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Study & Development of Short Term Load Forecasting Models Using Stochastic Time Series Analysis

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Abstract:- The present paper involves the study & development of various time series models for Short Term Electrical Load Forecasting Using Time series approach. Given one year load data, first six months data is used for model development and then these models can be tested using next six months data. Different models for Short term load forecasting using time series approach such as Autoregressive (AR) models, Autoregressive Moving Average (ARMA) models, Autoregressive Integrated Moving Average (ARIMA) models and are developed. The methodology involves Initial Model Development Phase, Parameter Tuning Phase and Forecasting Phase.

Index Terms:- Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), model. Autocorrelation function (acf), autocorrelation function (pacf).

I. INTRODUCTION

Load forecasting has always been the essential part of an efficient power system planning and operation.

Power system expansion planning starts with a forecast of anticipated future load requirement. Estimates of both demand and energy required are crucial to effective system planning. Demand forecasts are used to determine the capacity of generation, transmission, and distribution system additions and energy forecasts determine the type of facilities required. Load forecasts are also used to establish procurement policies for construction capital where for sound operation the balance must be maintained in the use of dept and equity capital. Further energy forecasts are used to determine future fuel requirement and if necessary when fuel prices soar rate relief to maintain an adequate rate of return. In summary good forecast reflecting current and future trends tempered with good judgment is the key to planning indeed to financial success. Short-term load forecasting activities include forecasting the daily load curve as a series of 24 hourly forecasted loads.

Various techniques for power system load forecasting have been proposed in the last few decades. Load forecasting with time leads, from a few minutes to several days helps the system operator to efficiently schedule spinning reverse allocation, can provide information which is able to be used for possible energy interchange with other utilities. In addition to these economical reasons it is also useful for system security. The idea of time series approach is based on the understanding that a load pattern is nothing more than a time series signal with known seasonal, weekly and daily predictions. These predictions give a rough prediction of the load at the given season, day of the week and time of the day. Time series forecasting methods are based on the premises that we can predict future performance of a measure simply by analyzing its past results. These methods identify a pattern in the historical data and use that pattern to extrapolate future values. Past results can, in fact, be very reliable predictor for a short period into the future.

In this context, the development of an accurate, fast and robust short term load forecasting methodology is of importance to both the utility and its customers. An attempt has been made for studying Short Term Hourly Load Forecasting using time series approach by developing Autoregressive (AR), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA) models.

The power load demand is sensitive to weather variables. The effect of the weather variables such as Temperature, Humidity, Wind speed and Cloud coverage on the load demand can be considered in the development of these models for short term load forecasting using time series approach. Also non weather variables can be taken into consideration. Also while developing these models Holidays and special events can be separately considered.

II. TIME SERIES MODELS IN LOAD FORECASTING:

This method appears to be the most popular approach that has been applied and is still being applied in electric power industry for short term load forecasting.

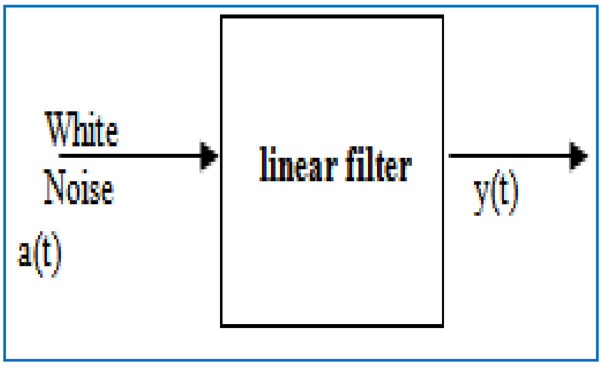

Fig2(a). Load time series modeling

The power system load is assumed to be time dependent evolving according to a probabilistic law. It is a common practice to employ a white noise sequences **a(t)** as input to a linear filter whose output **y(t)** is the power system load. This is an adequate model for predicting the load time series. The noise input is assumed normally distributed with zero mean and some variance **σt**. Time series models can use non weather as well as weather variables. These models are most widely used for load forecasting.

2.1 The Autoregressive (AR) process:

In the Autoregressive process, the current value of the time series y (t) is expressed linearly in terms of its 'p' previous values [y (t-1), y (t-2)……. y (t-p)] and a random noise a (t).
For an autoregressive process of order 'p' i.e. AR (p), the model can be written as,

$$\mathbf{y\ (t) = Ø_1\ y\ (t-1) + \ldots\ldots.. + Ø_p\ y\ (t-p) + a\ (t)} \qquad \text{----------- } \mathbf{1}$$

In order to write this in more convenient form the following operators are introduced.

$B\ y\ (t) = y\ (t-1);$

$B^m\ y\ (t) = y\ (t-m);$

And

$$\mathbf{A\ (q) = 1- Ø_1 B^1 – Ø_2 B^2 - \ldots\ldots\ldots\ldots\ldots - Ø_p B^p\ ;}$$

So equation **1** can be written as,

$$\mathbf{A\ (q)\ y\ (t) = a\ (t)} \qquad \text{------------ } \mathbf{2}$$

Where,

y (t) – output or the load at time't'
B - Backshift operator
A (q) – delay polynomial
$Ø_1 \ldots Ø_p$ – coefficients of delay
Polynomial
p – Order of the delay polynomial
a (t) – random noise

2.2 The Moving Average (MA) Process:

In the moving average process, the current value of the time series y (t) is expressed linearly in terms of current and previous 'q' values of a white noise series [a (t), a (t-1)………a(t-q)].The noise series is constructed from the forecast errors or residuals when load observations become available.
For a moving average of order 'q' i.e. MA (q), the model can be written as,

$$\mathbf{y\ (t) = a\ (t) + θ_1\ a\ (t-1) + \ldots\ldots\ldots + θ_q\ a\ (t-q)}$$

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A similar application of backshift operator on white noise series would allow equation **3** to be written as,

$$\mathbf{y\ (t) = C\ (q)\ a\ (t)} \qquad \text{------------- } \mathbf{4}$$

And

$$\mathbf{C\ (q) = 1 + \theta_1 B^1 + \theta_2 B^2 + \ldots\ldots\ldots + \theta_q B^q\ ;}$$

Where,

y (t) – output or the load at time‘t’
B - Backshift operator
C (q) – delay polynomial
$\theta_1 \ldots\ldots \theta_q$ - coefficients of delay polynomial
q – Order of the delay polynomial
a (t) – random noise

2.3 The Autoregressive Moving-Average (ARMA) Process:

In the autoregressive moving average process, the current value of the time series y (t) is expressed linearly in terms of its previous ‘p’ values [y (t-1), y (t-2)……..y (t-p)] and in terms of current and previous ‘q’ values of a white noise [a (t), a (t-1)…....a (t-q)].

For an autoregressive moving average process of order ‘p’ and ‘q’ i.e. ARMA (p, q), the model is written as,

$$\mathbf{y\ (t) = Ø_1\ y\ (t-1) + \ldots\ldots\ldots + Ø_p\ y\ (t-p) + a\ (t) + \theta_1 a(t-1) + \ldots\ldots + \theta_q a(t-q)} \qquad \text{-----------------} \ \mathbf{5}$$

By using the backshift operator defined earlier equation **5** can be written as,

$$\mathbf{A\ (q)\ y\ (t) = C\ (q)\ a\ (t)} \qquad \text{------------- } \mathbf{6}$$

Where,

A (q) & C (q) – delay polynomials
p & q – Orders of the delay polynomials
A (q) & C (q) respectively.

2.4 The Autoregressive Integrated Moving-Average (ARIMA) Process:

The time series defined previously as an AR, MA or as an ARMA process is called a stationary process. This means that the mean of the series of any of these processes and the covariances among its observations do not change with time. If the process is non-stationary, transformation of the series to a stationary process has to be performed first. This can be achieved, for the time series that are non-stationary in mean, by a differencing process.

By introducing the ▼ operator, a differenced time series of order 1 can be written as,

▼y (t) = y (t) – y (t-1) = (1-B) y (t); using the definition of backshift operator, B. Consequently, an order ‘d’ differenced time series is written as,

$▼^d$ y (t) = $(1\text{-B})^d$ y (t);

The differenced stationary series can be modeled as an AR, MA, or an ARMA to yield an ARIMA time series processes.

For a series that needs to be differenced ‘d’ times and has the orders ‘p’ and ‘q’ for AR and MA components i.e. ARIMA (p,d,q) model is written as,

$$\mathbf{A\ (q)\ ▼^d\ y\ (t) = C\ (q)\ a\ (t)} \qquad \text{-----------------} \ \mathbf{7}$$

Where A (q) , $▼^d$, and C (q) have been defined earlier.

III. MAIN GOALS OF TIME SERIES ANALYSIS:

There are two main goals of time series analysis:

- Identifying the nature of the phenomenon represented by the sequence of observations
- Forecasting or predicting the future values of the time series.

Both of these goals require that the pattern of the observed time series data is identified and more or less formally described. Once the pattern is established, we can interpret and integrate it with other data. In time series analysis it is assumed that the data consists of a systematic pattern and a random noise which usually makes the pattern difficult to identify. Most time series analysis techniques involve some form of filtering out noise in order to make the pattern more salient.

IV. TWO GENERAL ASPECTS OF TIME SERIES PATTERNS

Most time series patterns can be described in terms of two basic classes of components:

- **Trend**
- **Seasonality**

The former represents a general systematic linear or (most often) nonlinear component that changes over time and does not repeat or at least does not repeat within the time range captured by our data. The latter may have formally similar nature; however it repeats itself in systematic intervals over time.

There are no proven “automatic” techniques to identify trend components in the time series data: however, as long as the trend is monotonous (consistently increasing or decreasing) that part of data analysis is typically not very difficult. If the time series data contain considerable error, then the first step in the process of trend identification is smoothing. Smoothing always involves some form of local averaging of data such that nonsystematic components of individual observations cancel each other out.

Seasonal dependency (seasonality) is another general component of the time series pattern. It is formally defined as correlation dependency of order ‘k’ between each ‘i^{th}’ element of the series and the $(i\text{-}k)^{th}$ element and measured by autocorrelation :‘k’ is usually called the lag. If the measurement error is not too large, seasonality can be visually identified in the series as a pattern that repeats every ‘k’ elements.

4.1 Autocorrelation Function (Acf):

Autocorrelation is a mathematical tool used for analyzing functions or series of values. Informally, it the measure of how well a signal matches a time-shifted version of itself, as a function of the amount of time shift. Autocorrelation is useful in finding repeating patterns in a signal. The autocorrelation function describes inherent correlation between observations of a time series which are separated in time by some lag ‘k’.

It is given by,

$$\rho_k = \O_1 \rho_{k-1} + \ldots\ldots\ldots\ldots\ldots + \O_p \rho_{k-p} \quad ;$$

Where,

$$\rho_k = \gamma_k / \gamma_o \, ;$$

$$\gamma_k = E\,[\, y\,(t)\;\; y\,(t+k)\,]\, ;$$

If the function ρ is well defined its value must lie in the range [-1 1], with 1 indicating perfect correlation and -1 indicating perfect anticorrelation.

Seasonal patterns of time series can be examined via correlograms. The Autocorrelation correlograms displays graphically and numerically the autocorrelation function, i.e. serial correlation coefficients for consecutive lags in a specified range of lags.

4.2 Partial Autocorrelation Function (Pacf):

Another useful method to examine serial dependencies is to examine the partial autocorrelation function. Here correlations with all the elements within the lag are partialled out. If the lag of 1 is specified (i.e. there are no intermediate elements within the lag), then the partial autocorrelation is equivalent to autocorrelation. In the sense, the partial autocorrelation provides a clearer picture of serial dependencies for individual lags.

Serial dependency for a particular lag of ‘k’ can be removed by differencing the series, i.e. converting each i^{th} element of the series into its difference from the $(i\text{-}k)^{th}$ element. There are two major reasons for such transformations. First; we can identify the hidden nature of seasonal dependencies in the series. As mentioned earlier, autocorrelations for consecutive lags are interdependent. Therefore, removing some of the autocorrelations will change other autocorrelations and it may eliminate them or it may make some other seasonalities apparent. The other reason for removing seasonal dependencies is to make the time series stationary which is necessary for ARIMA model.

Hence techniques for preliminary identification of time series models rely on the analysis of autocorrelation and partial autocorrelation function. These methods are very systematic and are extremely helpful in the determination of model order, in preliminary estimation of model parameters and model refinement.

V. MODEL DEVELOPMENT

To implement the proposed methodology, a statistical study of load demand has to be carried out for short term load forecasting. This statistical study includes daily hourly loads for one year. The Autoregressive (AR), Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) models can be developed using time series approach for short term load forecasting on first six months data and these models are used for forecasting on the next six months data in order to provide comparisons with the forecasts.

Development of these models comprises of three major computational steps:

- Initial model development phase
- Parameter tuning phase
- Forecasting phase

In initial model development phase techniques for preliminary identification of time series models rely on the analysis of the autocorrelation function (acf) and partial autocorrelation function (pacf).These methods are very systematic and are extremely helpful in the determination of model order, preliminary estimation of model parameters, diagnostic checking and model refinement. For an Autoregressive process, partial autocorrelation function (pacf) is useful in determination of the order of the AR model & autocorrelation function (acf) for Moving Average (MA) process is useful in determining the orders of the MA model.

In Parameter tuning phase, all the various proposed models calculates the coefficients of the delay polynomials using gradient based efficient estimation method i.e. Least Square method so that the energy of the noise term is minimized. Minimum forecasting error is viewed as the principal criterion in determining both model orders and its parameters.

Once the parameters of the models have been estimated, they can be substituted in the various model equations discussed earlier & the adequacy of the model has to be tested known as the diagnostic checking. This testing procedure is performed so as to check if the parameter estimate is significantly different from zero & if the models pass the above test, they can be used for forecasting.

VI. CONCLUSION

Hence study of various time series models & model developments are discussed .Hence an attempt has been successfully made for short term load forecasting using time series approach by studying & by knowing how to develop Autoregressive (AR), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA) models.

Three computational steps for time series model development, initial model development phase, parameter tuning phase & forecasting phase are also discussed. The methodology identifies the proper initial model orders, proper selection of input variables and involves estimation of model parameters. Then these models are used to forecast the future hourly load.

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