DESIGNING AN OPTIMIZED MODEL TO FORECAST SHORT-TERM ELECTRICITY DEMAND BASED ON ARIMA AND WAVELET DECOMPOSITION NEURAL NETWORK: COMPOSITION OF LINEAR AND NON-LINEAR MODEL (A CASE STUDY IN IRAN)

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ABSTRACT

In this paper we designed a new model that it integrate the linear and no linear models also we surveyed the trend electricity daily demand of country and the effective factors on daily demand of this energy carrier. Next, we have forecasted the electricity daily demand for next 10 days in forms of "step to step" by models of ARIMA, Feed forward Artificial Neural Network, and Neural Network-Wavelet Transform and Proposal model. Finally, the quantities have been forecasted by each one of models tested by criterions of forecast accuracy. Results present that proposal model has fewer forecasting error and high accuracy in forecasting of electricity daily demand of country. Its behind, the Neural Network-Wavelet Transform, Feed forward Artificial Neural Network and ARIMA lie respectively in further preferences.

INTRODUCTION

one of the provisions of moving into a competitive market which can secure the highest impart value for the market, is to have sufficient detailed information on market stream particularly the amount of demand.
The most important target of this research is providing a model consistent with the situation of country in addition to its possible use in forecasting other time series variables.
In this regard, several methods have been introduced to forecast time series. Forecasting methods can be generally divided into linear and nonlinear groups. However, the most used linear forecasts are ARMA and ARIMA. Recent years have witnessed widespread utilization of nonlinear models among economists due to improvements in software and calculation capabilities as well as data processing. One nonlinear model which has proved good potential to forecast time series is Artificial Neural Network (ANN).
On the other hand, there has been an increasing tendency towards linear developments of signals especially using wavelets and their relevant extensions. Wavelet theory will provide a mathematical tool to analyze signals so it offers a useful technique to represent signals at different levels.

CONTEXT

Studies on using ARIMA model lonely have been rarely done and this model has been compared with various neural networks in most cases.
The most important advantage of neural networks is learning ability in data input, so required potential to give publicity to the neural network will be produced. In other words, an acceptable outlet for input data is created which was not seen previously.
This prediction has significant importance. Another advantage of this network is its nonlinear nature.
Thus a lot of problems can be solved.
Flexibility and ability to give publicity without the further assumption of the model design can be introduced as its other benefits.
Feed-Forward Neural network equipped with hidden layer, sigmoid activation function in the hidden layer, linear activation function in the output layer and sufficient neurons in the hidden layer, can approximate any function with desired accuracy.

Hence, this type of neural network structure has been called comprehensive approximation.

SIMULATION MODEL

The suggested method presents useful information out of the impact of different events on time series. This method is a combination of Artificial Neural Network, wavelet transfer with Artificial Neural Network models that have been used for the first time to furcate, predict and analyze the time series . At the first step of this method, time-series are analyzed using the wavelet (Debuchi) until the approx level appears as a fairly direct line or a procedure. Taking into account that ARMA has a higher ability to forecast line-series, the series is forecasted. Next, we obtain a deprocessed series by summing up function details, which only consists of variations during the period (components), due to the below equation:
Original series = (approx) smoothed series+ sum of function detail series (components).
Later, we determine varied factors on these variations. Having determined the influential factor on the variations, they are disposed to the Neural Network as inputs of explanatory variables and then, sum of details functions are determined as outputs which were later designed and estimated in Neural Network.
Finally, the variations are forecasted by Neural Network-considering the impact factors in future-and sum it up in order to forecast values of the smoothed series through

ARIMA. This method has two advantages: First, by using this technique, three linear and non-linear patterns of ARIMA, Neural Network and wavelet transform are combined together, such that shortcomings of each pattern will be omitted or mitigated by advantages of the other one during forecast. Second, by considering time series, the method will insert the impact factors on these series which must regularly increase the capability of forecasting time series.

DESIGN AND ESTIMATION OF MODELS

The data used in this study was Iran's daily electricity demand for the period 2005/1/25 to 2009/3/4 with total 1500 observations. These data were composed of two parts: First from 2005/1/25 to 2009/2/22 (1490 reads) which is related to the model used to estimate ARIMA, training and simulation, artificial wavelet; Second from 2009/2/23to 2009/3/4 which was used for prediction and comparison.
Data of temperature and darkness hours were obtained from Meteorological Organization.
Generally, the electricity demand is increasing regarding its annual trend.
Noteworthy in electricity demand is its seasonal fluctuations, such that there is an increase in power demand during the warm months.
The most prevalent reason of this can be usage of cooling devices that consume a lot of energy. Long daytime hours during hot months of the year will increase use of these utensils.
However, lighting consumption is decreases given limited dark hours of these days.
One other reason to understand the fluctuations is that many activities in open areas are suspended or limited during cold months of the year and they start working in warm months again.
Consequently, these activities will affect electricity demand to some extent (welding for example). Another point in electricity demand is its daily fluctuations. Power consumption decreases during holidays (some of these fluctuations are particularly observed for Noruz holidays). Electricity demand increases at the first days of the week and decreases at the last days of the week, it reaches its minimum during Fridays and this process is repeated on Saturday again.

ARIMA

In the recent study, time series were stabilized through first order differentiating from 2005/1/25 to 2009/2/22.
Then the number of their regressive expressions (p) and moving average expressions (p), was calculated based on Box – Jenkins procedure using their correlation functions (AC) and partial correlation functions (PAC).
But since other models may exist with lower Akaike or Schwartz values which may be preferred upon the pattern, other models were studied additionally.

Neural Network

Depending on the research objectives, different types of Artificial Neural Network can be applied. In the present research, multilayered feed-forward neural network (MFNN)1 was employed.
It should be noted that where one of the main goals of this paper is raise the performance of the wavelet neural network, so the structure of neural network models and neural networks is the same with wavelet neural networks.

Wavelet Transform Design

One power demand time series is first considered as a combination of separate components at different scales and fluctuation levels. Thus wavelet decomposition will be obtained first and then, one neural network model is designed for each component (detail function) which has been decomposed from the initial series.What remains is an approximation series (concomitant) which is also modeled by the neural network. It is called Wavelet Decomposed Neural Network (WDNN)2. Forecasting the main series is obtained from total smoothed forecast series and components. In order to study the performance of decomposition, data is split into 4 levels using the Debuchi wavelet4 and the smoothed level is obtained with one to three level details which are modeled by using the neural network.

PROPOSED MODEL

Interpretation of the daily power demand showed that this time series has an incremental regime considering the annual average demand. At the first step, time series is decomposed using the wavelet (Debuchi type) to a level which makes the smoothed level almost linear (series of daily electricity demand is split into 10 levels) and taking this point in mind that the ARIMA model is strong enough in forecasting linear series, this series is forecasted for the next 10 days by ARIMA model. Figure1, exhibits the approximate smoothed level for daily power demand.

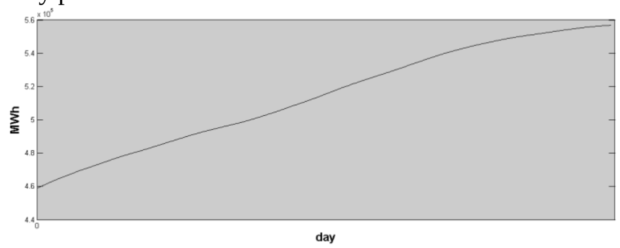

Figure1. Approximation of smoothed level for daily.

power demand using A pprox.level 10 for db5,ARIMA
In the present study, the time series of daily electricity demand was stabilized by second order differentiation from 2005/1/25 to 2009/2/22. The number of auto-

1 Multilayered Feedforward Neural Network
2Wavelet Decomposition Neural Network

regressive expressions (p) as well as the number of moving average expressions (p) was calculated using AC and PAC functions on the basis of Box-Jenkense. However, some other models were also assessed since there may exist some other models with lower Akaike or Schwarz values which are preferred over the pattern.
So, In the next step, a series is produced by summing up other detailed functions which is deprocessed and includes only the fluctuations along the period. Figure6, depicts this series.

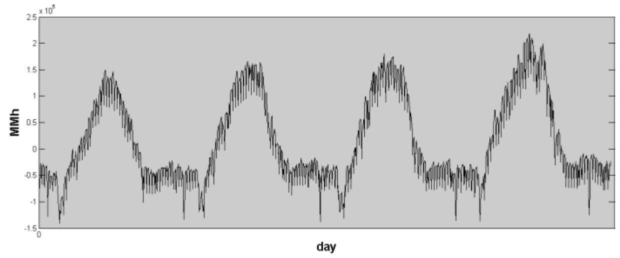

Figure2. Summing up other detailed functions for daily electricity using

Afterwards, effective factors on these fluctuations are defined. The most significant parameter on the daily power demand is assumed to be the temperature degree (the maximum daily temperature is considered regarding the implemented studies), total daylight times (during warm months of the year, electricity demand will be increased due to use of cooling equipments which are working for long because of long daytimes; during cold months, use of lighting equipments is increased due to shorter daytimes), days of week, holidays and special occasions (Ramadan for example) that are reflected on the entrance layer of the neural network. Besides, one seasonal variable has also been devised in network design to distinguish between warm and cold months of the year. Now there is 6 entrance neurons and 1 exit neuron in design and modeling multi-layer feed-forward neural networks which are the set of detail functions deproceeded before.
Sigmoid and linear functions are used for hidden and exit layers, respectively.

For instructions, teaching to testing ratio of 0.90 to 0.10 was selected with 0.01 learning rate. The other characteristics were similar to those described in 4.6. Finally, for the next 10 days, one linear regime from ARIMA was added to the fluctuations forecasted from ANN to yield the main series of forecasts. Thus, the neural network will have 3 neurons in the entrance layer with 18 neurons in the hidden one. Other properties of the network structure were according to 4.2. Figures (3) and (4) show structures of the proposed model and wavelet decomposition-neural network, respectively.

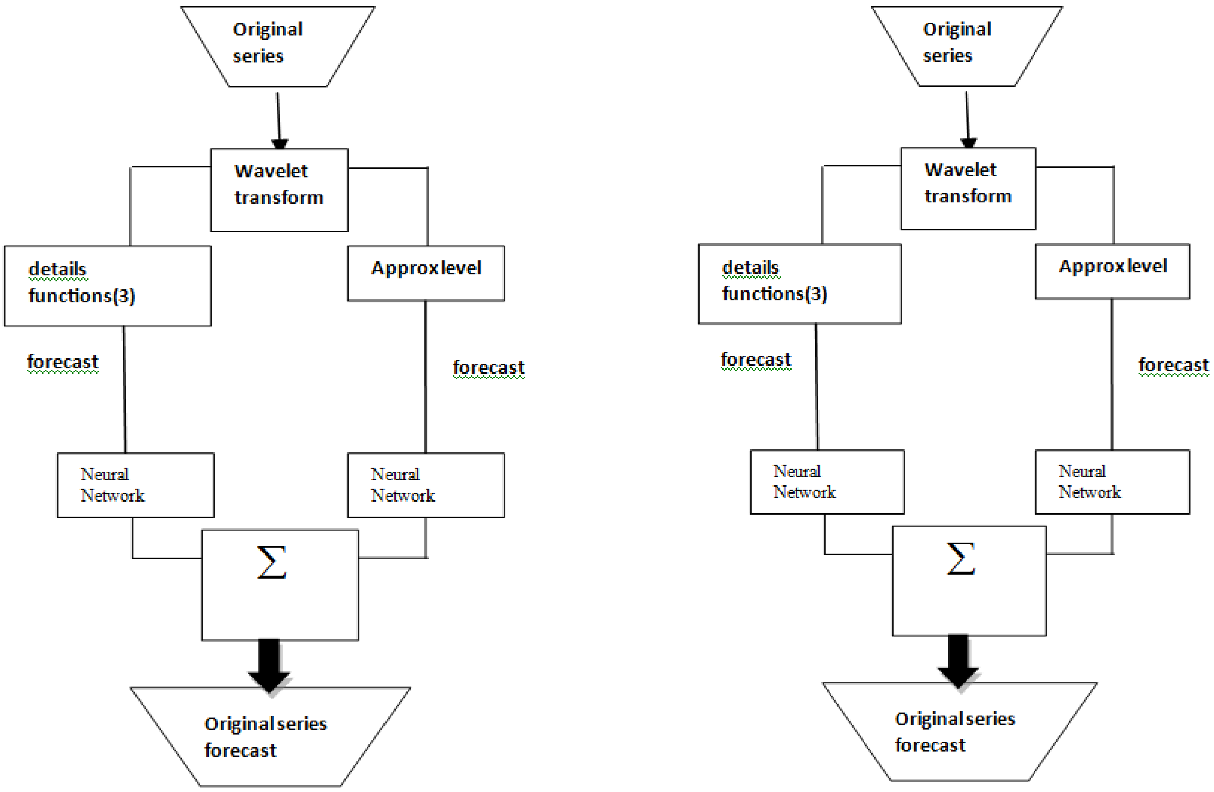

Figure3.(a)Neural Network-Wavelet structure (b) proposed model structure

Figure7 shows the forecasted values by feed-forward neural network (NN), Wavelet decomposition neural network (WDNN), ARIMA process in addition to the new proposed model (NEW) with the actual values for the next 10 days from **2009/2/23to 2009/3/4.**

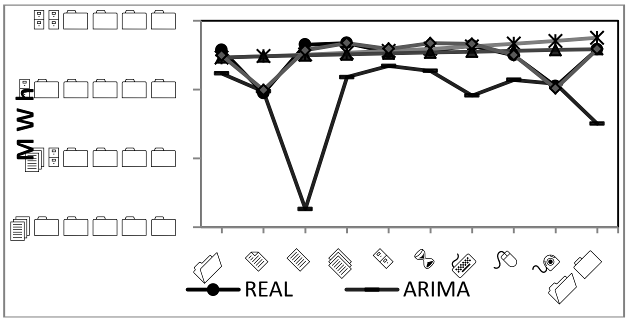

Figure4. Forcasting valus by 3 approaches for the next 10 days

Considering figure (4) the actual regime of power demand values for the next 10 days implies that the demand reaches its minimum on Fridays (days 2 and 9) whose most important reason is suspension of many governmental and nongovernmental organizations. When the next week begins, there would be an increase in the demand and the other days will show respectively stabilized behavior. By approaching to end of the week particularly Thursdays, there would be a significant decrease in electricity consumption which can be attributed to the suspension of many companies and partial activity of the others. This regime continues for the day after. In order to compare the strength of forecasting models, mean standard error (MSE), root of mean standard error (RMSE), mean absolute value of error (MAE) and mean absolute value percentage error (MAPE) criteria have been employed stepwise (from first day to the tenth).

The reason to use stepwise forecast is that for instance in a model, among 10 different forecasts, one model may perform better than other one during the first days of this period but total evaluation may yield completely different result. Any step is indicative of one day for example, the second step forecasts models for the next 2 days and the step 7 will forecast models for the next 7 days. These values are calculated based on comparison between actual values from2009/2/23to 2009/3/4.based on each 4 evaluation criteria, proposed model has the least error among all steps and has higher accuracy in forecast. After the proposed model, wavelet decomposition-neural network has smaller forecast error based on MSE and RMSE criteria in 1 to 3 and 8 to 10 steps compared with the feed-forward neural network. In other steps (4 to7) feed-forward neural network has higher accuracy than wavelet decomposition-neural network. On the basis of MAE and MAPE criteria, wavelet decomposition-neural network has smaller error in steps 1,2,9 and 10 after the proposed model, while in the remaining steps, feed-forward neural network has higher accuracy. ARIMA model posses the last place in terms of forecasting based on each four criteria and among all steps. Generally speaking, the proposed model has higher ability to forecast daily electricity demand considering the effective factors on power demand particularly by executing a combination of linear and nonlinear models.

6. CONCLUSIONS

Taking into account the importance of this issue, above information should be as accurate as possible based on future realities. Thus, forecasting the future power demand has been a critical issue in each time period based on which it would be possible to secure the required demands timely specially in short-term. A new model was provided in this paper to forecast the electricity demand. It was adjusted to the climatic conditions of the country with considering effective variables on the daily electricity consumption.

Then, the proposed model was compared with ARIMA, Feed-Forward Neural Network and Wavelet Decomposition-Neural Network techniques in terms of MSE, RMSE, MAE and MAPE criteria. Results of the research showed that the proposed model has had high accuracy in forecasting the daily electricity demand in terms of all evaluation criteria when compared with other proposed models. Wavelet Decomposition-Neural Network (which was first used in studies conducted in Iran on forecasting energy conveyers), Feed-Forward Neural Network and ARIMA process posses the next priorities with less forecasting errors.

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