PROJECT REPORT

(Project Semester January – May 2012)

Determination of Investment opportunities for setting up a Gas based power plant in Punjab through Electricity Spot Price Forecasting and Load Dispatch Planning

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January – May, 2013
DECLARATION

We hereby declare that the project work **entitled “Determination of Investment opportunities for setting up a Gas based power plant in Punjab through Electricity Spot Price Forecasting and Load Dispatch Planning”** is an authentic record of our own work carried as per the requirements of six months project semester for the award of degree of B.E. Electrical Engineering, PEC University of Technology, Chandigarh, under the guidance of **Prof. Jagdish Kumar** during Jan to May, 2013.

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Certified that the above statement made by the students is correct to the best of my knowledge and belief.

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**Prof. Jagdish Kumar**
(Project Mentor)
ACKNOWLEDGEMENT

It has been an enriching experience for us to undertake Capstone Project at PEC UNIVERSITY OF TECHNOLOGY, CHANDIGARH. At the outset we would like to express our gratitude our mentor Prof. Jagdish Kumar, who assigned us this project after assessing our aptitude in this particular field and spent his valuable time in giving inputs related to the project and clearing our doubts on the same.

There are some people without whom the completion of this Project was not possible. We would like to express our deep regards to Prof. K.K. Garg for wise inputs and the time he spared for discussions and evaluations. We would also like to thank the entire faculty of Electrical Engineering Department for giving their valuable time to our Project.
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Chapter 1: Why This Project

Main sources of electricity in Punjab are Thermal (coal) and Hydro. About 27% of the total energy of the state is provided by the Ropar Thermal Plant while the Bhakra Nangal complex provided 20.3% of the total power for the state and the Guru Nanak Thermal plant at Bhatinda accounts for about 21% of the energy to the state. Other important sources of power are the Dehar Power plant (13%), Shanan Power house at Joginder Nagar (5%), Pong Power project (4%) and UBDC power houses (2%) Mukerian Hydel Project3%.

The common pool projects are the Bhakra Nangal Complex, the Dehar Power Plant and the Pong Power Plant. Punjab shares about 51% of the power generated from the Bhakra Nangal Complex and 48% from the power generated at the Pong Project.

Gas based power plants (Natural Gas), to a great extent, have not been exploited as sources of power in Punjab. Natural Gas based power plants have a bright future due to following reasons:

1. **Expected Coal Shortages**- Coal India Limited (CIL) has predicted a substantial shortfall in the quantum of its coal production and committed linkages during this decade. Also, the production from captive coal blocks is slow to take off.

2. **Smaller Gestation Periods**- Greenfield LNG based power plants can be set up in a period of 28-30 months leading to faster capacity additions whereas other conventional sources have gestation periods ranging from 48-84 months.

3. **Peaking Ability**- Dedicated plants operating in open cycle in proximity to load centers can meet peak demands.

4. **Comparatively Clean and Lean source of power**- For such plants, emissions are 50% lesser than coal based power stations. Land and water requirement is also substantially lower.

5. **Fuel Diversification**- India’s power generation mix is considerably gravitated towards coal based power generation. Gas based capacity addition will accentuate this ependence on coal as generation source.

Therefore, through the proposed project we shall check the viability of setting up a gas engine power plant in Punjab by calculating the return on investment for the lifecycle of the project.
Chapter 2: Introduction

2.1 Power scenario in Punjab

Coal shortage will be a major problem for new upcoming projects in Punjab as there is no surplus coal with Coal India Ltd. (CIL) at the moment.

According to official sources CIL has committed to supply coal of 347 million tons (MT) to power sector projects as per fuel supply agreement and 42 MT coal as per memorandum of understanding (MOU) made during 2012-13. It may not be possible to enhance coal supply beyond these levels. Last year CIL supplied 312MT against the target of 328.21mn tons for Power Utilities. In view of above the coal supply may be a major problem for the upcoming thermal projects in Punjab.

This coal shortage problem will also be faced by those plants that already have coal supply agreements. The plants will have to make do with what they have since there is no extra coal available for replenishing stocks. Coal imports are likely to double by the end of this five year plan. Specifically, from the existing 90 MT, imports are expected to reach a level of 180 MT by 2016-17.

Punjab State Electricity Board (PSEB) is a vertically-integrated utility and enjoyed the status of a regulated monopoly with its own generation, transmission and distribution of power in the state of Punjab. The financial position of PSEB as furnished by the Board is indicated below:-
Bouyed by the higher agricultural sales the total operating income has increased by 2% over FY09. Power for agriculture consumer is supplied for free in Punjab. The Govt. of Punjab (GoP) provides 100% subsidy to PSEB for its sales to agriculture consumers. Higher agriculture sales have resulted in higher income from subsidies from GoP during the year.

PSEB has stated that the financial position deteriorated from FY 1998 onwards on account of the factors mentioned below:-

- Supply to agriculture tubewells was made free w.e.f. 14.2.1997 and cash compensation promised by the Government of Punjab was not made available to the PSEB.
- Provision of free supply upto certain units per month to the SC families w.e.f. April 1998.
- Provision of urban pattern 24 hours supply to villages.
- Intermittent and inadequate revision of tariff, incongruent to the growth in expenditure and loss of revenue.
- Very little financial support from the Government even for the execution of capital works (excluding RSD).
- RE subsidy being provided by the State Government limited to interest on Government loans was sanctioned only up to 1997-98.
- Resultant heavy debt exposure of the Board to the Financial Institutions to support its cash deficit and capital works.

It is further stated by the Board that deterioration in the financial position of the PSEB also led to an increase in the incremental cost of funds for the Board exerting further pressure on the Board to shore up its cash flows and the Board had also to resort to diversion of loans raised for capital expenditure towards revenue expenditure.

2.2 The ratio of Power generated by different plants in Punjab

![Pie chart showing the distribution of power sources in Punjab]

Since, Thermal and Hydro are major sources of power in Punjab, the purpose of our project is to explore the possibility of setting up a Gas based power plant from investment point of view.
Chapter 3: Review of Literature

1. Introduction

Load forecasting is a central and integral process in the planning and operation of electric utilities. It involves the accurate prediction of both the magnitudes and geographical locations of electric load over the different periods (usually hours) of the planning horizon. The basic quantity of interest in load forecasting is typically the hourly total system load. However, according to Gross and Galiana (1987), load forecasting is also concerned with the prediction of hourly, daily, weekly and monthly values of the system load, peak system load and the system energy. Srinivasan and Lee (1995) classified load forecasting in terms of the planning horizon’s duration: up to 1 day for short-term load forecasting (STLF), 1 day to 1 year for medium-term load forecasting (MTLF), and 1±10 years for long-term load forecasting (LTLF).

Accurate load forecasting holds a great saving potential for electric utility corporations. According to Bunn and Farmer (1985), these savings are realised when load forecasting is used to control operations and decisions such as dispatch, unit commitment, fuel allocation and on-line network analysis. The accuracy of load forecasts has a significant effect on power system operations, as economy of operations and control of power systems may be quite sensitive to forecasting errors. Haida and Muto (1994) observed that both positive and negative forecasting errors resulted in increased operating costs. Hobbs et al. (1999) quantified the dollar value of improved STLF for a typical utility; a 1% reduction in the average forecast error can save hundreds of thousands or even millions of dollars.

The system load is a random non-stationary process composed of thousands of individual components. The system load behaviour is influenced by a number of factors, which can be classified as: economic factors, time, day, season, weather and random effects.

Load forecasting techniques are classified into nine categories. In subsequent sections, one section is devoted to each category, where a brief description is given of the technique and a literature review offers a representative selection of principal publications in the given category. Arranged in roughly chronological order, the nine categories of load forecasting techniques to be discussed are: multiple regression; exponential smoothing; iterative reweighted least-squares; adaptive load forecasting; stochastic time series; ARMAX models based on genetic algorithms; fuzzy logic; neural networks; and knowledge-based expert systems.

2. Multiple regression

Multiple regression analysis for load forecasting uses the technique of weighted least-squares 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 dened amount of historical data. Mbamalu and El-Hawary (1993) used the following load model for applying this analysis:

$$Y_t = v_t a_t + \varepsilon_t,$$

where

- $t$: sampling time,
- $Y_t$: measured system total load,
- $v_t$: vector of adapted variables such as time, temperature, light intensity, wind speed, humidity, day type (workday, weekend), etc.,
- $a_t$: transposed vector of regression coefficients, and
- $\varepsilon_t$: model error at time $t$.

The data analysis program allows the selection of the polynomial degree of influence of the variables from 1 to 5. In most cases, linear dependency gives the best results. Moghram and Rahman (1989) evaluated this model and compared it with other models for a 24-h load forecast. Barakat et al. (1990) used the regression model to apply data and check seasonal variations. The model developed by Papalexopoulos and Hesterberg (1990) produces an initial daily peak forecast and then uses this initial peak forecast to produce initial hourly forecasts. In the next step, it uses the maximum of the initial hourly forecast, the most recent initial peak forecast
error, and exponentially smoothed errors as variables in a regression model to produce an adjusted peak forecast.

Haida and Muto (1994) presented a regression-based daily peak load forecasting method with a transformation technique. Their method uses a regression model to predict the nominal load and a learning method to predict the residual load. Haida et al. (1998) expanded this model by introducing two trend-processing techniques designed to reduce errors in transitional seasons. Trend cancellation removes annual growth by subtraction or division, while trend estimation evaluates growth by the variable transformation technique. Varadan and Makram (1996) used a least-squares approach to identify and quantify the different types of load at power lines and substations.

Hyde and Hodnett (1997a) presented a weather-load model to predict load demand for the Irish electricity supply system. To include the effect of weather, the model was developed using regression analysis of historical load and weather data. Hyde and Hodnett (1997b) later developed an adaptable regression model for 1-day-ahead forecasts, which identifies weather-insensitive and sensitive load components. Linear regression of past data is used to estimate the parameters of the two components. Broadwater et al. (1997) used their new regression-based method, Nonlinear Load Research Estimator (NLRE), to forecast load for four substations in Arkansas, USA. This method predicts load as a function of customer class, month and type of day.

Al-Garni et al. (1997) developed a regression model of electric energy consumption in Eastern Saudi Arabia as a function of weather data, solar radiation, population and per capita gross domestic product. Variable selection is carried out using the stepping-regression method, while model adequacy is evaluated by residual analysis. The non-parametric regression model of Charytoniuk et al. (1998) constructs a probability density function of the load and load effecting factors. The model produces the forecast as a conditional expectation of the load given the time, weather and other explanatory variables, such as the average of past actual loads and the size of the neighbourhood.

Alfares and Nazeeruddin (1999) presented a regression-based daily peak load forecasting method for a whole year including holidays. To forecast load precisely throughout a year,
different seasonal factors that affect load differently in different seasons are considered. In the winter season, average wind chill factor is added as an explanatory variable in addition to the explanatory variables used in the summer model. In transitional seasons such as spring and Fall, the transformation technique is used. Finally for holidays, a holiday effect load is deducted from normal load to estimate the actual holiday load better.

3. 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. In exponential smoothing models used by Moghram and Rahman (1989), the load at time $t$, $y_{t}$, is modelled using a fitting function and is expressed in the form:

$$y(t) = \beta(t)^{T} f(t) + \varepsilon(i),$$

(2)

where

- $f(t)$ fitting function vector of the process,
- $\beta(t)$ coefficient vector,
- $\varepsilon(t)$ white noise, and
- $T$ transpose operator.

The Winter’s method is one of several exponential smoothing methods that can analyse seasonal time series directly. This method is based on three smoothing constants for stationarity, trend and seasonality. Results of the analysis by Barakat et al. (1990) showed that the unique pattern of energy and demand pertaining to fast- growing areas was difficult to analyse and predict by direct application of the Winter’s method. El-Keib et al. (1995) presented a hybrid approach in which exponential smoothing was augmented with power spectrum analysis and adaptive autoregressive modelling. A new trend removal technique by Infield and Hill (1998) was based on optimal smoothing. This technique has been shown to compare favorably with conventional methods of load forecasting.

4. Iterative reweighted least-squares

Mbamalu and El-Hawary (1992) used 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 sub-optimal 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. Consider the parameter estimation problem involving the linear measurement equation:

\[ Y = X\beta + \varepsilon, \]  

(3)

where \( Y \) is an \( n \times 1 \) vector of observations, \( X \) is an \( n \times p \) matrix of known coefficients (based on previous load data), \( \beta \) is a \( p \times 1 \) vector of the unknown parameters and \( \varepsilon \) is an \( n \times 1 \) vector of random errors. Results are more accurate when the errors are not Gaussian can be obtained by iterative methods (Mbamalu and El-Hawary 1992). Given an initial, one can apply the Newton method. Alternatively, one can also use the Beaton-Turkey iterative reweighted least-squares algorithm (IRLS). In a similar work, Mbamalu and El-Hawary (1993) proposed an interactive approach employing least-squares and the IRLS procedure for estimating the parameters of a seasonal multiplicative autoregressive model. The method was applied to predict load at the Nova Scotia Power Corporation.

5. 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, as described by equation (1).

Lu et al. (1989) developed an adaptive Hammerstein model with an orthogonal escalator structure as well as a lattice structure for joint processes. Their method used a joint Hammerstein non-linear time-varying functional relationship between load and temperature. Their algorithm
performed better than the commonly used RLS (Recursive Least-square) algorithm. Grady et al. (1991) enhanced and applied the algorithm developed by Lu et al. An improvement was obtained in the ability to forecast total system hourly load as far as 5 days. McDonald et al. (1989) presented an adaptive-times eories model, and simulated the effects of a direct load- control strategy.

Park et al. (1991b) developed a composite model for load prediction, composed of three components: nominal load, type load and residual load. The nominal load is modelled such that the Kalman filter can be used and the parameters of the model are adapted by the exponentially weighted recursive least-squares method. Fan and McDonald (1994) presented a practical real-time implementation of weather adaptive STLF. Implementation is performed by means of an ARMA model, whose parameters are estimated and updated online, using the WRLS (Weighted Recursive Least squares) algorithm.

Paarmann and Najar’s (1995) adaptive online load forecasting approach automatically adjusts model parameters according to changing conditions based on time series analysis. This approach has two unique features: autocorrelation optimization is used for handling cyclic patterns and, in addition to updating model parameters, the structure and order of the time series is adaptable to new conditions. An important feature of the regression model of Hyde and Hodnett (1997b) is adaptability to changing operational conditions. The load-forecasting software system is fully automated with a built-in procedure for updating the model. Zheng et al. (2000) applied a wavelet transform-Kalman filter method for load forecasting. Two models are formed (weather sensitive and insensitive) in which the wavelet coefficients are modelled and solved by the recursive Kalman filter algorithm.

6. 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.

6.1. Autoregressive (AR) model

If the load is assumed to be a linear combination of previous loads, then the autoregressive (AR) model can be used to model the load profile, which is given by Liu et al. (1996) as:

$$\hat{L}_k = -\sum_{i=1}^{m} \alpha_{ik} L_{k-i} + w_k \quad (4)$$

where $\hat{L}^k$ is the predicted load at time $k$ (min), $w_k$ is a random load disturbance, $\alpha_i, i = 1, \ldots, m$ are unknown coefficients, and (4) is the AR model of order $m$. The unknown coefficients in (4) can be tuned on-line using the well-known least mean square (LMS) algorithm of Mbamalu and El-Hawary (1993). The algorithm presented by El-Keib et al. (1995) includes an adaptive autoregressive modelling technique enhanced with partial autocorrelation analysis. Huang (1997) proposed an autoregressive model with an optimum threshold stratification algorithm. This algorithm determines the minimum number of parameters required to represent the random component, removing subjective judgement, and improving forecast accuracy. Zhao et al. (1997) developed two periodical autoregressive (PAR) models for hourly load forecasting.

6.2. Autoregressive moving-average (ARMA) model

In the ARMA model the current value of the time series $y(t)$ is expressed linearly in terms of its values at previous periods $[y(t-1), y(t-2), \ldots]$ and in terms of previous values of a white noise $[a(t), a(t-1), \ldots]$. For an ARMA of order $(p; q)$, the model is written as:

$$y(t) = \phi_1 y(t - 1) + \cdots + \phi_p y(t - p) + \alpha(t) + \Theta_1 \alpha(t - 1) + \cdots + \Theta_q \alpha(t - q). \quad (5)$$

The parameter identification for a general ARMA model can be done by a recursive scheme, or using a maximum-likelihood approach, which is basically a non-linear regression algorithm. Barakat et al. (1992) presented a new time-temperature methodology for load forecasting. In this method, the original time series of monthly peak demands are decomposed into deterministic and stochastic load components, the latter determined by an ARMA model. Fan and McDonald
(1994) used the WRLS (Weighted Recursive Least-Squares) algorithm to update the parameters of their adaptive ARMA model. Chen et al. (1995) used an adaptive ARMA model for load forecasting, in which the available forecast errors are used to update the model. Using minimum mean square error to derive error learning coefficients, the adaptive scheme outperformed conventional ARMA models.

6.3. Autoregressive integrated moving-average (ARIMA) model

If the process is non-stationary, then transformation of the series to the stationary form has to be done first. This transformation can be performed by the differencing process. By introducing the delta operator, the series \( \Delta^d y(t) = (1-B)^d y(t) \). For a series that needs to be differenced \( d \) times and has orders \( p \) and \( q \) for the AR and MA components, i.e. ARIMA\((p,d,q)\), the model is written as:

\[
\phi(B) \Delta^d y(t) = \theta(B) a(t).
\]  

(6)

The procedure proposed by Elrazaz and Mazi (1989) used the trend component to forecast the growth in the system load, the weather parameters to forecast the weather sensitive load component, and the ARIMA model to produce the non-weather cyclic component of the weekly peak load. Barakat et al. (1990) used a seasonal ARIMA model on historical data to predict the load with seasonal variations. Juberias et al. (1999) developed a real time load forecasting ARIMA model that includes the meteorological influence as an explanatory variable.

7. ARMAX Model based on genetic algorithms

The genetic algorithm (GA) or evolutionary programming (EP) approach is used to identify the autoregressive moving average with exogenous variable (ARMAX) model for load demand forecasts. By simulating natural evolutionary process, the algorithm offers the capability of converging towards the global extremum of a complex error surface. It is a global search technique that simulates the natural evolution process and constitutes a stochastic optimization algorithm. Since the GA simultaneously evaluates many points in the search space and need not assume the search space is differentiable or unimodal, it is capable of asymptotically converging towards the global optimal solution, and thus can improve the setting accuracy of the model.
The general scheme of the GA process is briefly described here. The integer or real valued variables to be determined in the genetic algorithm are represented as a D-dimensional vector \( P \) for which a fitness \( f(p) \) is assigned. The initial population of \( k \) parent vectors \( P_i, i = 1, \ldots, k \), is generated from a randomly generated range in each dimension. Each parent vector then generates an offspring by merging (crossover) or modifying (mutation) individuals in the current population. Consequently, \( 2k \) new individuals are obtained. Of these, \( k \) individuals are selected randomly, with higher probability of choosing those with the best fitness values, to become the new parents for the next generation. This process is repeated until \( f \) is not improved or the maximum number of generations is reached.

Yang et al. (1996) described the system load model in the following ARMAX form:

\[
A(q)y(i) = B(q)u(i) + C(q)e(i),
\]

where

- \( y(i) \) load at time \( t \),
- \( u(i) \) exogenous temperature input at time \( t \),
- \( e(i) \) white noise at time \( t \), and
- \( q^{-1} \) back-shift operator.

\( A(q), B(q), \) and \( C(q) \) are parameters of the autoregressive (AR), exogenous (X), and moving average (MA) parts, respectively. Yang et al. (1996) chose the solution(s) with the best fitness as the tentative model(s) that should further pass diagnostic checking for future load forecasting. Yang and Huang (1998) presented a fuzzy autoregressive moving average with exogenous variable (FARMAX) model for load demand forecasts. The model is formulated as a combinatorial optimization problem, then solved by a combination of heuristics and evolutionary programming. Ma et al. (1995) used a genetic algorithm with a newly developed knowledge-augmented mutation-like operator called the forced mutation. Lee et al. (1997) used genetic algorithms for long-term load forecasting, assuming different functional forms and comparing results with regression.

**8. 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. Liu et al. (1996) observed that a fuzzy logic system has great capability in drawing similarities from huge data. The similarities in input data \((L_{L0})\) can be identified by
different first-order differences ($V_k$) and second-order differences ($A_k$), which are defined as:

$$V_k = (L_k - L_{k-1})/T, \quad A_k = (V_k - V_{k-1})/T. \quad (8)$$

The fuzzy logic-based forecaster works in two stages: training and on-line forecasting. In the training stages, the metered historical load data are used to train a 2m-input, 2n-output fuzzy-logic based forecaster to generate patterns database and a fuzzy rule base by using first and second-order differences of the data. After enough training, it will be linked with a controller to predict the load change online. If a most probably matching pattern with the highest possibility is found, then an output pattern will be generated through a centroid defuzzifier.

Several techniques have been developed to represent load models by fuzzy conditional statements. Hsu (1992) presented an expert system using fuzzy set theory for STLF. The expert system was used to do the updating function. Short-term forecasting was performed and evaluated on the Taiwan power system. Later, Liang and Hsu (1994) formulated a fuzzy linear programming model of the electric generation scheduling problem, representing uncertainties in forecast and input data using fuzzy set notation. Al-Anbuky et al. (1995) discussed the implementation of a fuzzy-logic approach to provide a structural framework for the representation, manipulation and utilization of data and information concerning the prediction of power commitments. Neural networks are used to accommodate and manipulate the large amount of sensor data.

Srinivasan et al. (1992) used the hybrid fuzzy-neural technique to forecast load. This technique combines the neural network modelling and techniques from fuzzy logic and fuzzy set theory. The models were later enhanced by Dash et al. (1995a, b). This hybrid approach can accurately forecast on weekdays, public holidays, and days before and after public holidays. Based on the work of Srinivasan et al., Dash et al. (1995a) presented two fuzzy neural network (NN) models capable of fuzzy classification of patterns. The first network uses the membership values of the linguistic properties of the past load and weather parameters, where the output of the network is defined as the fuzzy class membership values of the forecasted load. The second network is based on the fact that any expert system can be represented as a feed forward NN.

Mori and Kobayashi (1996) used fuzzy inference methods to develop a non-linear optimization model of STLF, whose objective is to minimize model errors. The search for the optimum
solution is performed by simulated annealing and the steepest descent method. Dash et al. (1996) used a hybrid scheme combining fuzzy logic with both neural networks and expert systems for load forecasting. Fuzzy load values are inputs to the neural network, and the output is corrected by a fuzzy rule inference mechanism. Ramirez-Rosado and Dominguez-Navarro (1996) formulated a fuzzy model of the optimal planning problem of electric energy. Computer tests indicated that this approach out-performs classical deterministic models because it is able to represent the intrinsic uncertainty of the process.

Chow and Tram (1997) presented a fuzzy logic methodology for combining information used in spatial load forecasting, which predicts both the magnitudes and locations of future electric loads. The load growth in different locations depends on multiple, conflicting factors, such as distance to highway, distance to electric poles, and costs. Therefore, Chow et al. (1998) applied a fuzzy, multi-objective model to spatial load forecasting. The fuzzy logic approach proposed by Senjyu et al. (1998) for next-day load forecasting offers three advantages. These are namely the ability to (1) handle non-linear curves, (2) forecast irrespective of day type and (3) provide accurate forecasts in hard-to-model situations.

Mori et al. (1999) presented a fuzzy inference model for STLF in power systems. Their method uses tabu search with supervised learning to optimize the inference structure (i.e. number and location of fuzzy membership functions) to minimize forecast errors. Wu and Lu (1999) proposed an alternative to the traditional trial and error method for determining of fuzzy membership functions. An automatic model identification is used, that utilizes analysis of variance, cluster estimation, and recursive least-squares. Mastorocostas et al. (1999) applied a two-phase STLF methodology that also uses orthogonal least-squares (OSL) in fuzzy model identification. Padmakumari et al. (1999) combined fuzzy logic with neural networks in a technique that reduces both errors and computational time. Srinivasan et al. (1999) combined three techniques: fuzzy logic, neural networks and expert systems in a highly automated hybrid STLF approach with unsupervised learning.

9. Neural networks

Artificial neural networks (ANN) have very wide applications because of their ability to learn. According to Damborg et al., (1990), 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 perceptron 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, and are added to a threshold to form an inner product number called the net function. The net function $NET$ used by Ho et al. (1992), for example, is put through the activation function $y$, to produce the unit’s final output, $y(NET)$.

The main advantage here is that most of the forecasting methods seen in the literature do not require a load model. However, training usually takes a lot of time. Here we describe the method discussed by Liu et al. (1996), using fully connected feed-forward type neural networks. The network outputs are linear functions of the weights that connect inputs and hidden units to output units. Therefore, linear equations can be solved for these output weights. In each iteration through the training data (epoch), the output weight optimization training method uses conventional back-propagation to improve hidden unit weights, then solves linear equations for the output weights using the conjugate gradient approach.

Srinivasan and Lee (1995) surveyed hybrid fuzzy neural approaches to load forecasting. Park and Osama (1991) used a NN approach for forecasting which, compared to regression methods, gave more flexible relations between temperature and load patterns. Extending this work, Park et al. (1991a) presented a NN algorithm that combines time series and regression approaches. Park et al. proposed an improved training procedure for training the ANN. Atlas et al. (1989) earlier compared a similar technique with other regression methods. Hsu and Yang (1992) estimated the load pattern of the day under study by averaging the load patterns of several past days, which are of the same day type (ANN being used for the classification). To predict the daily peak load, a feed-forward multilayer neural network was designed.

Peng et al. (1992) used a minimum distance measurement to identify the appropriate historical patterns of load and temperature weights to be used to find the network weights. They also proposed an improved algorithm that combined linear and non-linear terms to map past load and temperature inputs to the load forecast output. This work was an extension to a strategy by Peng et al. (1990) which was applied on daily load. The major difference lies in the alternate method for the selection of the training cases. Later, Peng et al. (1993) applied a neural network
approach to one-week ahead load forecasting based on an adaptive linear combiner called the adaline.

Ho and Hsu (1992) designed a multilayer ANN with a new adaptive learning algorithm for short term load forecasting. In this algorithm the momentum is automatically adapted in the training process. Lee and Park (1992) proposed a non-linear load model and several structures of ANNs were tested. Inputs to the ANN include past load values, and the output is the forecast for a given day. Lee and Park demonstrated that the ANN could be successfully used in STLF with accepted accuracy. Chen et al. (1992) presented an ANN, which is not fully connected, to forecast weather sensitive loads for a week. Their model could differentiate between the weekday loads and the weekend loads. Lu et al. (1993) conducted a computational investigation to evaluate the performance of the ANN methodology.

Djukanovic et al. (1993) proposed an algorithm using an unsupervised/supervised learning concept and historical relationship between the load and temperature for a given season, day type and hour of the day. They used this algorithm to forecast hourly electric load with a lead time of 24 h. Papalexopoulos et al. (1994) developed and implemented the ANN based model for the energy control centre of the Pacific Gas and Electric Company. Attention was paid to accurately model special events, such as holidays, heat waves, cold snaps and other conditions that disturb the normal pattern of the load. Ho et al. (1992) extended the three-layered feed forward adaptive neural networks to multilayers. Dillon et al. (1991) proposed a multilayer feed-forward neural net- work, using a learning algorithm for adaptive training of neural networks.

Srinivasan et al. (1991) used an ANN based on back propagation for forecasting, and showed its superiority to traditional methods. Liu et al. (1991) compared an econometric model and a neural network model, through a case study on electricity consumption forecasting in Singapore. Their results show that a fully trained NN model with a good setting performance for the past may not give a good forecasting performance for the future. Kalra et al. (1992) demonstrated how present methods for solving such problems could be converted to NN approaches.

Azzam-ul-Asar and McDonald (1994) trained a family of ANNs and then used them in line with a supervisory expert system to form an expert network. They also investigated the effectiveness of the ANN approach to short term load forecasting, where the networks were trained on actual
load data using back-propagation. AlAnbuky et al. (1995) presented fuzzy logic based neural networks for load forecasting. Dash et al. (1995a, b, 1996) also used fuzzy logic in combination with neural networks for load forecasting. Their work has been discussed in the previous section.

Chen et al. (1996) applied a supervisory functional ANN technique to forecast load for three substations in Taiwan. To enhance forecasting accuracy, the load was correlated with temperature as well as the type of customers served, which is classified as residential, commercial or industrial. Al-Fuhaid et al. (1997) incorporated temperature and humidity effects in an ANN approach for STLF in Kuwait. Vermaak and Botha (1998) proposed a recurrent NN to model the STLF of the South African utility. They utilized the inherent non-linear dynamic nature of NN to represent the load as the output of some dynamic system, influenced by weather, time and environmental variables.

McMenamin and Monforte (1998) used an econometric and statistical approach to NN-based load forecasting. Considering NN models as flexible non-linear equations, they used non-linear least-squares to estimate parameters, and simple statistics such as MAPE to determine the number of nodes. Papadakis et al. (1998) developed a three-step fuzzy ANN approach, involving the prediction of load curve peaks and valleys and mapping them to forecasted peak values. Dash et al. (1998) presented a fuzzy NN load forecasting system that accounts for seasonal and daily changes, as well as holidays and special situations. An adaptive mechanism is used to train the system on line, providing accurate results when tested with actual data of the Virginia Utility. Another adaptive NN technique, employing genetic algorithms in the design and training phase, was used by Kung et al. (1998) on the Taiwan power system.

ANN have been integrated with several other techniques to improve their accuracy. Chow and Leung (1996), for example, combined ANN with stochastic time-series methods, in the form of non-linear autoregressive integrated (NARI) model. They implemented an ANN capable of weather compensation, based on NARI, to forecast electric load in Hong Kong. Choueiki et al. (1997) used weighted least-squares procedure in the training phase of developing an ANN for load forecasting. Several other hybrid methods involving ANNs in combination with fuzzy logic and expert systems are discussed in Sections 6 and 10, respectively. It is very hard to keep track of all publications on load forecasting using NN, which is currently a very active area of
research. Niebur (1995) and Czernichow et al. (1996) surveyed methods and applications of electrical load forecasting with ANNs.

Oonsivilan et al. (1999) presented an approach for predicting electric power system commercial load using a wavelet neural network. Their results showed that wavelet NNs may outperform traditional architectures in approximation. Drenza et al. (1999) presented a new ANN-based technique for STLF. The technique implemented active selection of training data employing k-nearest neighbours concept. Excellent results were reported using this technique. Yoo and Pimmel (1999) developed a self-supervised adaptive NN to perform STLF for a large power system. They used the self-supervised network to extract correlational features from temperature and load data. Their results showed low forecasting errors. Kandil et al. (1999) used multilayer perceptron (MLP) type ANN for STLF using real load and weather data. Leyan and Chen (1999) used variable learning rate method combined with quasi-Newton method to expedite the learning process of ANN for STLF.

Nazarko and Styczynski (1999) presented load-modelling methods useful for long term planning of power distribution systems using statistical clustering and NN approach. Ijumba and Hunsley (1999) applied ANN model to predict hourly peak demands of loads in a newly electrified area. Sinha and Mandal (1999) presented an ANN-based model for bus-load prediction and dynamic state estimation in power systems. Drezga and Rahman (1999a) used phase-space concepts to embed electric load parameters, including temperature and cycle variables, into ANN-based STLF. Drezga and Rahman (1999b) applied another ANN-based technique that features the following characteristics: (1) selection of training data by the k-nearest neighbours concept, (2) pilot simulation to determine the number of ANN units and (3) iterative forecasting by simple moving average to combine local ANN predictions.

10. Knowledge-based expert systems

Expert systems are new techniques that have emerged as a result of advances in the field of artificial intelligence. An expert system is a computer program that has the ability to reason, explain, and have its knowledge base expanded as new information becomes available to it. To build the model, the ‘knowledge engineer’ extracts load forecasting knowledge from an expert in the field by what is called the knowledge base component of the expert system. This knowledge
is represented as facts and IF-THEN rules, and consists of the set of relationships between the changes in the system load and changes in natural and forced condition factors that affect the use of electricity. This rule base is used daily to generate the forecasts. Some of the rules do not change over time, while others have to be updated continually.

The logical and syntactical relationships between weather load and the prevailing daily load shapes have been widely examined to develop different rules for different approaches. The typical variables in the process are the season under consideration, day of the week, the temperature and the change in this temperature. Illustrations of this method can be found in Rahman (1990, 1993) and Ho et al. (1990). The algorithms of Rahman and Shreshta (1991) and Rahman and Hazim (1993) combine features from knowledge-based and statistical techniques, using the pairwise comparison technique to prioritize categorical variables. Rahman and Hazim (1996) developed a site-independent expert system for STLF. This system was tested using data from several sites around the USA, and the errors were negligible. Brown et al. (1999) used a knowledge-based load-forecasting approach that combines existing system knowledge, load growth patterns, and horizon year data to develop multiple load growth scenarios.

Several hybrid methods combine expert systems with other load-forecasting approaches. Dash et al. (1993, 1996) combined fuzzy logic with expert systems. Kim et al. (1995) used a two-step approach in forecasting load for Korea Electric Power Corporation. First, an ANN is trained to obtain an initial load prediction, then a fuzzy expert system modifies the forecast to accommodate temperature changes and holidays. Mohamad et al. (1996) applied a combination of expert systems and NN for hourly load forecasting in Egypt. Bataineh et al. (1996) used neural networks and fuzzy logic for data representation and manipulation to construct the expert system’s rule base. Chiu et al. (1997a, b) determined that a combined expert system-NN approach is faster and more accurate than either one of the two methods alone. Chandrashekara et al. (1999) applied a combined expert system-NN procedure divided into three modules: location planning, forecasting and expansion planning.
Chapter 4: The Project

4.1 Scope of the Project

The project aims developing a techno-economic tool that helps analyze in great detail the extent of profitability of any given plant for any particular time frame. It gives an appropriate idea about the initial investment that needs to be made and helps in determining the returns that the investor is likely to get thereby influencing the investment decisions. The scope of the project includes:

1. Spot Price Forecasting
2. Power Plant Dispatch Simulation
3. Economic Evaluation of Dispatch Simulation
4. Determination of power plant investment opportunities in next five years

4.2 Software Used
MS-Excel 2010 has been used to develop this tool. This spreadsheet application helps to store, organize and manipulate data with ease.

4.3 Steps Involved

1. **Spot Price Forecasting**: For the purpose of forecasting spot prices for the next five years, a time series comprising of Spot Price data or unconstrained Market Clearing Price for India) on daily basis for past three years (Source: [www.iexindia.com](http://www.iexindia.com)) is imported in excel. Using the concept of moving averages, a trend line is plotted to analyze the variations in spot prices (increasing/decreasing/random/seasonal trend) over a period of a year. Based on this analysis, forecasting of spot prices is done for the next five years by exploiting the forecasting tool of MS-Excel.

2. **Power Plant Dispatch Simulation**: The dispatch decision involves comparison of electricity spot prices with the Short Run Marginal Cost (SRMC) of Power Plant. Whenever the forecasted electricity Spot Price is greater than the SRMC, the power plant dispatches at maximum load and in case the forecasted Spot Price is less than SRMC, the power plant does not dispatch as it
suffers loss in such scenario. Based on this analysis, the number of hours for which the power plant was dispatching at maximum load in a year can be calculated.

3. **Economic Evaluation of Dispatch Simulation**: The Inputs values are given in the tool for the year 2011. For subsequent years, the escalations in fuel costs and variable O & M costs are considered. The addition of new fuel cost and O & M cost gives Short Run Marginal Cost (SRMC) for that year. Based on the number of hours for which the power plant was dispatching in a year, Plant Load Factor (PLF) and hence Annual Generation (in kWh) of electricity is calculated. Annual Revenue earned by power plant is calculated by adding up revenue earned on daily basis depending on whether power plant was dispatching or not. The expenses like the Fuel Cost and Variable O & M Costs (Operational Costs) are subtracted from the revenue to get the Gross Profit. From this further expenses of Fixed O & M Costs and Fixed Charge Recovery Costs are subtracted to get the Net Profit earned by the Plant.

4. **Determination of power plant investment opportunities**: Based on the Net Profit values the investors can take decisions of investing in a particular plant based on the profit values forecasted.

![Diagram](image_url)

**Figure 4.1**
5.1 Long Term Forecasting of Electricity Spot Prices using Time Series

Forecasting is an essential tool in any decision making process. The quality of forecasts that can be made is strongly related to the information that can be extracted and used from the past data. **Time Series Analysis** is one quantitative method that can be used to determine patterns in the data collected over time and based on the analysis make a forecast for future years.

5.1.1 Time Series and its Components

A **time series** is a collection of data recorded over a period of time—weekly, monthly, quarterly, or yearly. There are four components to a time series depending on the changes or variations in the series: the secular trend, the cyclical variation, the seasonal variation, and the irregular variation. These have been elaborated below.

1. **Secular trend**: A time series data may show upward trend or downward trend for a period of years and this may be due to factors like increase in population, change in technological progress, large scale shift in consumers demands, etc. For example, population increases over a period of time, price increases over a period of years, production of goods on the capital market of the country increases over a period of years. These are the examples of upward trend. The sales of a commodity may decrease over a period of time because of better products coming to the market. This is an example of declining trend or downward trend. The increase or decrease in the movements of a time series is called Secular trend.

2. **Seasonal variation**: Seasonal variations are short-term fluctuation in a time series which occur periodically in a year. This continues to repeat year after year. The major factors that are responsible for the repetitive pattern of seasonal variations are weather conditions and customs of people. More woollen clothes are sold in winter than in the season of summer. Regardless of the trend we can observe that in each year more ice creams are sold in summer and very little in winter season. The sales in the departmental stores are more during festive seasons that in the normal days.
3. **Cyclical variations:** Cyclical variations are recurrent upward or downward movements in a time series but the period of cycle is greater than a year. Also these variations are not regular as seasonal variation. There are different types of cycles of varying in length and size. The ups and downs in business activities are the effects of cyclical variation. A business cycle showing these oscillatory movements has to pass through four phases—prosperity, recession, depression and recovery. In a business, these four phases are completed by passing one to another in this order.

4. **Irregular variation:** Irregular variations are fluctuations in time series that are short in duration, erratic in nature and follow no regularity in the occurrence pattern. These variations are also referred to as residual variations since by definition they represent what is left out in a time series after trend, cyclical and seasonal variations. Irregular fluctuations results due to the occurrence of unforeseen events like floods, earthquakes, wars, famines etc.

For the purpose of forecasting, time series data of Spot Prices is exported from India Energy Exchange (IEX) Website. The graph (Figure 6.1) below indicates the variation of Spot price in the past three years.

![Graph showing variation of Spot price in the past three years.](image)

**Figure 5.1**
Analysis of the pattern of time series data reveals that it primarily consists of *seasonal variations* whose effect needs to be considered for accurate forecasting of electricity prices for next three years (2012, 2013 and 2014). In order to measure seasonal variations, *ratio-to-moving-average method* is used.

### 5.1.2 Moving Averages

A moving average is a method used to smooth data that have a high level of variance or volatility. The smoothed data can be used to show trends that might be hidden by the erratic nature of the raw data. They do not predict the direction of trend, but rather define the current direction with a lag. Moving averages lag because they are based on past prices. Despite this lag, moving averages help smooth data and filter out the noise. Moving averages commonly are used in financial applications and are one tool used to assess the technical strength of a stock or other investment instrument.

**Calculating Moving Averages: Example**

Let us consider the following example comprising of Production Data from 1987-2005.

<table>
<thead>
<tr>
<th>Year</th>
<th>Production</th>
</tr>
</thead>
<tbody>
<tr>
<td>1987</td>
<td>5</td>
</tr>
<tr>
<td>1988</td>
<td>6</td>
</tr>
<tr>
<td>1989</td>
<td>8</td>
</tr>
<tr>
<td>1990</td>
<td>10</td>
</tr>
<tr>
<td>1991</td>
<td>5</td>
</tr>
<tr>
<td>1992</td>
<td>3</td>
</tr>
<tr>
<td>1993</td>
<td>7</td>
</tr>
<tr>
<td>1994</td>
<td>10</td>
</tr>
<tr>
<td>1995</td>
<td>12</td>
</tr>
<tr>
<td>1996</td>
<td>11</td>
</tr>
<tr>
<td>1997</td>
<td>9</td>
</tr>
<tr>
<td>1998</td>
<td>13</td>
</tr>
<tr>
<td>1999</td>
<td>15</td>
</tr>
<tr>
<td>2000</td>
<td>18</td>
</tr>
<tr>
<td>2001</td>
<td>15</td>
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<td>2002</td>
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</tr>
<tr>
<td>2003</td>
<td>14</td>
</tr>
<tr>
<td>2004</td>
<td>17</td>
</tr>
<tr>
<td>2005</td>
<td>22</td>
</tr>
</tbody>
</table>
Three-Year Moving Average can be calculated as follows:

1989 SMA = 5+6+8 / 3 = 19 / 3 = 6.3
1990 SMA = 6+8+10 / 3 = 24 / 3 = 8
1991 SMA = 8+10+5 / 3 = 23 / 3 = 7.7 and so on.

Similarly Five-Year Moving Average can be calculated as follows:

1991 SMA = 5+6+8+10+5 / 5 = 34 / 5 = 6.8
1992 SMA = 6+8+10+5+3 / 5 = 32 / 5 = 6.4
1993 SMA = 8+10+5+3+7 / 5 = 33 / 5 = 6.6 and so on.

<table>
<thead>
<tr>
<th>Year</th>
<th>Production, Y</th>
<th>Three-Year Moving Total</th>
<th>Three-Year Moving Average</th>
<th>Five-Year Moving Total</th>
<th>Five-Year Moving Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>1987</td>
<td>5</td>
<td>8</td>
<td>6.3</td>
<td>19</td>
<td>6.0</td>
</tr>
<tr>
<td>1988</td>
<td>6</td>
<td>10</td>
<td>8.0</td>
<td>31</td>
<td>6.2</td>
</tr>
<tr>
<td>1989</td>
<td>8</td>
<td>19</td>
<td>6.3</td>
<td>34</td>
<td>6.8</td>
</tr>
<tr>
<td>1990</td>
<td>10</td>
<td>24</td>
<td>8.0</td>
<td>35</td>
<td>7.0</td>
</tr>
<tr>
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<td>5</td>
<td>23</td>
<td>7.7</td>
<td>34</td>
<td>6.8</td>
</tr>
<tr>
<td>1992</td>
<td>3</td>
<td>18</td>
<td>6.0</td>
<td>32</td>
<td>6.4</td>
</tr>
<tr>
<td>1993</td>
<td>7</td>
<td>15</td>
<td>5.0</td>
<td>33</td>
<td>6.6</td>
</tr>
<tr>
<td>1994</td>
<td>10</td>
<td>20</td>
<td>6.7</td>
<td>35</td>
<td>7.0</td>
</tr>
<tr>
<td>1995</td>
<td>12</td>
<td>29</td>
<td>9.7</td>
<td>37</td>
<td>7.4</td>
</tr>
<tr>
<td>1996</td>
<td>11</td>
<td>33</td>
<td>11.0</td>
<td>43</td>
<td>8.6</td>
</tr>
<tr>
<td>1997</td>
<td>9</td>
<td>32</td>
<td>10.7</td>
<td>49</td>
<td>9.8</td>
</tr>
<tr>
<td>1998</td>
<td>13</td>
<td>33</td>
<td>11.0</td>
<td>55</td>
<td>11.0</td>
</tr>
<tr>
<td>1999</td>
<td>15</td>
<td>37</td>
<td>12.3</td>
<td>60</td>
<td>12.0</td>
</tr>
<tr>
<td>2000</td>
<td>18</td>
<td>46</td>
<td>15.3</td>
<td>66</td>
<td>13.2</td>
</tr>
<tr>
<td>2001</td>
<td>15</td>
<td>48</td>
<td>16.0</td>
<td>70</td>
<td>14.0</td>
</tr>
<tr>
<td>2002</td>
<td>11</td>
<td>44</td>
<td>14.7</td>
<td>72</td>
<td>14.4</td>
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<td>40</td>
<td>13.3</td>
<td>73</td>
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<td>2004</td>
<td>17</td>
<td>42</td>
<td>14.0</td>
<td>75</td>
<td>15.0</td>
</tr>
<tr>
<td>2005</td>
<td>22</td>
<td>53</td>
<td>17.7</td>
<td>79</td>
<td>15.8</td>
</tr>
</tbody>
</table>

The actual data, three-year moving average and five-year moving average has been plotted in the chart below. As can be observed, greater the lag smoother is the trend line.
5.1.3 Calculation of Seasonal Index: Ratio-to-Moving-Average Method

This technique provides an index that describes the degree of seasonal variation. The index is based on a mean of 100, with the degree of seasonality measured by variations away from the base. This index is then used to deseasonalize past data which is then used for forecasting next year prices. The index for every month can be calculated in the following steps:

1. **The first step is to calculate 4 quarter moving total for the time series.** This moving total is associated with the middle data point in the set of values from which it was calculated (Table 5.1, col 3).

2. **In the second step, 4 quarter moving average is computed by dividing each of the 12-month totals by 4.** (Table 5.1, col 4)

3. **In the third step, the 4 quarter moving average is centered.** The moving average in column 5, fall halfway between the quarters. In order to associate moving averages with each quarter, the moving averages are centered. This is done associating the average of two 4-quarter moving average values falling just above and just below it. (Table 5.1, col 5)

4. **Next, the percentage of the actual value to the moving-average value for each quarter in the time series having 4-quarter moving average entry is calculated.** This step allows to recover the seasonal component for the quarters. (Table 5.1, col 6)
5. Collect all the percentage of actual to moving average values and arrange them by quarter. Then calculate the modified mean for each quarter. The modified mean is calculated by discarding the highest and lowest value of each quarter and averaging the remaining values. By eliminating the highest and lowest values from each quarter, the extreme cyclical and irregular variations get reduced. Averaging the remaining values will further smooth the cyclical and irregular components. Cyclical and irregular variations tend to be removed by this process, so the modified mean is an index of seasonality component. Since for our calculations there are just two values associated with each quarter, we will simply take average of these two values. (Table 5.2)

6. Adjust the modified mean slightly. The total of four indices is greater than 400. However, the base for an index is 100. Thus, the four quarterly indices should total 400 and their mean should be 100. To correct this error, each of the quarterly indices is multiplied by an adjusting constant. This number is found by dividing the desired sum of indices (400) by the actual sum. (Table 5.3 & 5.4)

7. The last step is to de-seasonalize time series data. To de-seasonalize time series we divide actual values in the series by appropriate seasonal index (expressed as a fraction of 100). Once the effect of seasonal variations has been removed, de-seasonalised trend line can be computed which can then be projected in the future. (Table 5.5)

Table 5.1

<table>
<thead>
<tr>
<th>Year</th>
<th>Quarter</th>
<th>Actual</th>
<th>MA (4)</th>
<th>Centered MA (4)</th>
<th>(Actual/Centered MA (4))*100</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012</td>
<td>1</td>
<td>2512.123516</td>
<td>3169.852639</td>
<td>3286.596259</td>
<td>100.12%</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>3294.448022</td>
<td>3202.166364</td>
<td>3277.374694</td>
<td>90.22%</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>3232.039231</td>
<td>3399.276867</td>
<td>3475.964576</td>
<td>87.61%</td>
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<tr>
<td></td>
<td>4</td>
<td>3240.799785</td>
<td>3552.652284</td>
<td>3843.363328</td>
<td>109.70%</td>
</tr>
<tr>
<td>2011</td>
<td>1</td>
<td>3370.2106</td>
<td>4134.074372</td>
<td>4136.852721</td>
<td>96.51%</td>
</tr>
<tr>
<td></td>
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<td></td>
<td>4</td>
<td>4216.017174</td>
<td>3552.652284</td>
<td>3843.363328</td>
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<td></td>
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<tr>
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<td>2010</td>
<td>96.51</td>
<td>135.66</td>
<td>76.95</td>
<td>48.14</td>
<td></td>
</tr>
<tr>
<td>2009</td>
<td>125.02</td>
<td>138.09</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table 5.2**

<table>
<thead>
<tr>
<th>Total of Indices</th>
<th>404.74</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjusting constant</td>
<td>0.988288778</td>
</tr>
</tbody>
</table>

**Table 5.3**

<table>
<thead>
<tr>
<th>Quarter</th>
<th>Unadjusted Indices</th>
<th>Adjusting Constant</th>
<th>Seasonal Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>109.2766667</td>
<td>0.988288778</td>
<td>107.9969034</td>
</tr>
<tr>
<td>2</td>
<td>121.3233333</td>
<td>0.988288778</td>
<td>119.9024888</td>
</tr>
<tr>
<td>3</td>
<td>88.23</td>
<td>0.988288778</td>
<td>87.19671888</td>
</tr>
<tr>
<td>4</td>
<td>85.91</td>
<td>0.988288778</td>
<td>84.90388892</td>
</tr>
</tbody>
</table>

**Table 5.4**

<table>
<thead>
<tr>
<th>Year</th>
<th>Quarter</th>
<th>Actual</th>
<th>Seasonal Index/100</th>
<th>De-seasonalized data</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012</td>
<td>1</td>
<td>2912.123516</td>
<td>1.079969034</td>
<td>2596.467977</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>3294.448022</td>
<td>1.199024888</td>
<td>2747.666038</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>3232.039231</td>
<td>0.871967189</td>
<td>3706.606478</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>3240.799785</td>
<td>0.849038889</td>
<td>3817.021607</td>
</tr>
</tbody>
</table>

**Table 5.5**
5.2 Forecasting with excel

5.2.1 Forecasting Add-ins

Microsoft Excel has various Add-ins which add optional commands and new features to it. One such add in is the Forecasting Add-in which has been used in the project for the purpose of forecasting electricity spot prices for the next three years.

The forecasting add-in in excel provides tools for selecting a model that describes the time series, selecting a method for estimating the parameters of the model and using the method to forecast future values of the time series. Models assume that observations vary according to some probability distribution about an underlying function of time.

Four forecasting methods are provided by this add-in: moving average, exponential smoothing, regression and exponential smoothing with a trend (double exponential smoothing). The add-in builds a form that accepts data from the user and provides functions that compute estimates of the model parameters. The menu installed by the forecasting add-in gives access to several options.

- **Add Forecast:** This allows the user to forecast one or more time series using one of the four methods.
- **Compare:** This option analyzes a single time series with more than one method.
- **Simulate:** This option simulates a time series using Monte Carlo simulation so that the response of one or more forecasting methods can be compared. The data changes in real time as the simulation parameters are changed.
- **Portfolio:** This option may have a number of time series representing the unit values of investments and the associated number of units owned. The add-in computes the total value of the portfolio and forecasts of the portfolio value.
- **Change:** This option provides the means to change an existing forecast.
- **Relink:** When a model is prepared on one computer and opened on another, the add-in functions will not work. The relink command rewrites the functions to link with the
current computer. **This option must be chosen to manipulate the demonstration workbook.**

- **About Add-in:** This option displays the author and date of the installed version of the add-in. New versions are placed on this web site in the Excel add-in section as new features are added and errors are corrected.

![Add OMIE...](image)

**Figure 5.2**

### 5.2.2 Installing Add-ins

In order to use the Forecasting Add-in, Jensen Library is required to be downloaded. The Jensen Library holds all the Excel add-ins in the Jensen.lib directory. This library can be downloaded from the following link: [http://www.me.utexas.edu/~jensen/ORMM/excel/library_windows.html](http://www.me.utexas.edu/~jensen/ORMM/excel/library_windows.html)

This library comprises of the complete collection of Operations Research Models and Methods (**ORMM**), Teach Operations Research (**Teach OR**) and Operations Management/Industrial Engineering (**OM/IE**) add-ins. Forecasting is an option under OM/IE add-ins.

After downloading the Jensen Library, the forecasting Add-in can be installed in the following manner:

Click on “Options” in the File menu and then choose “Add ins” command from the Options. A dialog box showing the current list of Add-ins appears as in the figure below. Add-ins are identified by name. A check in the box next to the name means that the add-in is installed, while
an unchecked box means that it is not installed. If an add-in that you want does not appear in the list use the Select... or Browse... button to move to the directory in which the OM/IE (Operations Management/Industrial Engineering) add-ins are stored (Figure 5.3). The most convenient way to use the OM/IE add-ins is to first install the Add OM/IE add-in. Forecasting add-in can then be installed from the dialog box of the Add OM/IE add-in by checking the forecasting box and clicking OK (Figure 5.4).

Figure 5.3
5.2.3 Working of Forecasting Add-in: An Example

For the purpose of forecasting, non-seasonal patterns and trends can be extrapolated using a *moving-average* or *smoothing* model. The basic assumption behind averaging and smoothing models is that the time series is "locally stationary" with a slowly varying mean. Hence, we take a *moving* (i.e., local) average to estimate the current value of the mean, and use this as the forecast for the same or subsequent years. Similar approach is followed by the forecasting add-in feature in excel.

The *Forecasting add-in* implements the moving average formulas. The example below shows the analysis provided by the add-in for the sample data in column B. The first 10 observations are indexed -9 through 0. Compared to the table above, the period indices are shifted by -10.
The first ten observations provide the startup values for the estimate and are used to compute the moving average for period 0. The $MA(10)$ column (C) shows the computed moving averages. The moving average parameter $m$ is in cell C3. The $Fore(1)$ column (D) shows a forecast for one period into the future. The forecast interval is in cell D3. When the forecast interval is changed to a larger number the numbers in the Fore column are shifted down.

The $Err(1)$ column (E) shows the difference between the observation and the forecast. For example, the observation at time 1 is 6. The forecasted value made from the moving average at time 0 is 11.1. The error then is -5.1. The standard deviation and Mean Average Deviation (MAD) are computed in cells E6 and E7 respectively. (Table 5.6)
After the electricity spot prices are forecasted, simulation of dispatch of power plant can be done. The economic evaluation of this dispatch simulation will calculate the profits the investors can make in future by investing in a power plant.

5.3 Economic Evaluation using Dispatch Simulation

5.3.1 Inputs to the tool

The following inputs are given to the tool:

1. Project Related
2. Fuel Related
3. Operation and Maintenance Related
4. Economic

Project Related

1. **Installed Capacity** - This means the summation of the name plate capacities of all the units of the generating station or capacity of generating station (reckoned at generator terminals).

2. **Auxiliary Consumption** - This means the quantum of energy consumed by auxiliary equipment of the generating station, and transformer losses within the generating station, expressed as a percentage of the sum of gross energy generated at the generator terminals of all the units of the generating station. These auxiliaries typically utilize 3 to 6% of a plant’s gross output, but a plant’s use of its’ own electricity can range as high as 12% if the plant is equipped with extensive pollution control equipment such as precipitators, scrubbers, NOx controls and cooling towers.

3. **Net Capacity** - This means the actual capacity available for dispatch after due consideration of the electrical power utilized in the plant by auxiliary equipment such as pumps, motors, pollution control devices etc.

   Net Capacity = Installed Capacity * (1-Aux %)

   Where Aux % = Auxiliary Consumption of a power plant in percentage
4. Maximum Annual Generation- This means the maximum units of electricity that can be generated at the generator terminals.

Maximum Annual Generation = Net Capacity * 8760

5. Capital Investment- Funds invested in a firm or enterprise for the purposes of furthering its business objectives. Capital investment may also refer to a firm's acquisition of capital assets or fixed assets such as manufacturing plants and machinery that is expected to be productive over many years.

Sources of capital investment are manifold, and can include equity investors, banks, financial institutions, venture capital and angel investors. While capital investment is usually earmarked for capital or long-life assets, a portion may also be used for working capital purposes.

For gas engine plants, capital investment is typically of the order of 3-4 cr per MW.

6. Fixed Charge Recovery Factor or Capital Recovery Factor (CRF) - CRF converts a present value into a stream of equal annual payments over a specified time, at a specified discount rate (interest). The capital recovery factor can be interpreted as the amount of equal (or uniform) payments to be received for n years such that the total present value of all these equal payments is equivalent to a payment of one dollar at present, if interest rate is i.

The value of an equal payment (A) to be made in each of n periods here is given by:

\[ A = P \frac{i(1+i)n}{(1+i)n-1} \]

That is, \( A = P \times CRF \)

Where, \( CRF = \frac{i(1+i)n}{(1+i)n-1} \)

Fuel Related

1. Gross Heat Rate (GHR) - This means the heat energy input in kCal required to generate one kWh of electrical energy at generator Terminals. This excludes all the internal (auxiliary) power consumptions.

2. Net Heat Rate (NHR) - This means the heat energy input in kCal required to generate one kWh of electrical energy at generator terminals if auxiliary power consumption is considered. It is calculated as follows:
NHR = \frac{GHR}{(1-\text{Aux\%})}

3. **Efficiency** - This refers to the thermal efficiency of a generating unit indicating the energy output at generator terminals per unit energy input from the fuel. Net Plant Heat Rate is used to determine the thermal efficiency of a generating unit by the following relationship:

Efficiency = \frac{860}{NHR} \times 100

**O & M Related**

1. **Variable O & M Cost** - The sum total of all the operation and maintenance expenses for the evaluated time frame is called the total variable O&M expense. This is incurred whenever the plant dispatches irrespective of whether at maximum or minimum output capacity.

2. **Fixed O & M Cost** - This O&M cost is incurred irrespective of whether a plant is dispatching or not on an annual basis. This includes cost of labour, station power, transmission O&M, spare parts etc.

**Economic Assumptions**

1. **Exchange Rate** - The price of one country’s currency expressed in another country’s currency. In the tool, the exchange rate of dollar to INR needs to be given as an input.

2. **Annual Fuel Price Escalation Rate** - This is the percentage at which an annual change in price levels of fuel occurs or is expected to occur.

3. **Annual O & M Escalation Rate** - This is the percentage at which an annual change in Operation and Maintenance expenses occurs or is expected to occur.

**5.3.2 Decision Logic**

The flowchart below (Figure 5.5) gives the logic involved in dispatch planning.
1. In the first step the logic undertakes a loop which checks whether 365 iterations have been undertaken or not. If not, the spot price data on daily basis for the remaining no of days of that year is exported.

2. Then the comparison between the spot price of that particular hour and short run marginal cost of the plant for that particular year takes place.

3. If the spot price is greater than the short run marginal cost for that particular hour the plant dispatches at maximum capacity. However if the spot price is less than the short run marginal cost, the plant does not dispatch.

4. The logic is repeated for the subsequent iterations till 365 iterations are complete.
5.3.3 Simulation Output Results

The algorithm mentioned above is used to generate the power plant dispatch for the next three years on a daily basis. This dispatch is then used further to evaluate a number of important factors that help in the economic evaluation of the power plant. This dispatch data is used for various calculations and is represented in a graphical format to determine the power plant dispatch for any given time frame within the year which has been simulated. The Output results of the simulation can broadly be classified as

- General Information
- Dispatch Information
- Fuel Information
- Financial Information

General Information

The general information about the power plant that can be derived as an output from the various inputs is Short Run Marginal Cost (SRMC), Net capacity and Annual Generation. The values of these fields represent the final calculated theoretical values of all these parameters. The SRMC can be calculated as follows:

\[
\text{SRMC} = \text{Variable O&M Costs} + \text{Fuel Cost}
\]

Dispatch Information

Dispatch Information represents the details of the power plant dispatch throughout the year. This gives us a qualitative and quantitative analysis about the performance of the power plant in that particular year. Two levels of dispatch have been considered i.e. Dispatch at maximum capacity and zero dispatch.

- The Total Fired Hours represent the total number of hours in that year that the power plant is designated to dispatch (at maximum capacity). This will give an indication on the availability throughout the year in various time frames.
Total Fired Hours = No. of days of maximum dispatch per year \* 24

- The Plant Load Factor represents the percentage of sum of kWh generated at generator terminals of all the units corresponding to scheduled generation to installed capacity, expressed in kilowatts (kW) multiplied by number of hours in that period.

\[
\text{PLF} = \frac{\text{Net Capacity} \times \text{Total Fired Hours} \times 100}{\text{Installed Capacity} \times 8760}
\]

**Fuel Information**

The Gross and Net Heat Rates of the fuel taken as inputs help in understanding the performance of various fuels in comparison to one another. The net heat rate values can also be used to calculate the fuel price.

\[
\text{Fuel Price (in Rs. /kWh)} = \frac{\text{Fuel Cost (in $/mmBtu)} \times \text{Exchange Rate (Rs./$)} \times \text{Net Heat Rate (kcal/kWh)}}{0.252 \times 1000000}
\]

**Financial Information**

The financial information denotes the detailed description of all the Costs incurred and the expected returns. It consists of the following:

- **Revenue:** This refers to the gross sales of the plant. The Revenue of a plant signifies the total income of the plant before any deductions regarding the cost incurred for running the plant are deducted.

\[
\text{Revenue} = \sum \text{SP} \times \text{CP}
\]

SP – Spot Price for that particular day

CP – Dispatch level at that hour (0 or Maximum)

- **Fuel Expense:** This signifies the total amount spent on the procurement and usage of the particular fuel in the power plant over the period of evaluation. The fuel expense is calculated as follows:
Fuel Expense = Fuel Price (in Rs./kWh) * Annual Generation (in kWh)

- **Variable O&M Expense**: The sum total of all the operation and maintenance expenses for the evaluated time frame is called the total variable O&M expense. This is incurred whenever the plant dispatches irrespective of whether it is dispatching at maximum or minimum output capacity.

  \[
  \text{Variable O&M Expense} = \text{Variable O&M Cost (in Rs./kWh)} \times \text{Annual Generation (in kWh)}
  \]

- **Fixed O&M Expense**: These are O&M expenses which are incurred irrespective of whether a plant is running or not. These expenses are due to labour, station power, transmission power O&M, on-going spare parts, A&G etc.

  \[
  \text{Fixed O&M Expense} = \text{Fixed O&M Cost (in Rs./kWh)} \times \text{Annual Generation (in kWh)}
  \]

- **Fixed Charge Recovery (FCR) or Capital Recovery Factor (CRF) Expenses**: The FCR expense is given by the following formula:

  \[
  \text{FCR Expense} = \text{FCR (in\%)} \times \text{Capital Investment (in Cr/MW)} \times \text{Installed Capacity}
  \]

- **Net Profit**: The return on the investment made for setting up the power plant will be determined by the profitability of the plant. Net Profit is determined by subtracting all the expenses from total revenue.

  \[
  \text{Net Profit} = \text{Revenue} - \text{All Expenses}
  \]

- **Internal Rate of Return (IRR)**: The discount rate often used in capital budgeting that makes the net present value of all cash flows from a particular project equal to zero. Generally speaking, the higher a project's internal rate of return, the more desirable it is to undertake the project. As such, IRR can be used to rank several prospective projects a firm is considering. Assuming all other factors are equal among the various projects, the project with the highest IRR would probably be considered the best and undertaken first. Two types of IRR can be calculated:
1) **Project IRR**: The project IRR takes as its inflows the full amount(s) of money that are needed in the project. The outflows are the cash generated by the project. The IRR is the internal rate of return of these cash flows. The calculation assumes that no debt is used for the project. For calculations in the project, the IRR function of MS-Excel is used.

\[ = \text{IRR}(\text{value 1}, \text{value 2}, \text{value 3}, \ldots, \text{value n}) \]

Where value 1 - Capital Investment in the project and should be entered as a negative value
Value 2, value 3 and so on are values of Gross Profits earned during the life cycle of the project and should be entered as positive values.

2) **Equity IRR**: Equity IRR assumes that you use debt for the project, so the inflows are the cash flows required minus any debt that was raised for the project. The outflows are cash flows from the project minus any interest and debt repayments. Hence, equity IRR is essentially the "leveraged" version of project IRR.

\[ = \text{IRR}(\text{value 1}, \text{value 2}, \text{value 3}, \ldots, \text{value n}) \]

Where value 1 - Capital Investment in the project and should be entered as a negative value
Value 2, value 3 and so on are values of Net Profits earned during the life cycle of the project and should be entered as positive values.

**5.4 Applications of Optimized Economic Dispatch Simulation**

“Economic dispatch” has a common, general meaning – the practice of operating a coordinated system so that the lowest-cost generators are used as much as possible to meet demand, with more expensive generators brought into production as loads increase (and conversely, more expensive generation eliminated from production as load falls). Economic Dispatch Simulation performs exactly the same purpose and analyses the whole situation from the view point of any particular power plant. Economic Evaluation helps in taking important decisions about any existing or any upcoming project.
Application in Power Plant Operation

Economic dispatch works to manage resources across time. Different resources have differing production capabilities and characteristics. Economic dispatch simulation helps in efficient and planned use of the available resources.

A generator’s production level this afternoon will be affected by its on-line status and production levels this morning and yesterday (e.g., a base-load coal plant) as well as whether maintenance was performed on it last quarter or last year (e.g., nuclear refueling, gas refurbishment). This implies that although the primary focus of economic dispatch simulation is daily or rather hourly operations, the process must look beyond a single day to optimize the operation and cost of resources across a longer time frame.

The most important application of Economic dispatch simulation is that it gives a very fair idea about the dispatch schedule that the plant is likely to follow in the coming year. This can help in scheduling the maintenance in those periods of the year when it is less likely that a profit will be made by running the power plant. Thus this can help the power plants plan their outages in advance.

Some of the other issues that the simulation addresses are, Whether the plant has both a firm fuel supply and firm fuel transportation, so it can perform reliably when dispatched; Whether the unit’s fuel source has take-or-pay provisions that would make it more expensive to idle than to run; Whether the dispatching entity or its regulators explicitly attempt to minimize environmental impacts such as air emissions from generation; Whether the area needs to maximize its efficiency of natural gas use because of high natural gas prices or limited deliverability.

Application in Grid Operation and Reliability

Economic dispatch allows the operator to deploy resources more efficiently and thus handle higher peak loads more reliably than would be possible without economic dispatch simulation. It can determine when and which units to place on-line and for how much time.

Economic dispatch, combined with Spot Prices, makes reliability needs clear and transparent to everyone in the region and the market. Because Spot Prices are highest where the need for power
is greatest, they immediately reflect the impact of grid conditions such as transmission bottlenecks, peak loads, or generating units losses, and create an incentive for every market participant to respond by supplying power (or reducing load) when most needed.

It helps in determining the Dispatchability – the ability to follow load closely- of various power plants in the grids. It can also be combined with the load flow studies to simulate other system parameters.

**Application of Economic Evaluation**

The main aim for setting up a power plant is ‘to be able to generate power profitably’. The economic evaluation of a power plant helps analyze in great detail the extent of profitability of any given plant for any particular time frame. It gives an appropriate idea about the initial investment that needs to be made and helps in determining the returns that the investor is likely to get.

A simulation model which can predict future scenarios is of great use to the people who are planning invest the huge sum of money required in setting up a power plant. The results produced by the simulation are likely to guide the investor in such a way that he can make a go or no decision on whether to invest or not, if yes then how much, when is he likely to earn a profit, which fuel is likely to give maximum returns, what could be future scenarios considering other capacity additions and the other unforeseen contingencies.
Chapter 6: Testing and Improvements

6.1 Testing

In order to test the forecasted results, load forecasting can be done by various other methods like regression, exponential smoothing and double exponential smoothing and results can be compared generating error values for greater accuracy.

**Exponential Smoothing:** This method considers the entire past in its forecast, but weighs recent experience more heavily than less recent. The computations are simple because only the estimate of previous period and the current data determine the new estimate. The method is useful for time series with slowly changing mean.

**Double Exponential Smoothing:** This method estimates both the constant term and the linear coefficient of linear forecasting equation that model trends given by:

\[ X = a + bt + E \]

where, \( E \) being the constant term

**Regression:** The moving average method does not respond well to a time series that increases or decreases with time. Here a linear term trend in the model is included. The regression method approximates the model by constructing a linear equation that provides the least squares fit to the last m observations.

6.2 Improvements

There is a scope of following improvements in the project:

1. Price forecasting can be done by giving other data inputs as Population growth, temperature, humidity, State Domestic Product (SDP), day of the week, time of the day, category of consumer etc. so that the forecasted values are more realistic.

2. While planning Load Dispatch, the plant outage factors, both planned and forced, should be taken into account for more accurate planning and greater no of days of maximum dispatch.
3. While checking the investment viability, calculation of profit values should be done after deduction of taxes and depreciation values.

4. Moving average should be taken for medium no. of values so that the trend line is a good approximation of spot price pattern and the extrapolated results are accurate.
Chapter 7: Results

7.1 Consolidated Output Sheet

All the above stated output parameters are assembled together in the Consolidated Output Sheet of the plant (shown in the figure 7.1).

![Consolidated Output Sheet](image)

*Figure 7.1*

7.2 Graphical Representation of Power Plant Dispatch

The power plant dispatch obtained as a result of analysis can also be viewed in a graphical format. The graphical format serves for a better viewing of the output results and also conveys...
the details of the daily dispatch for the time period of evaluation. In the graphs (Figure 7.2) below, 1 indicates maximum dispatch and 0 indicates no dispatch.

Figure 7.2
Chapter 8: Conclusions

Based on the study and analysis of the tool the following conclusions can be drawn:

1. Various Factors affect load demand and hence electricity prices

Load demand broadly depends on factors such as time of the year, weather conditions and possible customer classes which in turn affects the electricity prices. Spot prices increase as load demand increases and vice-versa.

The time factors include the month of the year, the day of the week, and the hour of the day. There are important differences in load between weekdays and weekends. The load on different weekdays also can behave differently. For example, Mondays and Fridays being adjacent to weekends, may have structurally different loads than Tuesday through Thursday. This is particularly true during the summer time. Holidays are more difficult to forecast than non-holidays because of their relative infrequent occurrence.

Weather conditions influence the load. In fact, forecasted weather parameters are the most important factors in short-term load forecasts. Various weather variables could be considered for load forecasting. Temperature and humidity are the most commonly used load predictors. Among these weather variables, two composite weather variable functions, the THI (temperature-humidity index) and WCI (wind chill index), are broadly used by utility companies. THI is a measure of summer heat discomfort and similarly WCI is cold stress in winter.

Most electric utilities serve customers of different types such as residential, commercial, and industrial. The electric usage pattern is different for customers that belong to different classes but is somewhat alike for customers within each class. Therefore, most utilities distinguish load behavior on a class-by-class basis.

The graph below (Figure 8.1) was plotted during the course of the project for the purpose of Electricity price forecasting. It indicates the demand for electricity during different months of the year in India.
The demand is high during peak summer months of March and April and peak winter months of December, January and February and is comparatively low during monsoon months like July, August and September.

![Monthly Indices](image)

**Figure 8.1**

2. **Mean Average Deviation is a measure of accuracy of Spot Price Forecasting**

The mean absolute deviation (MAD), also referred to as the mean deviation, is the mean of the absolute deviations of a set of data about the data’s mean. In other words, it is the average distance of the data set from its mean.

The equation for MAD is as follows:

\[
MAD = \frac{1}{n} \sum |e_i|, \text{ where } e_i = \text{Actual} - \text{Forecast}
\]

Hence, greater the value of Mean Average Deviation lower is the accuracy of forecast. In the Microsoft Excel Forecasting Add-In there is provision to shift the moving average values and corresponding values of MAD are displayed. So forecasted values can be adjusted so that they are accurate.

3. **Plant Load Factor (PLF) of a power plant should be as high as possible.**

PLF is the ratio of actual output of a power plant over a period of time and its output if it had been operated at full capacity during that time period. Therefore, as per the definition, a higher plant load factor means:
Plant is more efficiently used.

- Fixed cost of operational and fixed assets are efficiently used over per unit of electricity generated and sold.
- It means more output power and so more revenue from plant.

If the PLF is affected by non-availability of fuel, maintenance shut-down, unplanned break down and no off take (as consumption pattern fluctuates lower in nights), the generation has to be adjusted since power (electricity) storage is not feasible. The generation of power is controlled to match the off take. For any duration when a power plant generates below its full capacity, to that extent it is a capacity loss.

Plant Load Factor for Gas Engine Plants is dependent on the fuel and on whether it is simple cycle or combined cycle. For Simple Cycle Diesel Generators it is usually between 32-34%. In case of Generators with fuel as Natural Gas, for simple cycle the PLF is 38-49% and for combined cycle PLF is 75-90%.

4. **Up Time and Down Time of a power plant play key role in Dispatch Planning.**

There may be case when Short Run Marginal Cost of a plant may be more than Electricity Spot Price for some duration but shutting down plant during that period may result in loss. This happens when the Down Time of plant more than the number of hours for which SRMC is greater than Spot price in the market.

Similarly, there may be case when SRMC is less than Spot price but starting the plant at such an instant may not let the owner avail profits by dispatching since the plant has certain Up Time. In general, the plants with less Up-Time are used as Base-Load plants and the ones with high Up-Time are used as peaking plants.

Hence, considering the Up Time and Down Time of power plant during dispatch planning is of utmost importance.
5. Power systems are operated to minimize the avoidable (i.e. variable) cost (SRMC) of meeting instantaneous load.

Not all electric utility companies own each type of plant. Fuel availability, fuel prices, environmental constraints, construction and capital costs etc. determine the plant type (i.e., the mix) owned by specific power companies at any given time. Larger vertically integrated power companies typically own several plants in each category. Within a category, each plant’s marginal cost or marginal productivity might vary considerably based on age, technology, plant design, operating performance, fuel conversion (boiler) efficiency, heat rate, etc. System operators or dispatchers minimize costs by selecting plants in order of their running or production costs from the least to more expensive.

As demand is communicated to a power system dispatcher or operator, this simple least-cost operating rule requires that the dispatcher fire up and utilize the plants with the lowest marginal costs. As demand increases, more costly plants must be utilized. These costlier plants generally have: (1) lower heat rates or lower fuel efficiencies; (2) higher fuel costs; (3) higher labor costs or other equipment costs; and (4) other locational costs such as line losses or network congestion constraints. As demand increases, more costly plants are called into service (i.e., they are dispatched by the system operator to meet increasing load).

Actual dispatch cost is based upon a term known as “system lambda” that reflects losses that can occur when energy is transformed by voltage and transmitted over wires. Plants with low system “lambdas” are typically called base-load plants and are expected to be called upon nearly 8760 hours of the year. In practice, maintenance schedules and planned, as well as unplanned, outages affect actual use. The annual percentage of time a plant is in use is known as its capacity (or availability) factor (CF). Plants used next in the merit order are only used about half the year. These are known as intermediate plants. These intermediate plants could include older or less efficient plants previously acquired for base-load use that can no longer compete with other base-load plants. Finally, some plants are designed to be used, or their marginal cost makes them economic, for only a relatively small fraction of the year. These are called peaking plants.

If marginal operational costs and plant location were the only factors, most power systems would own only low marginal cost base-load plants. This is generally not the case because base-load units generally are more costly to construct than intermediate or peaking plants.
6. Accurate electricity price forecasting helps in making right investment decisions.

Forecasting of electricity prices helps to evaluate the profits a power plant would make in subsequent years which gives the investors an insight into the level of returns they would get if they chose to invest in a particular plant. Decisions must be made regarding assets that may be operated for 50 years; regulators require resource plans that extend 20 to 30 years; and many electricity and fuel contracts last 20 years or more. Not only is price forecasting increasing in importance, but decision-makers increasingly realize that common “singlepath,” most-likely estimates are inadequate. Single-path estimates, even when unbiased, provide no information on risk exposure. Furthermore, they provide no help evaluating resources that can be adapted, through operational changes and investments, to changes in prices, costs, and other factors. Risk and optionality can only be fully examined with a thorough, quantified picture of future uncertainty. Current and recent industry experience is replete with examples illustrating the importance of long-run electricity price forecasting, and the problems created with simplistic and/or inaccurate forecasts. In 2001, the State of California signed more than $40 billion in long-run electric contracts. These contracts are now considered so expensive, there is considerable effort being devoted to cost allocation, renegotiation, and litigation. Throughout the country, plans to build new capacity have been shelved as prices have not risen as expected. In Texas, 32 power projects totaling 17,801 MW have been delayed or canceled since 2001.

The bottom line is that a good long-run probabilistic forecast electricity prices is required to understand the potential value and risks of many investments.
Chapter 9: Future Scope of Work

In addition to the study done, the following areas can be worked on for enhanced understanding of Power economics:

1. **For the purpose of Long Term Load Forecasting, various other methods like regression, exponential smoothing and double exponential smoothing can be used and results can be compared for greater accuracy.**

   **Exponential Smoothing:** This method considers the entire past in its forecast, but weighs recent experience more heavily than less recent. The computations are simple because only the estimate of previous period and the current data determine the new estimate. The method is useful for time series with slowly changing mean.

   **Double Exponential Smoothing:** This method estimates both the constant term and the linear coefficient of linear forecasting equation that model trends given by:

   \[ X = a + bt + E, \text{ E being the constant term} \]

   **Regression:** The moving average method does not respond well to a time series that increases or decreases with time. Here a linear term trend in the model is included. The regression method approximates the model by constructing a linear equation that provides the least squares fit to the last m observations.

2. **Levelised Cost of Electricity (LCOE) can be calculated.**

   Producing energy typically requires making an investment in a technology that produces energy over a number of years. The value of such an investment to a private firm is the present discounted value of revenue from energy sales minus the present discounted value of the costs, where the discount rate represents the opportunity cost of investment funds -- typically the competitive rate of return. The levelized cost of energy is defined as the constant price per unit of energy that causes the investment to just breakeven: earn a present discounted value equal to zero. In other words, present discounted value of energy produced times the levelized cost equals the present discounted value of the fixed and variable costs over the life of the investment.
Calculation for the LCOE is the net present value of total life costs of the project divided by the quantity of energy produced over the system life.

\[
\text{LCOE} = \frac{\text{Total Life Cycle Cost}}{\text{Total Lifetime Energy Production}}
\]

LCOE equation is one analytical tool that can be used to compare alternative technologies when different scales of operation, investment or operating time period exists and decide which technology can reach commercialization.

The LCOE is calculated as follows:

\[
\text{LCOE} = \frac{I - D + C - S}{E}
\]

Where I= Initial investment

D= Depreciation Tax Shield

C= Annual Cost

S= Salvage Value of any physical assets at the end of life cycle

E= Total Energy Production

3. Up Time and Down Time of a power plant as well forced outage factor can be considered to make the dispatch simulation more realistic.

Such complex simulations can be done in MATLAB. A sample simulation is given below (Figure 9.1) when all these factors are considered:
The first graph is plotted is the Spot Price & Short Run Marginal Cost comparison curve. Both Spot price and the variable cost for the specified period of evaluation are plotted on the Y-Axis against Time in hours on the X-axis. The upper plot is plotted in such a way that it denotes the hourly Spot price variation and the Short Run Marginal cost for the optimized economic operation of the plant corresponding to it.

The second graph is the Hourly representation of the power plant dispatch. It represents the amount of energy that will be dispatched corresponding to each hour in the evaluated time frame.
REFERENCES


