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# Load Prediction Using Curve Fitting Algorithm

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***ABSTRACT:*** *In this paper, a method for forecast of electricity load with is being proposed using Curve Fitting Algorithm. I analyze the problem domain and choose the most adequate set of attributes in my proposed work. To obtain the best performance in prediction, I follow an experimental approach analyzing the entire dataset and apply curve fitting algorithm. Load forecasting is vitally important for the electric industry in the deregulated economy. It has many applications including energy purchasing and generation, load switching, contract evaluation, and infrastructure development. A large variety of mathematical methods have been developed for load forecasting.*

***INDEX TERMS****:* *Load, forecasting, Curve Fitting.*

## I. INTRODUCTION

Accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development. Load forecasts are extremely important for energy suppliers, ISOs, financial institutions, and other participants in electric energy generation, transmission, distribution, and markets.In this paper, I present an accurate model to forecast electricity load with Curve fitting algorithm. I analyze the problem domain and choose the most adequate set of attributes in my model. To obtain the best performance in prediction for power system planning. My study is based on one year data from jan to dec 2012 from shahpura area Mp Discom total load 70 MW (Commercial , Domestic) At the end, I used my curve fitting algorithm to study effect of different weather parameter (temperature, humidity)on Load Forecast for power system planning.Load forecasting plays an important role in power system planning, operation & control. Forecasting means estimating active load at various load buses a head of actual load occurrence.Load forecasting is broadly classified as
1.Very short term-a few second to several minutes.
2.Short term-half an hour to a few hours.
3.Medium term-afew days to a few weeks.
4.Long term-a few months to a few years.

FACTOR EFFECTING LOAD FORECASTING
(a).Time factor such as
- Hours of the day (day night)
- Day of the week (week day/weekend day)
- Time of year (season)

(b).Weather condition (temperature & humidity)
(c).Class of consumers (Residential, Domestic, Commercial, Industrial, Municipality, Agricultural)
(d).Special events(TV Programmers, Public Holidays ,etc).
(e).Population
(f).Economic indicators (per capita income Gross National product (GNP), Gross Domestic Product (GDP),etc).
(g).Trends in using new technologies.
(h).Electricity price.

LOAD FORECASTING TECHNIQUES ARE CLASSIFIED AS FOLLOWS; . Multiple regressions;
. Exponential smoothing;
. Iterative reweighted least-squares;
. Adaptive load forecasting;
. Stochastic time series;

. ARMAX models based on genetic algorithms;
. Fuzzy logic;
. Neural networks;and
. Curve fitting.

## II. MULTIPLE REGRESSIONS

Multiple regression analysis for load forecasting uses the technique of weighted least-square s estimation. Based on this analysis, the statistical relationship between Total load and weather conditions as well as the day type influences can be calculated. The regression coefficients are computed by an equally or exponentially Weighted least-squares estimation using the defined Amount of historical data. The data analysis program allows the selection of the polynomial degree of influence of the variables from 1 to5. In most cases, linear dependency gives the best results.

## III. EXPONENTIAL SMOOTHING

Exponential smoothing is one of the classical methods used for load forecasting. The approach is first to model the load based on previous data, then to use this model to predict the future load. This technique has been shown to compare favorably with conventional methods of load forecasting.

## IV. ITERATIVE REWEIGHTED LEAST-SQUARES

A procedure referred to as the iteratively reweighted least-squares to identify the model order and parameters. The method uses an operator that controls one variable at a time. An optimal starting point is determined using the operator.This method utilizes the autocorrelation function and the partial autocorrelation function of the resulting differenced past load data in identifying a suboptimal model of the load dynamics. The weighting function, the tuning constants and the weighted sum of the squared residuals form a three-way decision variable in identifying an optimal model and the subsequent parameter estimates.

## V. ADAPTIVE LOAD FORECASTING

In this context, forecasting is adaptive in the sense that the model parameters are automatically corrected to keep track of the changing load conditions. Adaptive load forecasting can be used as an on-line software package in the utilities control system. Regression analysis based on the Kalman filter theory is used. The Kalman filter normally uses the current prediction error and the current weather data acquisition programs to estimate the next state vector. The total historical data set is analysed to determine the state vector, not only the most recent measured load and weather data. This mode of operation allows switching between multiple and adaptive regression analysis. The model used is the same as the one used in the multiple regression section.

## VI. STOCHASTIC TIME SERIES

It has been observed that unique patterns of energy and demand pertaining to fast growing areas are difficult to analyse and predict by direct application of time-series methods. However, these methods appear to be among the most popular approaches that have been applied and are still being applied to STLF. Using the time-series approach, a model is first developed based on the previous data, then future load is predicted based on this model. The remainder of this section discusses some of the time series models used for load forecasting.

## VII. ARMAX MODEL

ARIMAX models for load forecasting used evolutionary programming (EP) approach to identify the ARMAX model parameters for one day to one week ahead hourly load demand forecast. Evolutionary programming is a method for simulating evolution and constitutes a stochastic optimization algorithm proposed a fuzzy autoregressive moving average with exogenous input variables (FARMAX) for one day ahead hourly load forecasts.

## VIII. FUZZY LOGIC

It is well known that a fuzzy logic system with centroid defuzzification can identify and approximate any unknown dynamic system (here load) on the compact set to arbitrary accuracy observed that a fuzzy logic system has great capability in drawing similarities from huge data. Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. An input under Boolean logic takes on a truth value of “0” or “1”. Under fuzzy logic an input has associated with it a certain qualitative ranges. For instance a transformer load may be “low”, “medium” and “high”. Fuzzy logic allows one to (logically) deduce outputs from fuzzy inputs. In this sense fuzzy logic is one of a number of techniques for mapping inputs to outputs (i.e. curve fitting).

Among the advantages of fuzzy logic are the absence of a need for a mathematical model mapping inputs to outputs and the absence of a need for precise (or even noise free) inputs. With such generic conditioning rules, properly designed fuzzy logic systems can be very robust when used for forecasting. Of course in many situations an exact output (e.g. the precise 12PM load) is needed. After the logical processing of fuzzy inputs, a "defuzzification" process can be used to produce such precise outputs describe applications of fuzzy logic to electric load forecasting.

## IX. NEURAL NETWORK

Neural networks (NN) or artificial neural networks (ANN) have very wide applications because of their ability to learn. According to neural networks offer the potential to overcome the reliance on a functional form of a forecasting model. There are many types of neural networks: multilayer perceptrons network, self-organizing network, etc.There are multiple hidden layers in the network. In each hidden layer there are many neurons. Inputs are multiplied by weights !*i* , and are added to a threshold to form an inner product number called the net function. The net function NET used for example, is put through the activation function *y*, to produce the unit's final output, *y*…(*NET*). The use of artificial neural networks (ANN or simply NN) has been a widely studied electric load forecasting technique. Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting.

## X. CURVE FITTING

Curve fitting or function approximation is the process of fitting to series of data points with curves. Developed package uses the curve fitting (CF) technique to obtain a forecasting polynomial curve based on criterion of minimum quadratic error using the peaks of loads. Curve Fitting Toolbox™ provides an app and functions for fitting curves and surfaces to data. The toolbox lets you perform exploratory data analysis, preprocess and post-process data, compare candidate models, and remove outliers. You can conduct regression analysis using the library of linear and nonlinear models provided or specify your own custom equations. The library provides optimized solver parameters and starting conditions to improve the quality of your fits. The toolbox also supports nonparametric modeling techniques, such as splines,interpolation, and smoothing. After creating a fit, you can apply a variety of post-processing methods for plotting, interpolation, and extrapolation; estimating confidence intervals; and calculating integrals and derivatives. Curve fitting is the process of constructing a curve, or mathematical function that has the best fit to a series of data points, possibly subject to constraints. Curve fitting can involve either interpolation, where an exact fit to the data is required, or smoothing, in which a "smooth" function is constructed that approximately fits the data. A related topic is regression analysis, which focuses more on questions of statistical inference such as how much uncertainty is present in a curve that is fit to data observed with random errors. Fitted curves can be used as an aid for data visualization, to infer values of a function where no data are available, and to summarize the relationships among two or more variables. Extrapolation refers to the use of a fitted curve beyond the range of the observed data, and is subject to a degree of uncertainty since it may reflect the method used to construct the curve as much as it reflects the observed data.
A multiplicative model of the following
form was developed

*f(t)=(a0+a1*cos(w*x)+b1*sin(w*x)+a2*cos(2*w*x)+b2*sin(2*w*x)………*

*where ao,a2,b1,b2=past loads*
*x=step size from 1 to 100*
*w=startpoint(w1=0.394,w2=0.245,w3=0.989,w4=0.8125,w5=0.124,w7=0.185,w8=0.508)*

In the curve fitting tool, select 2 Fourier from the model type.The toolbox calculates optimized start points for Fourier series model, based on the current data set.Y=a0+a1*cos(x*w)+b1*sin(x*w)+a2*cos(2*x*w)+b*2*sin(2*x*w)………
Where ao=97.2,a1=92.3,a2=90.1,b1=87.3,b2=88.1

f(t)=(97.2+92.3*cos(0.394*1)+87.3*sin(0.394*1)+90.1*cos(2*0.394*1)+88.1*sin(2*0.394)……..

Automatically generating MATLAB code to capture work and automate tasks.

**A. Fitting other curves to data points**

Other types of curves, such as conic sections (circular, elliptical, parabolic, and hyperbolic arcs) or trigonometric functions (such as sine and cosine), may also be used, in certain cases. For example, trajectories of objects under the influence of gravity follow a parabolic path, when air resistance is ignored. Hence, matching trajectory data points to a parabolic curve would make sense. Tides follow sinusoidal patterns, hence tidal data points should be matched to a sine Existing Work

Table 1 MP DISCOM SHAHPURA Area(Commercial & Domestic) from January to December 2012

| Month | Day | Hour | Power | Temperature |
|---|---|---|---|---|
| Jan-12 | 1 | 31*24 | 97.2 | 19.0000 |
| Feb-12 | 1 | 28*24 | 92.3 | 18.8500 |
| Mar-12 | 1 | 31*24 | 90.1 | 21.0316 |
| Apr-12 | 1 | 30*24 | 87.3 | 24.0650 |
| May-12 | 1 | 31*24 | 88.1 | 26.2350 |
| Jun-12 | 1 | 30*24 | 88.4 | 25.5675 |
| Jul-12 | 1 | 31*24 | 93.2 | 23.0000 |
| Aug-12 | 1 | 31*24 | 91.1 | 22.1000 |
| Sep-12 | 1 | 30*24 | 83.2 | 22.0555 |
| Oct-12 | 1 | 31*24 | 85.1 | 19.3000 |
| Nov-12 | 1 | 30*24 | 94.3 | 19.0000 |
| Dec-12 | 1 | 31*24 | 99.0 | 18.8500 |

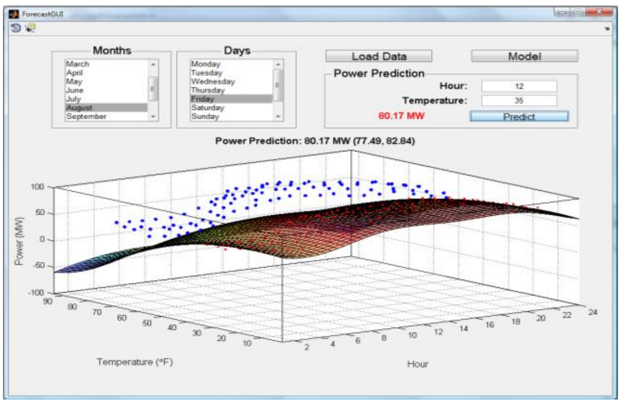


Fig 1 Output of Predicted electrical load

Fig.1 Illustrate the hourly load curve aug 2013 the fig shows daily load variations; the load behavior for morning /afternoon/evening at three different time has a same pattern but small random variation from varying weather parameter such as only temperature may 2013,aug 2013,dec 2013 comparing may/aug/dec three seasons summer/ fall/winter & the results were analyzed by using the curve fitting tool, select 2 fourier from the model type. The tool box calculates optimizes start points for fourier series model, based on the current data set. In jul 2013 peak fall seasons load during Friday 9 am 80.17 MW,12 am &17 pm …..is influenced by temperature and shows power profile in MW at 3 different time.

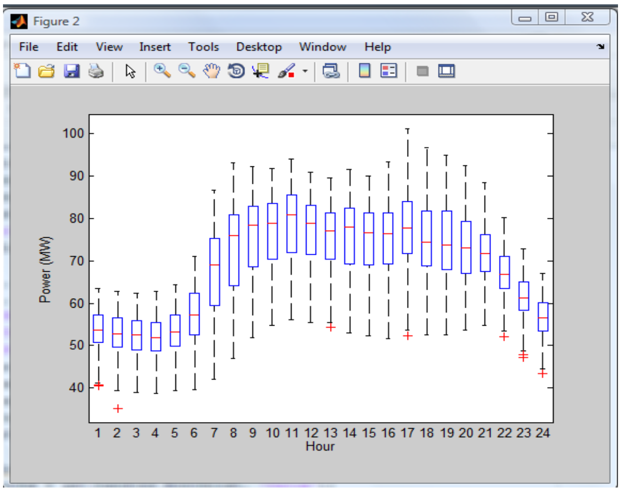


Fig 2 Output response of the daily load vs hours

Fig.2 Box plot illustrate the hourly load curve based on past data 2012 from jan to dec ,the load behavior for 24 hours has varying and different i.e at 17 pm shows maximum load profile this load profile shows that load is constant at morning time and at evening 17 pm load is increase.

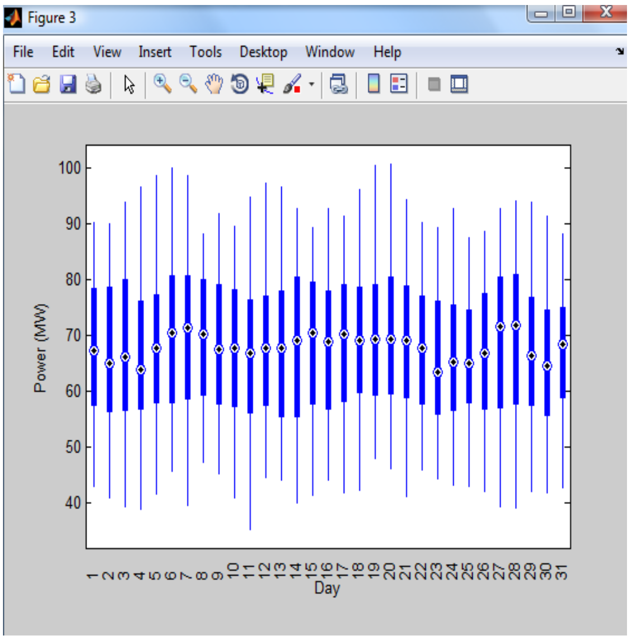


Fig 3 Output response of the month load vs power

Fig.3 Illustrate the general plot which is applicable for every month in this plot generally consider 31 days in month & power in MW is based on past load behavior.

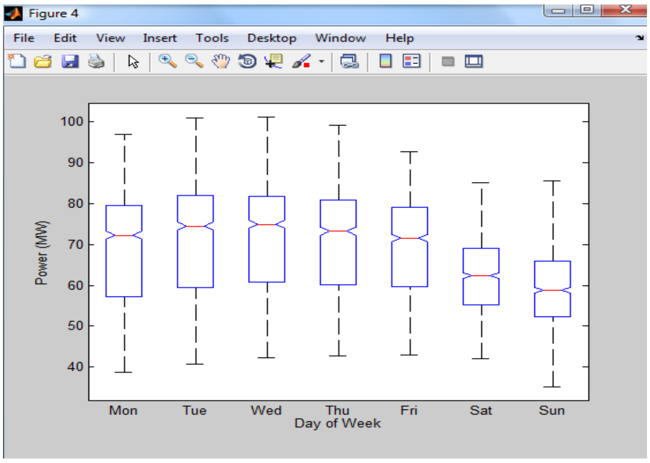


Fig 4 Output response of the weekly load vs power

Fig.4 The box plot shows the load bhaviour for week dyas(tue throug fri)has a same load pattern but small random pattern variation form varying weather condition etc.The weekday load pattern is different from Saturday, Sunday and Monday load patterns for example Monday load are effected by Sunday and Saturday loads and their patterns are similar.

## XI. CONCLUSION

Case studies for the proposed method were carried out for a hour/day/week/month forecasting electric loads using a historical utility data of MP DISCOM Shahpura area (commercial and domestic total load) .The result were obtained for three representative months in three seasons. These months are May,August & December 2013 for Summer,Fall & Winter respectively for different day of week and different time horizon at morning/afternoon/evening load profile and the results were analyzed by using curve fitting tool ,select 2 fourier series from the model type. The toolbox calculates optimized start points for 2 fourier series model, based on the 2013 current data set of adjusting the temperature only using the data for 3 latest hour/day/week/month for each load model.For example may/aug/dec 2013 the latest 24 hour data is predicted by using average of past load data. The model advances to predicted the future 24 hour loads on the basis of past data.

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