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Power Consumption Short Term Forecast Using Signal Auto Regressive Method

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Abstract: ***Short term forecast of power consumption plays a critical role in optimal exploiting of power system. Economic performance and reliability of a network significantly depends to load forecast's accuracy. This forecast is used for load management and planning for unit commitment (UC) and it has especial complexity due to influence of multiple nonlinear relations between daily periodic variations and load consumption changes. 30-60 minutes forecasts are employed extensively in power distribution network. This study aims to perform short term forecasts by using linear auto regressive (AR) modelling. In this paper, collected data from a 63 kV distribution station is modelled by a aforementioned method. It is demonstrated that AR method can model data properly using auto correlation functions residual error and sum of squares criteria. Since data is non-stationary, performance of auto regressive integrated moving average (ARIMA) is investigated and optimal rank of model and the best data length to perform modelling are presented. Regarding to forecasts, appropriate model's rank for AR and ARIMA are 20 and (1,1,0) respectively. In AR model forecast error is ±10% which is equal to 38.1 and in ARIMA method forecast mse is ±1.21% and equals to 0.7277 and mse value for neural network method is 0.952 that totally ARIMA method shows better performance than the other.***

Keywords: **forecast; short term; data; AR; ARIMA; Neural Networks**

I. Introduction

Short term forecast has many applications including shifting loads between lines, frequency control, electricity rubbery, participating in forecast, economic dispatch etc. So far several methods for short term load forecast are proposed including neural network, fuzzy logic, expert system, similar days etc.

Recently in advanced countries smart electricity meters are replacing traditional electricity meters. In Iran also the electricity meters are being replaced according to FAHAM[1] program aiming to providing a context for improving consumption pattern, load management by network beneficiary in normal and emergency conditions, reducing intervention and human error in reading and billing, and to improve collecting debts.

An ability of smart electricity meters is future load forecast and in this study we consider short term forecast. In this thesis we emphasis on AR modelling through which we forecast power consumption for next 30 minutes or next hour. Since data is not stationary, we use ARIMA method and finally we compare it with neural network method.

The remainder of this paper is organized as follows. In Section 2 we present time scales for load forecast. A review on short term load forecast methods is presented in section 3. Section 4 introduces AR method. ARIMA method is presented in section 5. Section 6 compares these methods with neural network method. Finally, section 7 concludes the paper.

II. Time Scales for Load Forecast

From time scale viewpoint, load forecast is divided into four groups:

1) Very short-term forecast (few minutes to one hour intervals)
2) Short-term forecast (one hour to few days' intervals which this paper focuses on it)
3) Medium-term forecast (one mount to few years' intervals)
4) Long-term forecast (few years to few decades' intervals)

III. A Review on Short-term Load Forecast Methods

1) Fuzzy systems

Figure (1) depicts MISO array of a multi input-multi output fuzzy system which is composed of four main parts: Fuzzy suppliers, databases, inference engine, and non-phase [1].

[1] Persian abbreviation for National smart metering program

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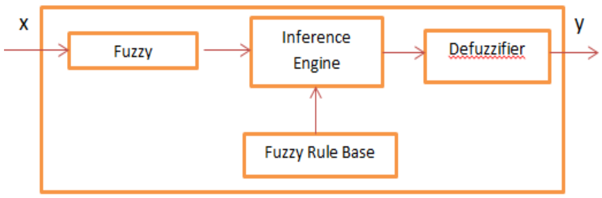

Figure1. Primary array of a fuzzy system

3) Expert System

Expert systems are new methods that result from two recent decades' advances in artificial intelligence. Briefly expert system is a computer program that is capable of running as unique expert. It means expert system is able to ratiocinate, to explain and to develop its knowledge base by receiving new information. In this method load forecast is performed using the knowledge related to load forecast of experts in respective technique [2].

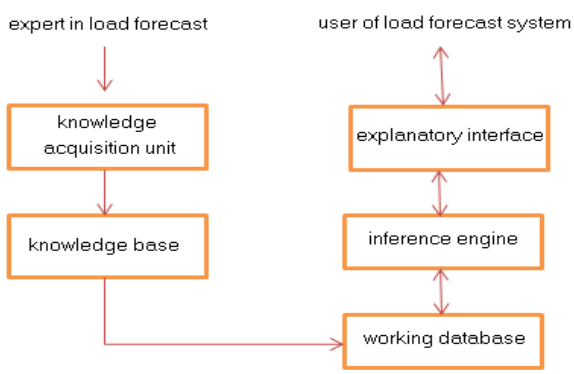

Figure2. Block diagram of an expert system

3) Neural Networks

Neural network is traditional method to load forecast using statistical results. In recent years several new methods are presented based on artificial intelligence. The purpose of artificial intelligence is to use computers not just as a calculator but also to train it with data regarding to load changes due to different past conditions and to find proper patterns and to forecast based on those patterns. Neural network efficiently forecasts loads.

4) Random Time Series Method

This is most usual method for forecast and it is yet applied to short term load forecast in power industry. Time series theory is described in different sources and there are many papers published about load forecast using this method. Synoptically load series y(t) are output of a linear filter that its input is random series a(t) usually called white noise. This model is depicted in figure 3 [3].

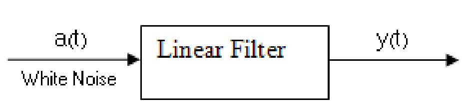

Figure3. Time series modelling for load forecast

According to linear filter's characterization, different models are classified into four groups:

1) Auto Regressive Method (AR)
2) Moving Average Method (MA)
3) Auto Regressive Moving Average Method (ARMA)
4) Auto Regressive Integrated Moving Average Method (ARIMA)

In this study we only use AR and ARIMA method.

4.1) Auto Regressive Method (AR)

In auto regressive method (AR) current value of time series y(t) is described linearly based on its previous values (y(t-1) and y(t-2)) and random noise a(t). The degree of this process depends on primitive value to which y(t) referred. In a process, AR method's degree is P (AR (P)) and is written as:

$$y(t) = \varphi_1 y(t-1) + \varphi_2 y(t-2) + \dots + \varphi_p y(t-p) + \varepsilon(t) \qquad (1)$$

Introducing L operator as y(t-1)=Ly(t), we have y(t-m)=Ly(t) and the equation is written as:

$$\varphi(L).y(t) = \varepsilon(t) \qquad (2)$$

4.2) Auto Regressive Integrated Moving Average Method (ARIMA)

Above defined time series like AR, MA, and ARMA are referred as stationary methods that means average series of each process and covariance between observations doesn't change with time. If the process is non-stationary, then first it should be converted to stationary process. This can be done for time series with non-stationary averages, but through a different method by introducing operator D. time series different from degree 1 can be written as follow using definition B:

$$Dy(t) = y(t) - y(t-1) = (1-L)y(1) \qquad (3)$$

Similarly, time series with difference degree of d are converted to:

$$D\,dy(t) = (1-L)^d\, y(t) \qquad (4)$$

Different stationary time series can be modelled as AR, MA, or ARMA and consequently give ARI, IMA, or ARIMA time series. Respective model for series which need to d times derivations and have p and q degrees as parameters of AR and MA (i.e. ARIMA (p ‹d ‹q)), is written as: [4]

$$\Phi(L).D^d\, y(t) = \theta(L).a(t) \qquad (5)$$

$\Theta(L), D^d, \Phi(L)$ Are defined previously.

4) Analysing by AR Method

Temperature and weather influence on power consumption. As figure 4 shows, power consumption increases gradually

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during July and August and as temperature declines, power consumption decreases.

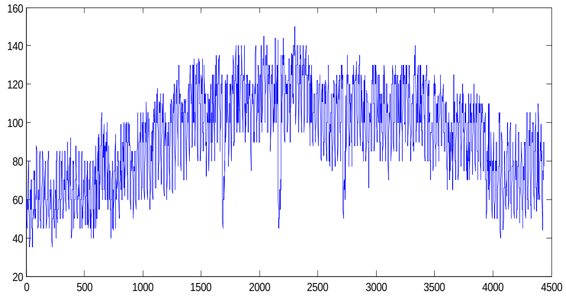

Figure4. Power load during March 21st to September 22th 2015

In AR method, data should be stationary. Since our data is obtained during spring and summer, so data is not stationary and we use sorter rang data for carrying out forecast and modelling so that it can be assumed stationary.

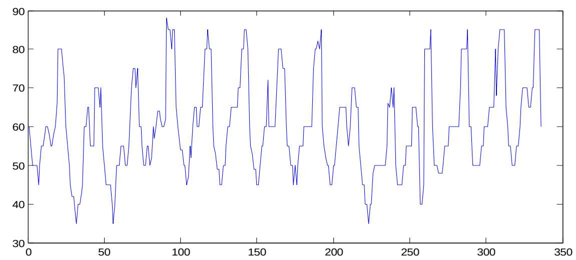

Figure5. Two weeks' data (each day and night, 24 samples)

4.1) Determining Proper Modelling order

Now we obtain proper modelling order considering mean squares error. For instance, for model of order M=10 and M=20, we have MSE=48 and MSE=38.1 respectively.

$$\text{Coefficient of variation} = \frac{\sqrt{\text{variance}}}{\text{mean}} = \frac{38.1}{70} = 10\%$$

Error rate of this forecast is ±10%.

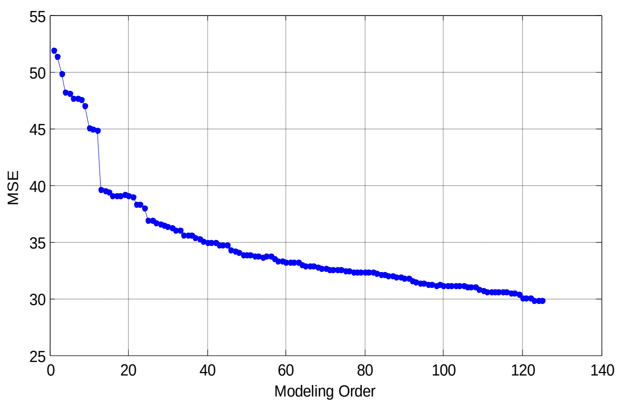

Figure6. Mean square error as a function of modelling order

Figure 6 shows that as modelling order increases, MSE value decreases and this downswing is not steady. After some order, MSE doesn't change significantly and then order complexity is important. Increasing the order larger than 20 just adds to complexity and doesn't increase accuracy.

4.2) Forecast by AR method

Regarding to determining proper modelling order, we forecast with the order 20.

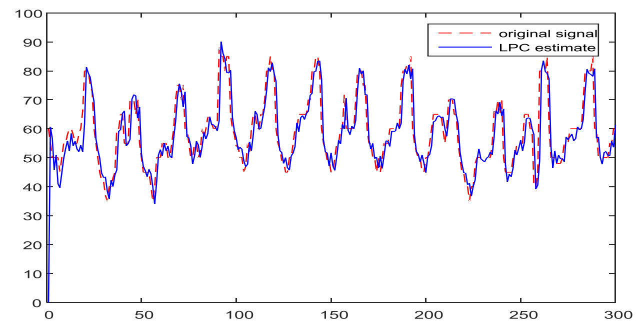

Figure7. Diagrams of original and predicted signal

In figure 7 diagrams of original data is shown in red and forecast diagram is depicted in blue. As it can be seen, forecasted diagram almost matches original diagram. We calculate the difference between two signals (i.e. error signal), if the noise is white noise then this model performs well.

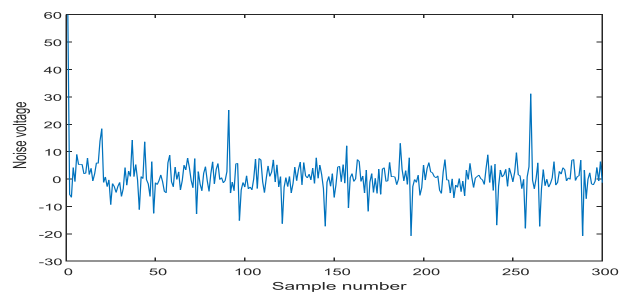

Figure8. Error signal (MSE=38.1)

To ensure that error signal noise in figure 8 is a white noise, we calculate noise correlation coefficients from error signal. If correlation function is an impulse function, it means the noise is a white noise.

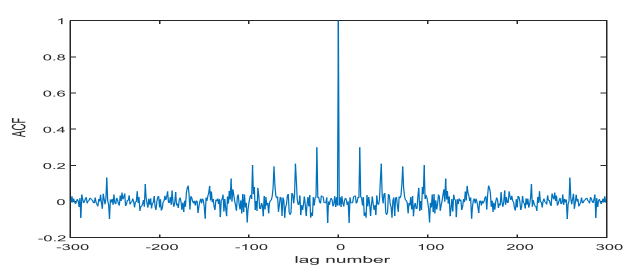

Figure9. Estimation of correlation function

Noise correlation function is drawn in figure 9 and it is an impulse function. Therefore, error signal is a white noise signal and our model performs well.

5) Analyzing by ARIMA Method

Since data is influenced by season variation and is not stationary, we should use convert it to stationary data using different models. Therefore, we consider a short length of data for forecast and modeling. ARIMA model has three parameters: p, d, and q.

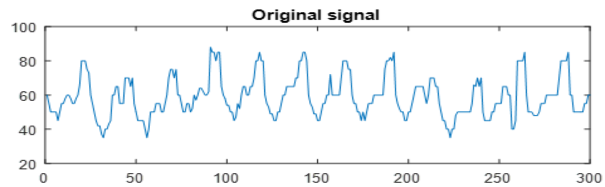

Figure10. First 300 data samples

As can be seen in figure 10, we consider first 300 data samples and assume d=1 (d can have any value, signal should be d times derived to convert to white noise) and then as its depicted in figure 11, after one-time derivation signal converts to white noise.

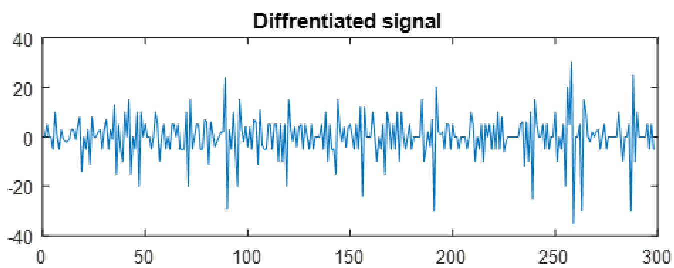

Figure11. Differentiating data

Then we draw autocorrelation function and partial autocorrelation function diagrams to find p and q values.

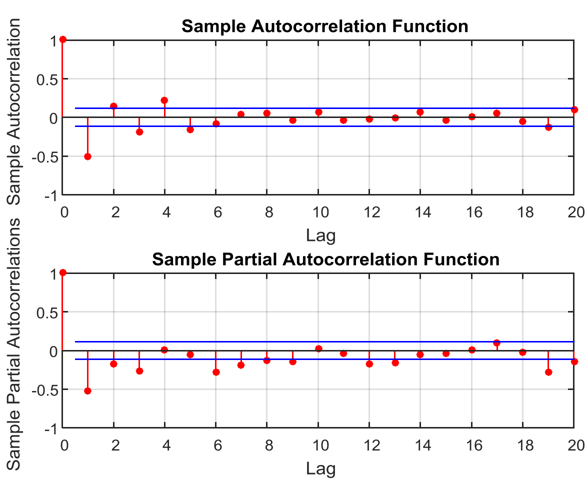

Figure12. Autocorrelation function and partial autocorrelation functions diagrams

According to autocorrelation function and partial autocorrelation function diagrams drawn in figure 12, we select p coefficients. On the other hand, as autocorrelation diagram declines exponentially, we conclude that data is stationary and as you can see in autocorrelation diagram, after 1, coefficients converge to zero. Therefore, p=1. In this study we consider that q is equal to zero [5].

5.1) Forecast by ARIMA Method

We use ARIMA model to forecast. As it can be seen from figure 12, best modeling order is (1,1,0).

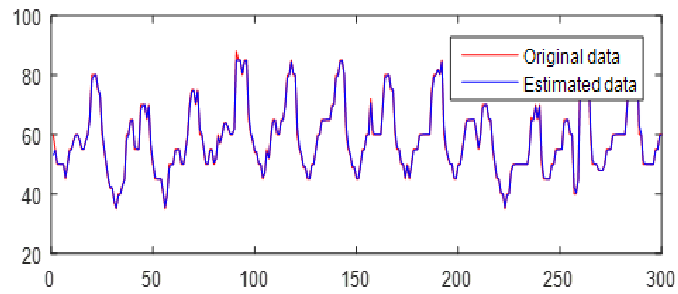

Figure13. Original diagram and predicted diagram by ARIMA model

As you can see in figure 13, forecasted diagram has very little difference with the original diagram.

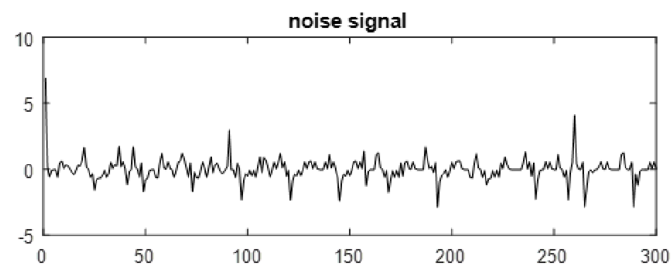

Figure14. Difference between original and forecasted signals

Figure 14 shows that the difference between original and forecasted signals is very low. Therefore, our model performs well and its mse value is 0.7277.

$$\text{coefficient of variation} = \frac{\sqrt{\text{variance}}}{\text{mean}} = \frac{\sqrt{0.7277}}{70} = \pm 1.21\%$$

Forecasted error value by this method is $\pm 1.21\%$.

6) Comparing Results with Neural Network Method

To compare with neural network method, we forecast using existing data [6].

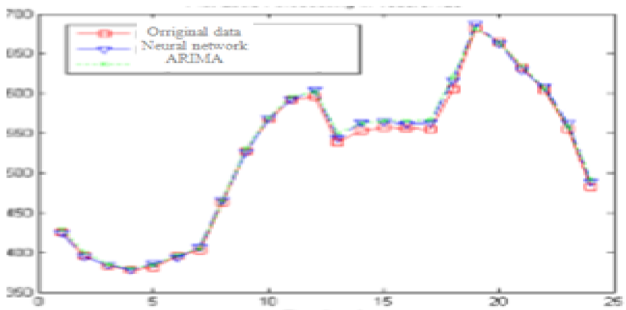

Figure5. Comparing neural network method with ARIMA method

As can see in figure 15, diagrams of neural network method and ARIMA method are close together.

Table1. MSE value for ARIMA and Neural Network methods

Methods	MSE
ARIMA	0.7277
Neural Network	0.952

Comparing MSE values show that ARIMA outperforms neural network and has less errors.

IV. Conclusion

Short term forecast of power consumption for 30-60 minutes plays a critical role in optimal exploiting of power system. This research aims to perform short term forecast of power consumption using liner autoregressive modelling. In this paper collected data form Amir Kabir 63 kV dispatch station feeder No 3 of Kashan is modelled by AR method.

Since we just have data of two seasons and data is non-stationary, then we also use ARIMA method. Since both data and ARIMA method are non-stationary, forecasted signal is more accurate than of AR method. Best modelling order for AR method is 20 and for ARIMA method is (1,1,0). Error rate for AR and ARIMA methods are $\pm 10\%$ and $\pm 1.21\%$ respectively. Mean square mse value for AR and ARIMA methods are 38.1 and 0.7277 respectively. Prediction in both methods was carried out well. Comparing with Neural Network method that its mean square mse value is 0.952, we conclude that AR method outperforms Neural Network method and has smaller Error.

V. References

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