does not module the system, instead, the indefeasible supposition between a series of inputs

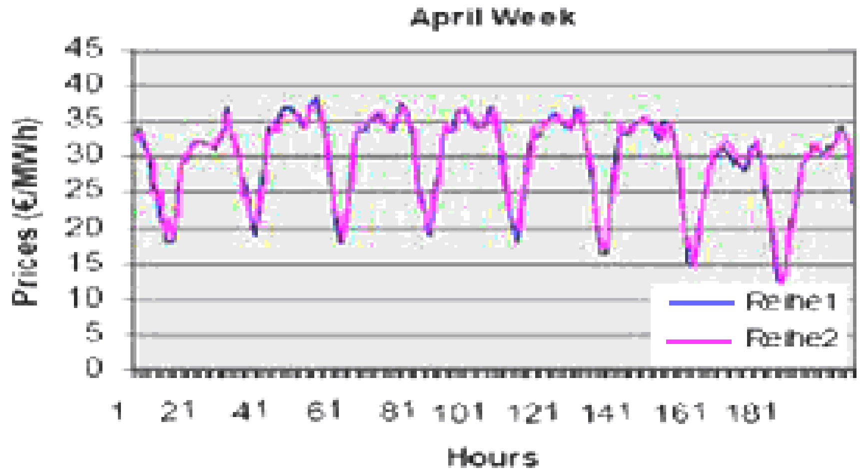

Figure 5. Selection week forecasting results of April for California market.

case and energy cost, by the data and former samples, is filled with more output. Particularly, neural networks are set to charge the forecasting of network that are used as output and high efficiency in exact naiveté, thereby providing enough information for instruction of the network, and selecting input samplings and a suitable number of invisible units output. Finally, accounting sources are very powerful and reference tools for forecasting (Yamin et al., 2004).

Cost forecasting structure based on neural networks

Forecasting, by neural networks, is performed in two stages (training and learning). Train dates from data and former observations embrace the related performance to access and apply them to the network. In the learning process of neural network, by regulating the step to step weights and based on the minimum module error between networks output and the study's favorite output, a supposition is set between input and output.

The major learning pattern style is used, especially, in cost forecasting problems, that is, after the report back propagation algorithm. Other algorithms studied the network from tens to hundreds of square, but it was the Levenberg-Marquardt algorithm that was an altered algorithm based on Newton method. The amount of change in a parameter is updated for that parameter's minimum function V(x) rather than the x vector, which is given by the following frame:

$$\Delta(x) = -[\nabla^2 V(x)]^{-1} \nabla V(x) \tag{9}$$

where $\nabla V(x)$ is Hessian matrix and $\nabla V(x)$ is the gradiant vector. With due attention to $V(x)$, the total error squares are defined as follow:

$$V(x) = \sum_{h=1}^{N} e_h^2(x) \tag{10}$$

It results that:

$$\nabla V(x) = 2J^T(x)e(x) \tag{11}$$

$$\nabla^2 V(x) = 2J^T(x)J(x) + 2S(x) \tag{12}$$

Where e(x) is the error vector and J(x) is the Jacobin matrix, which gives the following matrix:

$$J(x) = \begin{bmatrix} \frac{\partial e_1(x)}{\partial x_1} & \ldots\ldots & \frac{\partial e_1(x)}{\partial x_n} \\ . & \ldots\ldots & . \\ \frac{\partial e_N(x)}{\partial x_1} & \ldots\ldots & \frac{\partial e_N(x)}{\partial x_n} \end{bmatrix} \tag{13}$$

Finally, S(x) defines the following:

$$S(x) = \sum_{h=1}^{N} e_h(x) \nabla^2 e_h(x) \tag{14}$$

By overlooking the second stage derivatives of the error vector, considering $S(x) \approx 0$ of relation (12), Hessian matrix is as follows:

$$\nabla^2 V(x) = 2J^T(x)J(x) \tag{15}$$

By replacing values $J^T(x)$ and $J(x)$ in relation (15), the

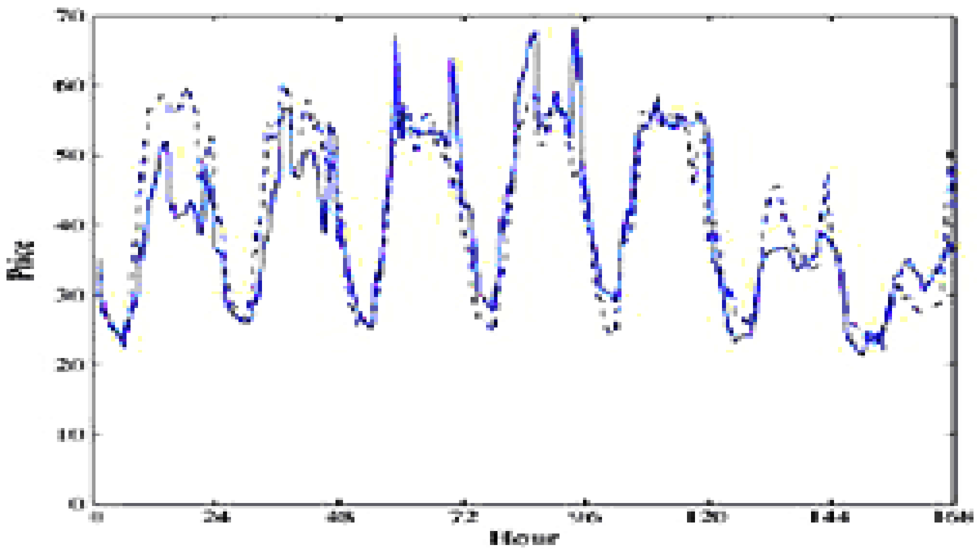

Figure 6. Selection week forecasting results of spring (20 to 26 May) for Spain market.

amount of x parameter changes by updating Goss-Newton in the following relation.

$$\Delta(x) = -[J^T(x)J(x)]^{-1} J^T(x)e(x) \quad (16)$$

In fact, this technique take-over the algorithm problem of Liebenberg-Marquardt that is updated in relation (17).

$$\Delta(x) = -[J^T(x)J(x) + \alpha I]^{-1} J^T(x)e(x) \quad (17)$$

Here, parameter α is optimum during algorithm practices when α is very small or in effect, but Liebenberg-jacquard algorithm changes into Goose-Newton algorithm till a faster convergence is provided; while for values α, in relation (17), a connivance is seen in the first part of the bliss inside the phrase, rather than in the second part.

Numeral results of the neural network model

The advanced neural network, learnt by Levenberg-Marquardt algorithm for cost forecasting, is suggested for one week. In this order, the toolbox of the software's neural network and MATLAB is selected for flexible, accounting high power.

The used transfer function for output and hidden layers consists of linear and unlinear transfer function of MATLAB, tansing (Hyperbolic tangent sigmoid transfer function) and purling (pure linear transfer function). In the instruction stage, the number of difference units is tested in hidden layers, while the best results of the 5 hidden layers got their own unit.

The output layer has a unit and so, the major energy cost suggested for day-ahead market is adjusted. The former cost data of the main electricity market inputs are offered for network instruction. In offering the neural network method of day-ahead market cost in Spain, California electricity markets got theirs for one week. For Spain market, the selective week is in the spring of 20th to 26th May, 2002. The time information used for forecasting the week of eighth spring was obtained in 19th April of the same year.

Figure 6 shows the selection week forecasting results for Spain market. For California electricity market, the selection week is from the spring of 3rd to 9th April, 2000. This was the week (before vibrations and instability of the cost started) that caused a closure of this market and the main review in the structure of it. The time information used by the cost of the former data is from 21st February to 2nd April of the same year. Figure 7 shows the forecasting results and real cost values for this selection week.

Comparison of ARIMA methods and neural network

(1) Neural network forecasting is more accurate.
(2) A successful ARIMA model is related to the linear data production process, while neural networks can register unlinear relation or render it to the model.
(3) ARIMA method needs about 5 min for the selection week cost forecasting, while the neural network performs this work with less than 20 seconds.

Table 1 accounted for the mean absolute percentage error (MAPE) that showed the neural network and ARIMA model. As shown in this table, the mean error in neural

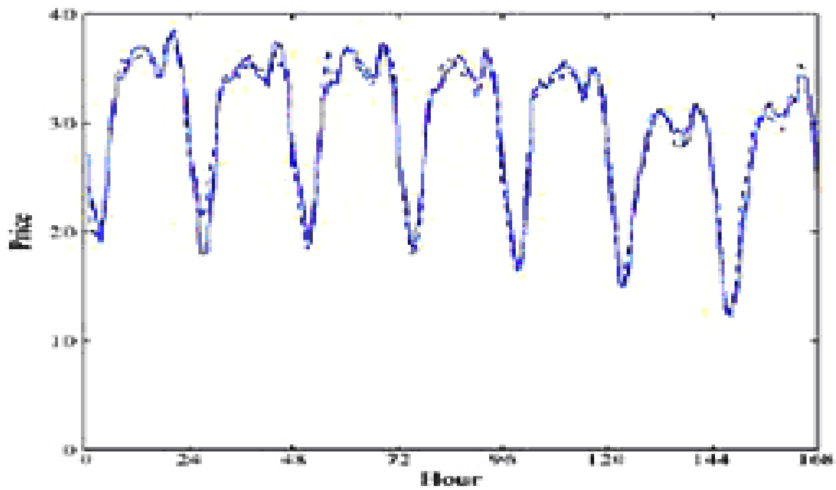

Figure 7. Selection week forecasting results of spring (3 to 9 April) for California market.

Table 1. Comparison of accuracy between ARIMA methods and neural network.

Market	Week	Neural network (%)	ARIMA (%)
Spain	February	5.23	6.32
Spain	May	5.36	6.32
Spain	August	11.40	13.39
Spain	November	13.65	13.78
California	April	3.09	5.01

network is less in comparison to ARIMA model.

CONCLUSION

With due consideration of the new Iran's electricity market and the existing limitations in this market, the cost suggests problems for participating companies in this market and they include incoming trade and profit for these companies. Also, considering the high truck volume, there is a synchronic market. This forecasting meets so many importances. So, using the exact methods for cost forecasting includes different importance with diverse point of views. Nowadays, time series methods and methods based on artificial intelligence techniques and neural network are used for energy cost forecasting. Among these two methods, neural networks forecasting is more accurate than time series methods.

REFERENCES

Ott AL (2003). Experience with PJM Market Operation, System Designand Implementation, IEEE tran. power syst., 18(2).

Amjadi N, Hemmati M (2006). Energy Price Forecasting, Problems and proposals for such predictions, IEEE Power Energy Magazine.

Nogales FJ, Conejo AJ (2006). Electricity price forecasting through transfer function models, J. Operational Res. Soc., 57: 350–356.

Nogales FJ, Contreras J, Conejo AJ, Espínola R (2002). Forecasting next-day electricity prices by time series models, IEEE Trans. Power Syst., 17: 342–348.

Conejo AJ, Plazas MA, Espínola R, Molina AB (2005). Day-Ahead Electricity Price Forecasting Using the Wavelet Transform and ARIMA Models, IEEE Trans. Power Syst., 20(2).

Garcia RC, Contreras J, Akkeren MV, Garcia JBC (2005). A GARCH forecasting model to predict day- ahead electricity prices, IEEE Trans. Power Syst., 20.

Yamin HY, Shahidehpour SM, Li Z (2004). Adaptative short-term electricity price forecasting using artificial neural networks in the restructured power markets, Electr. Power Energy Syst., 26(8): 571–581.