Parameter Estimation Based On Particle Swarm Optimization for Short Term Load Forecasting

Thesis submitted in the partial fulfillment of the requirements for the award of the degree of

Masters of Engineering

in

Power Systems & Electric Drives

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Certificate

I hereby certify that the work which is being presented in the thesis entitled "**Parameter Estimation Based on Particle Swarm Optimization for Short Term Load Forecasting**" in partial fulfillment of award of degree of **Master of Engineering in Power Systems and Electric Drives** submitted in Electrical and Instrumentation Engineering department, Thapar University, Patiala is an authentic record of my own work carried under the supervision of **Mrs. Manbir Kaur**, Assistant Professor, Electrical and Instrumentation Engineering department, Thapar University, Patiala, Punjab.

The matter in this thesis has not been submitted for the award of any other degree of this or any other university.

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Abstract

Load forecasting is an important component for power system energy management system. Precise load forecasting helps the electric utility to make unit commitment decisions, reduce spinning reserve capacity and schedule device maintenance plan properly. Besides playing a key role in reducing the generation cost, it is also essential to the reliability of power systems. The algorithms and networks were having been demonstrated using simulation studies. The techniques proposed in this thesis have been simulated using data obtained from State Load Dispatch Centre, Ablowal, Punjab and Rajasthan for the duration of one week and technique is used to estimate the parameters of linear and quadratic model and the results obtain for peak load forecasting are compared with the least error square method.

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CHAPTER 1

INTRODUCTION

1.1 Review

The growing tendency towards unbundling the electricity system is continually confronting the different sectors of the industry (generation, transmission, and distribution) with increasing demand on planning management and operations of the network. The operation and planning of a power utility system requires an adequate model for electric power load forecasting. Load forecasting is traditionally viewed as a key issue in helping an electric utility to make important decisions on energy planning, being useful to support analysis of eventual strengthening or expansion of the existing infrastructure, implementation of a maintenance scheduling valuable to unit commitment or even helpful to plan the integration of dispersed generation, adoption of an optimized network configuration, load switching, voltage control, and infrastructure development. With liberalization, the energy markets and the subsequent unbundling of the value chain activities, load forecast gains even more importance, being essential to the suppliers interested to buy the necessary energy to provide their customers needs. Adequate energy transactions can be scheduled and forecasts below or above the real consumption is avoided because it could result in increased operational costs and loss of revenue.

Electric power grids are considered the most complex manmade systems mainly due to their wide geographical coverage, various transactions among different utilities, and diversity in individual electric power companies' layouts, size, and equipment used. Some of the tools are economic dispatch, unit commitment, state estimation, automatic generation control, security analysis, optimal power flow, and load forecast. The latter tool can be categorized into three main categories: long term, medium term, and short term. Results obtained from load forecasting process are used in planning and operation.

Electric load forecasting is the process used to forecast future electric load demand given historical load and current & forecasted weather information. Unfortunately, it is quite difficult to forecast load demand over a planning period of certain length is due to the uncertain nature of the forecasting process. There are large numbers of influential factors that characterize and directly or indirectly affect the underlying forecasting process; most of them are uncertain and uncontrollable like measurement of date, error in weather prediction, aging effect. It is most important to be taken care of that the energy forecast is neither too conservative nor too optimistic. If the forecast is too conservative, then it is very likely that the generating capacity may fall short of the actual power demand, resulting in restrictions being imposed on the power supply that may be detrimental to the economic development of the country. On the other hand, if the forecast is too optimistic, it may lead to the creation of an excess generating capacity, resulting in more investment without getting any immediate returns [1].

1.2 Load Forecasting

Based on time span, load forecasting techniques can be divided into three major categories:

1.2.1 **Long-term forecasting** used to supply electric utility company management with prediction of future needs for expansion, equipment purchases, or staff hiring. It takes a pretty long time to plan (12 months to 52 months), install and commission additional generating capacity.

1.2.2 **Medium-term forecasting,** that covers period of few weeks used for the purpose of scheduling fuel supplies and unit maintenance. It takes time less than long term electric load forecasting and more than the short term forecasting.

1.2.3 **Short-term forecasting** results hourly, daily values are used to supply necessary information for the system management of day-to-day operations and unit commitment. Short term forecasts, in particular, have become increasingly important since the rise of the competitive energy markets.

When the study horizon is short, conditional forecasts, which make use of weather forecast information to refine the load estimate, can be used to perform hourly, daily, and weekly planning tasks. The long- and the medium-term forecasts are used to determine the capacity of generation, transmission, or distribution system additions, and the type of facilities required in transmission expansion planning, annual hydrothermal maintenance scheduling, *etc.*. The short-term forecast is needed for control and scheduling of power system, and also as inputs to load flow study or contingency analysis.

1.3 Significance of Electric Load forecasting

Load forecasting is a task of singular importance in planning, analysis, and operation in energy markets and it is fundamental to:

1. compute the electric and energetic balances;
2. plan the scheduling and execution of the operation;
3. elaborate the plans of expansion, investments, and replacements;

4. estimate the economic/commercial transactions of energy and services;
5. budget for the revenues and outlays for the aforementioned transactions; and
6. calculate the margin of expected losses and profits for the agents.

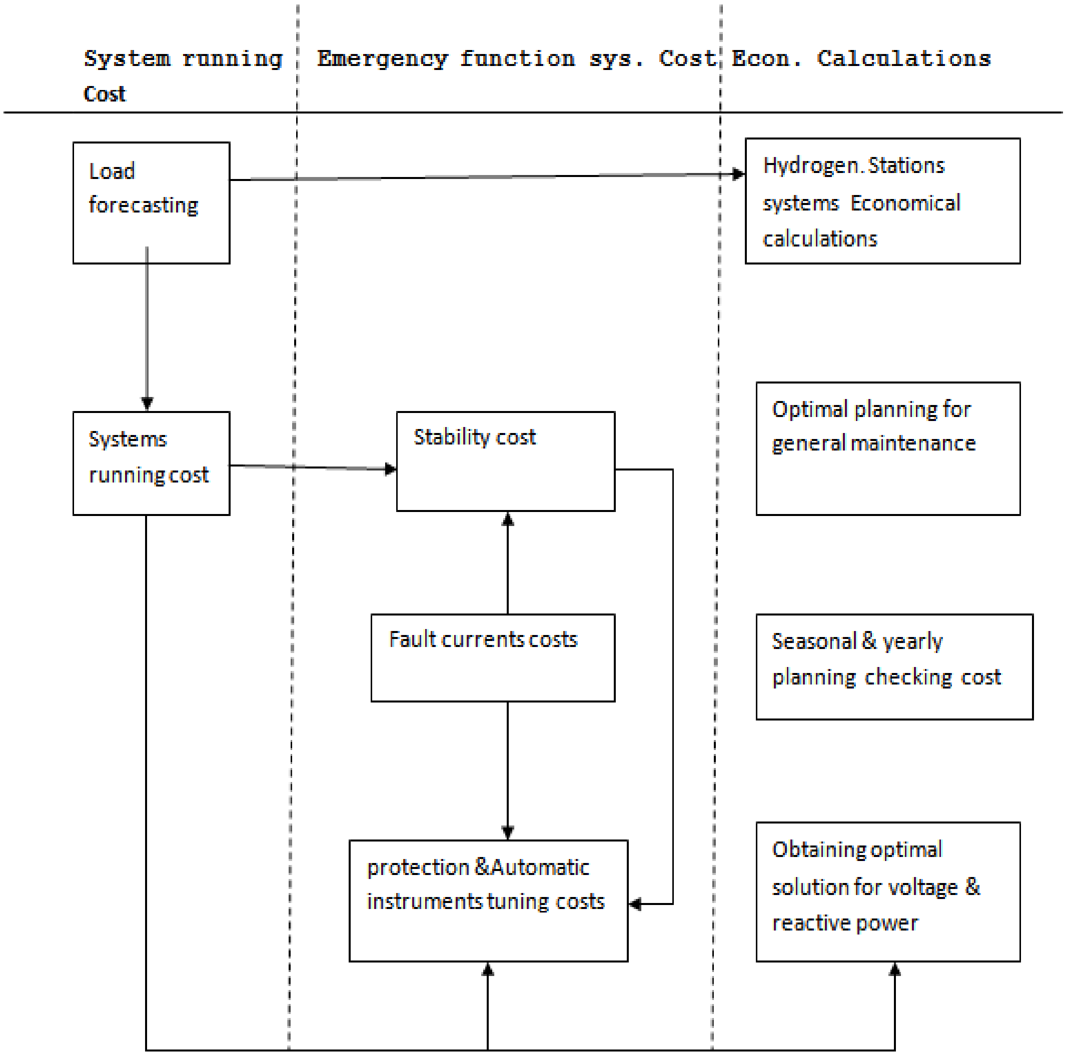

Fig 1.1 Cost functions of load forecasting

1.4 Factors affecting Load Forecasting

The factors that effect accurate load forecasting can be split into two different categories:

Endogenous variables: Those variables that relate uniquely with past values of the variable being predicted. The past load statistics that are used as inputs.

Exogenous variables: Those variables that relate with external variables that can directly or indirectly affect the load behavior. In this category, factors such as day type, day time, season, weather, and electricity price can be pointed as principal exogenous variables. The usual ways to achieve the relationships between those variables and load values is through auto-correlation functions or partial auto correlation functions. One commonly used strategy is that to relate load with weather variables being appropriate to separate seasonal effects.

First, because the load series is complex and non linear in nature and exhibits several levels of seasonality. The load at a given hour is dependent not only on the load at the previous hour, but also on the load at the same hour on the previous day, and on the load at the same hour on the day with the same denomination in the previous week. Secondly, due to important exogenous variables that must be considered, especially weather-related variables. It is relatively easy to get forecasts with about 10% mean absolute percent error (MAPE).

Various forecasting models have been developed so far using various graphical and statistical methods, the auto regressive and moving average models being the most popular. Some load models which use no weather information have been represented by time sequences. The former is based on the extrapolation. And the load behavior is represented by Fourier series or trend curves in terms of time functions.

Accurate and robust load forecasting is of great importance for power system operation. It is the basis of economic dispatch, hydro-thermal coordination, unit commitment, transaction evaluation, and system security analysis among other functions. Because of its importance, load forecasting has been extensively researched and a large number of models were proposed during the past several decades, such as Box-Jenkins models, ARIMA models, Kalman filtering models, and the spectral expansion techniques-based models. Generally, the models are based on statistical methods and work well under normal conditions, however, they show some deficiency in the presence of an abrupt change in environmental or sociological variables which are believed to affect load patterns. Also, the employed techniques for those models use a large number of complex relationships, require a long computational time, and may result in numerical instabilities.

1.5 Literature Review

Rashidi *et.al* [2] presented the approach for estimating parameters of long term load forecast models. C.-M.Huang and H.-T.Yang [3] gave a short-term load forecasting (STLF) approach using evolving wavelet-based networks (EWNs). EWNs have a three-layer structure: which contains the wavelet (input-layer), weighting (intermediate-layer), and summing (output-layer) nodes respectively. Comparisons of forecasting error and constructing time reveal that the performance of the EWNs could be superior to that of the existing artificial neural networks (ANNs).

Shayeghi. *et.al* [4] have presented an idea that the quality of short term load forecasting can improve the efficiency of planning and operation of electric utilities. Artificial Neural Networks (ANNs) are employed for nonlinear short term load forecasting owing to their powerful nonlinear mapping capabilities.

A global optimum model was presented for 24 hour short-term electric load forecasting using recurrent neural networks by Marin *et.al* [5]. The development of the model consists of three phases: starting from historical data, each day is classified according to its load profile by means of self-organising feature maps. This has offered a greater ability to adapt to different meteorological and social environments than other neural methods. A.Sfetsos [6] has proposed the method using a clustering algorithm to group data with similar characteristics and a function approximation to capture the underlying characteristics of each cluster of data, form a special class. The analysis of the forecasting results showed the reduction of forecasting error by *7.5%* and 9%, respectively.

H.S. Hippert and C.E. Pedreira [7] have developed a model that related load profile to temperature profile. Fan *et.al* [8] have proposed a novel method of forecasting short-term electricity price based on a two-stage hybrid network of self-organised map (SOM) and support-vector machine (SVM). Pan Duan *et.al* [9] have presented a new hybrid method for the short-term load forecasting of electric power systems based on the Fuzzy c-means (FCM) clustering, particle swarm optimization (PSO) and support vector regression (SVR) techniques to accurate non linearity in the data. Elattar *et.al* [10] have presented a modified version of the support vector regression (SVR) to solve the load forecasting problem. Alfares and Nazeeruddin [11] have presented a trend removal technique based on optimal smoothing. The Winter's method is one of several exponential smoothing methods that can analyse seasonal time series directly. The method is based on three smoothing constants for stationarity, trend and seasonality.

Hsu, Y. Y. [12] has presented an expert system using fuzzy set theory for short term load forecasting. The expert system was used to do the updating function. Later, Liang & Hsu [13] have formulated a fuzzy linear programming model of the electric generation scheduling problem, representing uncertainties in forecast and input data using fuzzy set notation.

Yong Yu *et.al* [14] presented an intelligent fabric hand prediction system with fuzzy neural network. Hasan *et. al* [15] have presented an efficient hybrid model to load forecasting approach of Neural Network (NN) along with Particle Swarm Optimization (PSO), called NN–PSO, to resolve the short–term load forecasting (STLF)

1.6 Organization of the Thesis

The work carried out has been summarized in five chapters.

Chapter I highlight the brief introduction, summary carried out by various researchers.

Chapter II describes the Short term load forecasting. Different types of conventional and non conventional techniques are discussed in Chapter II.

Chapter III describes about the particle swarm optimization.

Chapter IV discusses the problem formulation and results.

Chapter V includes the conclusions obtain and future scope of the work.
MATLAB (R2010) is used for programming .

CHAPTER 2

SHORT TERM LOAD FORECASTING

2.1 Introduction

Load forecasting facilitates to maintain a balance between electricity supply and demand. Accurate forecast provides basis for decisions in unit commitment, hydrothermal coordination, hydro scheduling, fuel allocation, economic load dispatch and optimal power flow calculations, which leads to savings for electric utilities. In terms of planning short term load forecasting (STLF) having prediction period of one day or a week, provides basis for economic purposes STLF facilitates with necessary information on the basis of power system characteristics to perform daily operational tasks economically. It plays an important role for secure operational strategies and economic optimization. Short-term load forecasting of electric power not only plays a very important role in operation scheduling, but also has a significant impact on the secure operation of power systems

2.1.1 Importance of Short term Load Forecasting:

The principal objective of the STLF function is to provide the load predictions for

1. basic generation scheduling functions,
2. corrective actions based on future conditions for off-line security and
3. timely dispatcher information as shown in fig. 2.1.

2.2 Application of Short Term Load Forecasting

2.2.1 Economic Operation

Forecasting errors result in the form of increased operational costs. Under prediction of STLF leads to a failure for providing the required reserves, thus resulting in increased operational costs by using costly peaking units. On the other hand large reserve capacity and high operational costs are caused due to over prediction of STLF.

2.2.2 Reliability

Short term load forecasting (STLF) is a key issue for reliable and economic operation of power systems. STLF usually consists of prediction of load demand for one hour up to one week ahead. Today, however, importance of bus load forecast is also becoming evident, especially with introduction of advanced operational procedures, e.g., security constrained unit commitment (SCUC), SCUC incorporates the network constraints in the unit commitment (UC) problem to obtain a financially viable generation dispatch that is

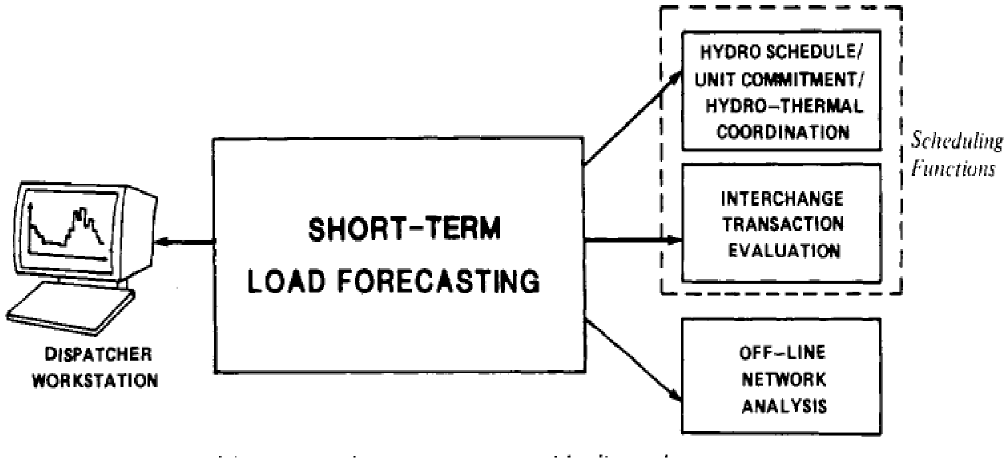

Fig. 2.1 Applications of STLF

physically feasible. Execution of SCUC, for instance, by independent system operator (ISO) in the electricity markets, requires bus load forecast to perform the power flow and determination of possible violations of security constraints, e.g., limits of transmission flows and bus voltages.

2.2.3 Energy Management

STLF traditionally has been an essential component of Energy Management Systems (EMS), as it provides the input data for load flow and contingency analysis.

2.2.4 Deregulation

With the worldwide deregulation of the power industry, load forecasting is becoming even more important, not only for system operators, but also for market operators, transmission owners, and any other market participants, so that adequate energy transactions can be scheduled and appropriate operational plans and bidding strategies can be established. In electricity markets, in addition to the traditional load affecting factors such as season, day type and weather, electricity price, which is voluntary and may have a complicated relationship with system load, is also becoming an important factor influencing the load. High forecasting accuracy and speed are required not only for reliable system operation, but also for adequate market operation, as both under-forecasts and over-forecasts would result in increased operational costs and loss of revenue.

2.3 Terminology

The term which are used in load forecasting are explained in this section:

2.3.1 Load Duration Curve: A **load duration curve** (LDC) is used in electric power generation to illustrate the relationship between generating capacity requirements and capacity utilization.

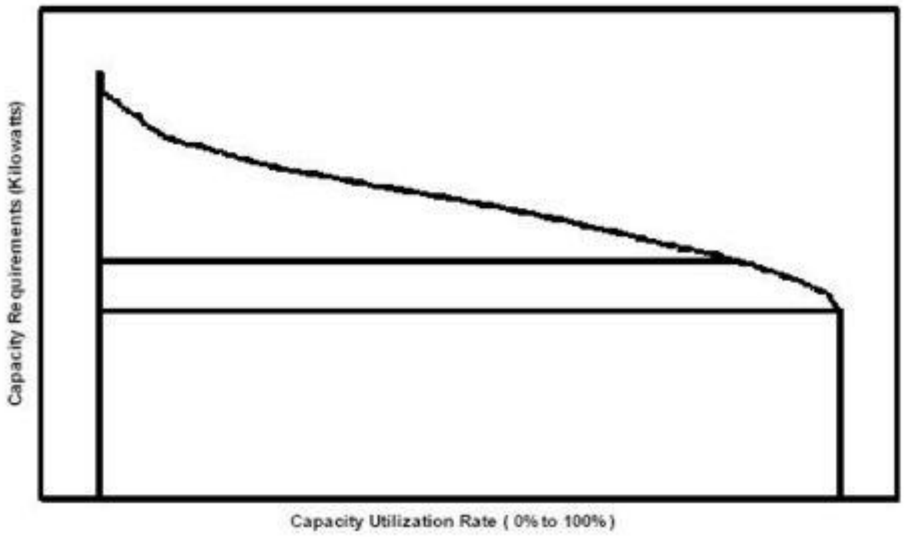

Fig. 2.2 Load Duration Curve

A LDC is similar to a load curve but the demand data is ordered in descending order of magnitude, rather than chronologically. The LDC curve shows the capacity utilization requirements for each increment of load. The height of each slice is a measure of capacity, and the width of each slice is a measure of the utilization rate or capacity factor. The product of the two is a measure a consumer means that maximum of electrical energy (e.g. kilowatt-hours).

2.3.2 Maximum Demand: The maximum demand of power that his circuit is likely to draw at any time. The connected load of a consumer means that the sum of continuous ratings of all the devices and outlet installed on his distribution circuit.

Demand Factor = Maximum demand/ Connected load

Maximum demand of each consumer is less than his connected load.

2.3.3 Load Factor: Load factor for a system or a plant is the ratio of average load to the peak load, for a certain period of time.

Load Factor = average load/ Peak load

Load factor can also be defined as the ratio of energy consumed in a certain time to the energy which would be consumed if the load is maintained at the maximum value throughout that time.

Load Factor = Energy consumed during a time of t hours/ peak load *(t_s)

2.4 Types of Load

Electric loads in the system are categorized as domestic, industrial, commercial, municipal, traction, agricultural.

2.4.1 Domestic or Residential Load: Residential load consists of lights, fans and other appliances like radio, heaters, electric irons, refrigerators, etc. For big house demand factor may be only around 0.5. During summer the major part of the domestic load may consists of refrigerator load, fan load during day and light and fan load during evenings. During winter, the major load is light load during evenings and early mornings and some heater load and refrigerator load.

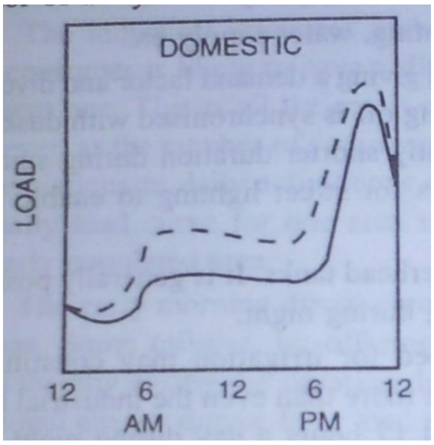

Fig 2.3 Chronological Load Curve for Domestic Loads

-------- Winter , ______ Summer

2.4.2 Industrial Load: The industry may be sub divided into small, medium and heavy. The approximation based on power consumption. The demand factor may vary from about 0.8 for small industries to about 0.5 for heavy industries. During night the load is mostly lighting plus some loads like refrigeration load which requires continuous supply.

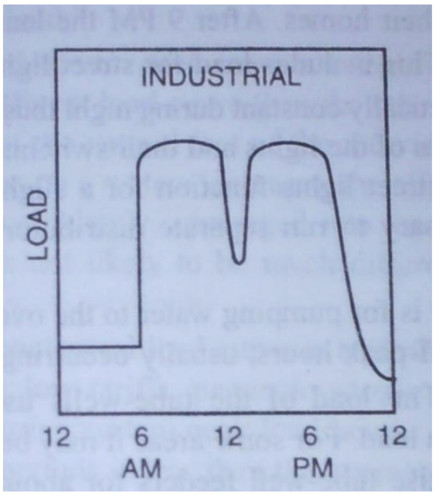

Fig 2.4 Chronological Load Curve for Industrial Load

2.4.3 Commercial Load: The load mainly consists of lighting, fans and small electric appliances. The demand factor is fairly high. The load is fairly constant from around 9 AM to 8 PM. During night the load may consist of some lighting load.

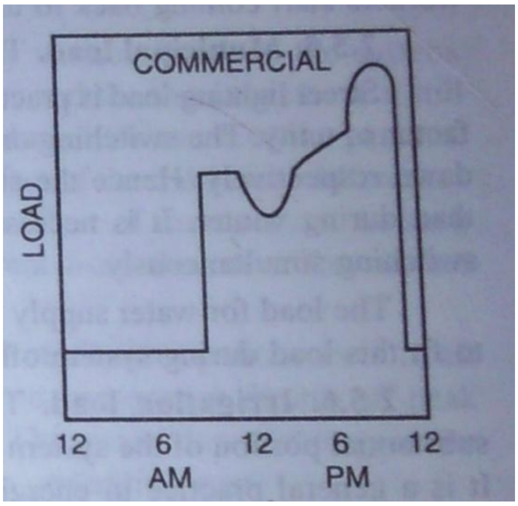

Fig 2.5 Chronological Load Curve for Commercial Load

2.4.4 Urban Traction Load: This load consists of tram cars, suburban trains and associated railway stations. From midnight to around 4 AM, the load is small and limited to mostly lighting load. Around 4 AM train starts running and the load starts increasing. Then load rises towards evening. After 9 PM load falls rapidly.

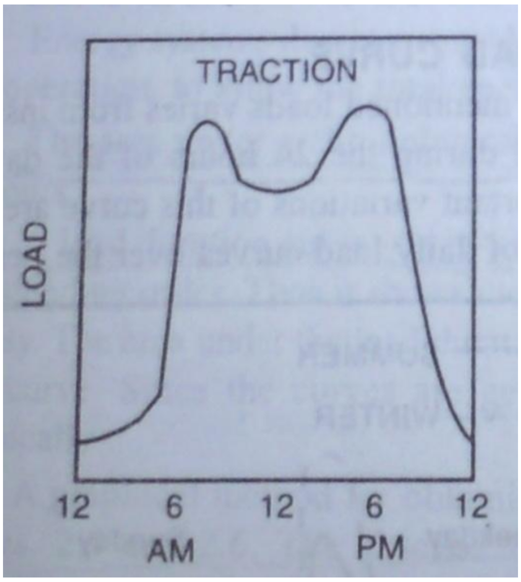

Fig 2.6 Chronological Load Curve for Traction Load

2.4.5 Other Loads: This include load like municipal load and irrigation load. Municipal load consists of street lighting, water supply etc. The load for water supply is for pumping water to the overhead tanks. The load of tube-wells used for irrigation may constitute a substantial portion of the system load.

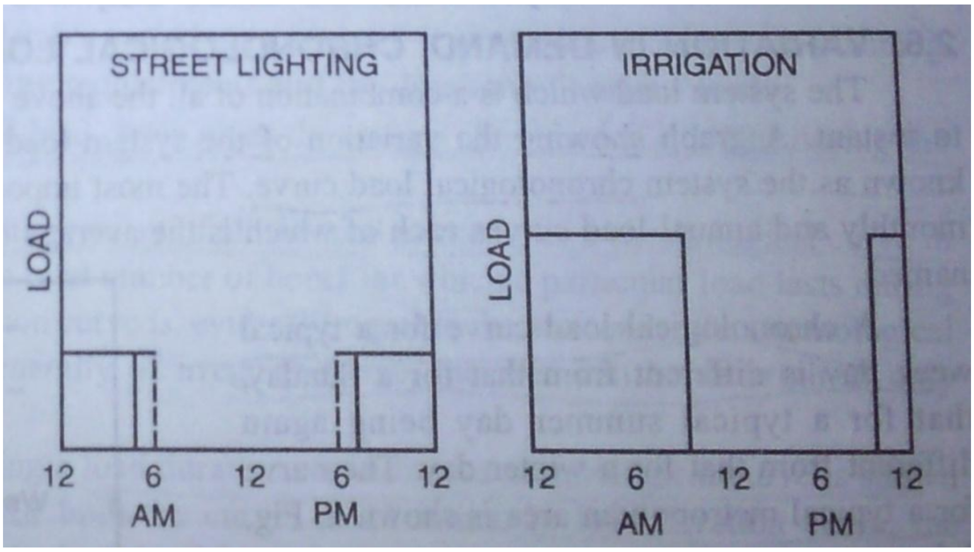

Fig 2.7 Chronological Load Curve for Municipal and Irrigation Load

2.5 Modeling of Short Term Load Forecasting

There are two types of techniques used for short term load forecasting:

1. Conventional.
    - Regression Analysis

- Time series method
- Exponential Smoothing

2. Non-conventional
    - Expert system
    - Fuzzy Logic
    - Artificial Neural Network
    - Genetic Algorithm
    - Particle Swarm Optimization

2.5.1 Conventional Techniques

Load models are developed to mathematically represent the relationship between load and influential variables such as time, weather etc. The final accuracy of the forecast process depends on the model selected and the accuracy of the estimated parameters. Reviewers of load forecasting models have found that techniques almost in use today can be categorized as being of multiple regression, general exponential smoothing and statistical methods.

2.5.1.1 Regression analysis

Regression analysis or trend analysis is the study of the behavior of a time series or process in the past and its mathematical modeling so that the future behavior can be extrapolated from it [17]. A time variant event such as power system load can be broken down into four components, basic, trends, seasonal variations, cyclic variations and random variations. The last three variations have a long-term zero mean. Regression curves used in power system load forecasting are; linear, polynomial, and exponential. A multi-variable regression model can be related to (n+1) independent variables (repressors) and can be written as:

$$P(t) = a_0 + \sum_{i=1}^{n} a_i t^i i + r(t) \qquad (2.1)$$

Where P(t) is the peak load demand at time t, a_o, a_i are the regression coefficients relating the load P(t) to the time t. r(t) is the residual load at year (t). Although the relationship between P and t may be non-linear for i=2, 3…, the model is still said to be linear since t and t^2 can be transformed into Y_1, Y2 … where $Y_1=t^2$, $Y_2=t^3$…. …

Another type of regression technique involves nonlinear regression models. Nonlinear regression models are not linear in terms of the parameters and can not be made so by any transformation. For many years, generation planners have used regression techniques as an aid in predicting annual peak system demands. Peak demands are known to be influenced by weather conditions, number and type of consumers and general economic conditions. However, a simple relationship in which demand increases exponentially with time is generally found to be yield an adequate forecast for system peak demand [17]. Forecasts are frequently obtained from the following simple relationship:

$$P(t) = e^{a+bt} \tag{2.2}$$

In order to identify the most adequate model for forecasting application among all available linear and nonlinear regression models, different types of graphs must be examined.

2.5.1.2 Time series method

A time series is defined as a set of data generated sequentially in time. The time series models assume that in the absence of major disruptions to critical factors of a recurring event, the data of this event in the future will be related to that of the past events and can be expressed via models developed from the past events [18]. In this analysis, two time series models, the Multiplicative Decomposition Model and the Seasonal ARIMA Model, are employed.

2.5.1.2.1 Multiplicative Decomposition Model

Multiplicative decomposition model assumes that a time series can be described as

$$x(t) = T(t)* S(t)* C(t)* R(t), t = \ldots.-1,0,1,2 \tag{2.3}$$

where x(t) is the time series, T(t) is the trend component, S(t) is the seasonal component, C(t) is the cyclic component and R(t) represents the random component.

The cyclic component is usually in the duration of one year to a few years and is not applicable to short-term load forecasting. Thus, we propose to simplify the above combination to only three terms

$$x(t) = T(t)* S(t)* R(t) ; \qquad t = \ldots.-1,0,1,2 \tag{2.4}$$

In order to apply this model, it requires that the trend of the time series be found and extended into the future. Intuitively, the trend component of a series made up of these three components can be found if the other two could be taken off the series. A typical load series contains daily seasonal indexes, which when used to divide a typical week's data, would remove the seasonal component from the series. To find the indexes, data of the most recent week without any holiday are divided by the average of a few recent weeks and using the average of these weeks tends to minimize the random effect. With these two components removed or minimized, the series now contains mainly the trend component. The equation of this trend line is extrapolated to estimate the trend in the future. Seasonal effects can then be incorporated into these future trend forecasts to account for the intra-day variation and obtain reasonably comprehensive forecasts.

2.5.1.2.2 Seasonal ARIMA Model

Two of the most basic models in time series are the autoregressive model (AR) and the moving average model (MA). In autoregressive models, the next value in the time series is represented as a linear combination of previous values and a random shock.

$$x_t = \emptyset_1 x_{t-1} + \emptyset_2 x_{t-2} + \emptyset_p x_{t-p} + w_t \tag{2.5}$$

where

x_t = An observation at time *t* of a time series

Φ_i = Autoregressive component parameter of lag *i* observation

w_t = Random shock component of a time series

The backshift operator $Bx_t = x_{t-1}$ or $B^m x_t = x_{t-m}$ and the auto aggressive operator

$\Phi(B) = 1 - \Phi_1 B - \Phi_2 B^2 \ldots . \Phi_p B^p$

are introduced so that expression (2.5) simplifies to (2.6).

$$\Phi(B)x_t = w_t \tag{2.6}$$

where B^i is a backshift operator of lag i.

Moving average models assume that the next observation is made up of q previous random shocks.

$$x_t = w_t + \theta_1 w_{t-1} + \theta_2 w_{t-2} \ldots + \theta_q w_{t-q} \tag{2.7}$$

where θ_i is a moving average component parameter of lag ‘i’ observation. Similarly, the moving average operator is defined as

$$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \ldots \ldots \theta_p B^p \tag{2.8}$$

and (2.7) can be converted into the form (2.9)

$$x_t = \theta(B) w_t \tag{2.9}$$

when a process involves characteristics of both AR and MA models, an autoregressive moving average model, or ARMA can be used.

$$x_t = \emptyset_1 x_{t-1} + \cdots \emptyset_p x_{t-p} + w_t + \theta_1 w_{t-1} + \cdots \theta_q w_{t-q} \tag{2.10}$$

Equivalently, we have (2.11)

$$\Phi(B)x_t = \theta(B)w_t \tag{2.11}$$

2.5.1.3 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, the load at time t, $y \ldots t$+1 is modelled using a fitting function [19] and is expressed in the form:

$$y(t) = \beta(t)^T f(t) + \in(t) \qquad (2.12)$$

where

f(t) is fitting function vector of the process,

β(t) is coefficient vector,

$\in(t)$ is white noise, and

T is transpose operator.

2.5.2 Non-Conventional Techniques

Following are the non conventional heuristic techniques which are intelligence based that include expert system, artificial neural network, fuzzy logic, genetic algorithm and particle swarm optimization etc.

2.5.2.1 Expert systems. Rule based forecasting makes use of rules, which are often heuristic in nature, to do accurate forecasting. Expert systems, incorporates rules and procedures used by human experts in the field of interest into software that is then able to automatically make forecasts without human assistance. Expert systems work best when a human expert is available to work with software developers for a considerable amount of time in imparting the expert's knowledge to the expert system software. Also, an expert's knowledge must be appropriate for codification into software rules (i.e. the expert must be able to explain his/her decision process to programmers). An expert system may codify up to hundreds or thousands of production rules. Ho *et al.* [20] proposed a knowledge-based expert system for the short term load forecasting of the Taiwan power system. Operator's knowledge and the hourly observations of system load over the past five years were employed to establish eleven day types. Weather parameters were also considered. The developed algorithm performed better compared to the conventional Box-Jenkins method. Rahman and Hazim [21] developed a site-independent technique for short-term load forecasting. Knowledge about the load and the factors affecting it are extracted and represented in a parameterized rule base. This rule base is complemented by a parameter database that varies from site to site. The load model, the rules, and the parameters presented have been designed using no specific knowledge about any particular site. The results can be improved if operators at a particular site are consulted.

Advantages: - Rule based forecasting model offers following advantages.

1. It provides consistent answers for repetitive decisions, processes and tasks
2. It holds and maintains significant levels of information
3. It encourages organizations to clarify the logic of their decision-making

4. It never "forgets" to ask a question, as a human right

5. It can work round the clock

6. It can be used by the user more frequently

7. A multi-user expert system can serve more users at a time

Disadvantages

1. Lacks common sense needed in some decision making

2. Cannot make creative responses as human expert would in unusual circumstances

3. Domain experts not always able to explain their logic and reasoning

4. Errors may occur in the knowledge base, and lead to wrong decisions

5. Cannot adapt to changing environments, unless knowledge base is change

2.5.2.2 Fuzzy logic

Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. An input under Boolean logic takes on a truth value of “0” or “1”. Under fuzzy logic an input has associated with it a certain qualitative ranges. In this sense fuzzy logic is one of a number of techniques for mapping inputs to outputs (i.e. curve fitting).

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 2*m*-input, 2*n*-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.

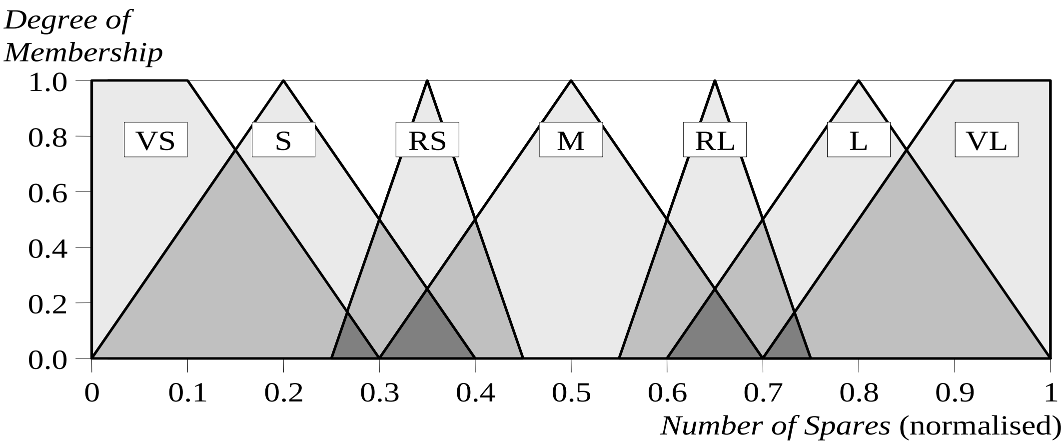

Fig 2.8 Membership Functions

Among the advantages of fuzzy logic are the absence of a need for a mathematical model mapping inputs to outputs and the absence of a need for precise (or even noise free) inputs.

With such generic conditioning rules, properly designed fuzzy logic systems can be very robust when used for forecasting. After the logical processing of fuzzy inputs, a "defuzzification" process can be used to produce such precise outputs. Yang and Huang proposed a fuzzy autoregressive moving average with exogenous input variables (FARMAX) for one day ahead hourly load forecasts. [20]

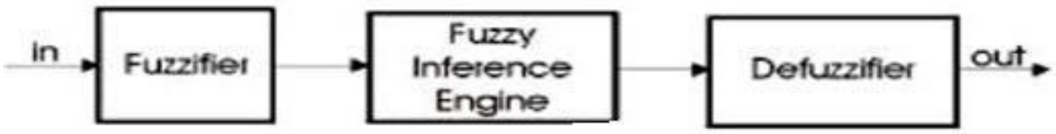

Fig 2.9 Fuzzy Controller Block Diagram

Advantages

Fuzzy logic allows the use of vague linguistic terms in the rules.

Disadvantages

1. Difficult to estimate membership functions
2. There are many ways of interpreting fuzzy rules, combining the outputs of several fuzzy rules and defuzzifying the output.

2.5.2.3 Artificial Neural Networks

The use of artificial neural networks (ANN or simply NN) has been a widely studied electric load forecasting technique since 1990 [22]. Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting. The outputs of an artificial neural network are some linear or nonlinear mathematical function of its inputs. In practice network elements are arranged in a relatively small number of connected layers of elements between network inputs and outputs. Feedback paths are sometimes used.

In applying a neural network to electric load forecasting, one must select one of a number of architectures (e.g. Hopfield, back propagation, Boltzmann machine), the number and connectivity of layers and elements, use of bi-directional or uni-directional links, and the number format (e.g. binary or continuous) to be used by inputs and outputs. The most popular artificial neural network architecture for electric load forecasting is back propagation. Back propagation neural networks use continuously valued functions and supervised learning. That is, under supervised learning, the actual numerical weights assigned to element inputs are determined by matching historical data (such as time and weather) to desired outputs (such as historical electric loads) in a pre-operational "training session". Artificial neural networks with unsupervised learning do not require pre-operational training.

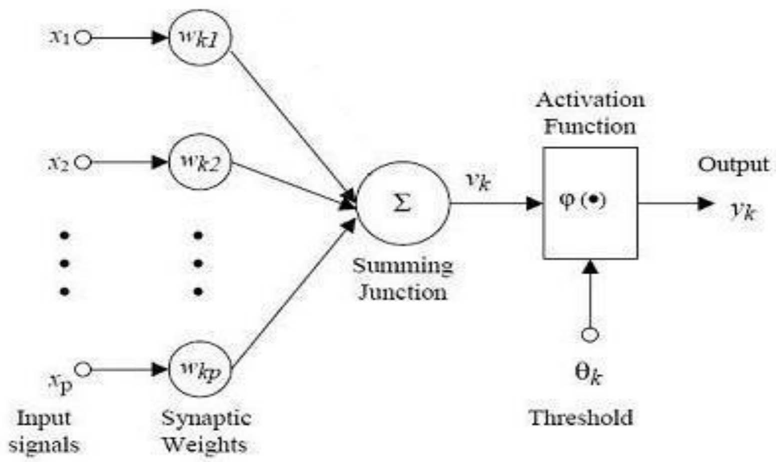

Fig. 2.10 Mathematical Model of ANN

From this model the interval activity of the neuron can be shown to be:

$$v_k = \sum_{j=1}^{p} w_{kj} x_j \quad (2.13)$$

The output of the neuron, y_k, would therefore be the outcome of some activation function on the value of v_k.

Activation functions

The activation function acts as a squashing function, such that the output of a neuron in a neural network is between certain values (usually 0 and 1, or -1 and 1). In general, there are three types of activation functions, denoted by Φ (.). First, there is the threshold function which takes on a value of 0 if the summed input is less than a certain threshold value (v), and the value 1 if the summed input is greater than or equal to the threshold value.

$$\phi(v) = \begin{Bmatrix} 1 & if\ v \geq 0 \\ 0 & if\ v < 0 \end{Bmatrix} \quad (2.14)$$

Secondly, there is the Piecewise-Linear function. This function again can take on the values of 0 or 1, but can also take on values between that depending on the amplification factor in a certain region of linear operation

$$(\mathrm{v}) = \begin{Bmatrix} 1 & \text{if v} \geq \frac{1}{2} \\ \mathrm{v} & \frac{-1}{2} > v > \frac{1}{2} \\ 0 & \text{if v} \leq -\frac{1}{2} \end{Bmatrix} \quad (2.15)$$

Thirdly, there is the sigmoid function. This function can range between 0 and 1, but it is also sometimes useful to use the -1 to 1 range. An example of the sigmoid function is the hyperbolic tangent function.

$$\phi(v) = \tanh\left(\frac{v}{2}\right) = \frac{1 - \exp(-v)}{1 + \exp(-v)} \tag{2.16}$$

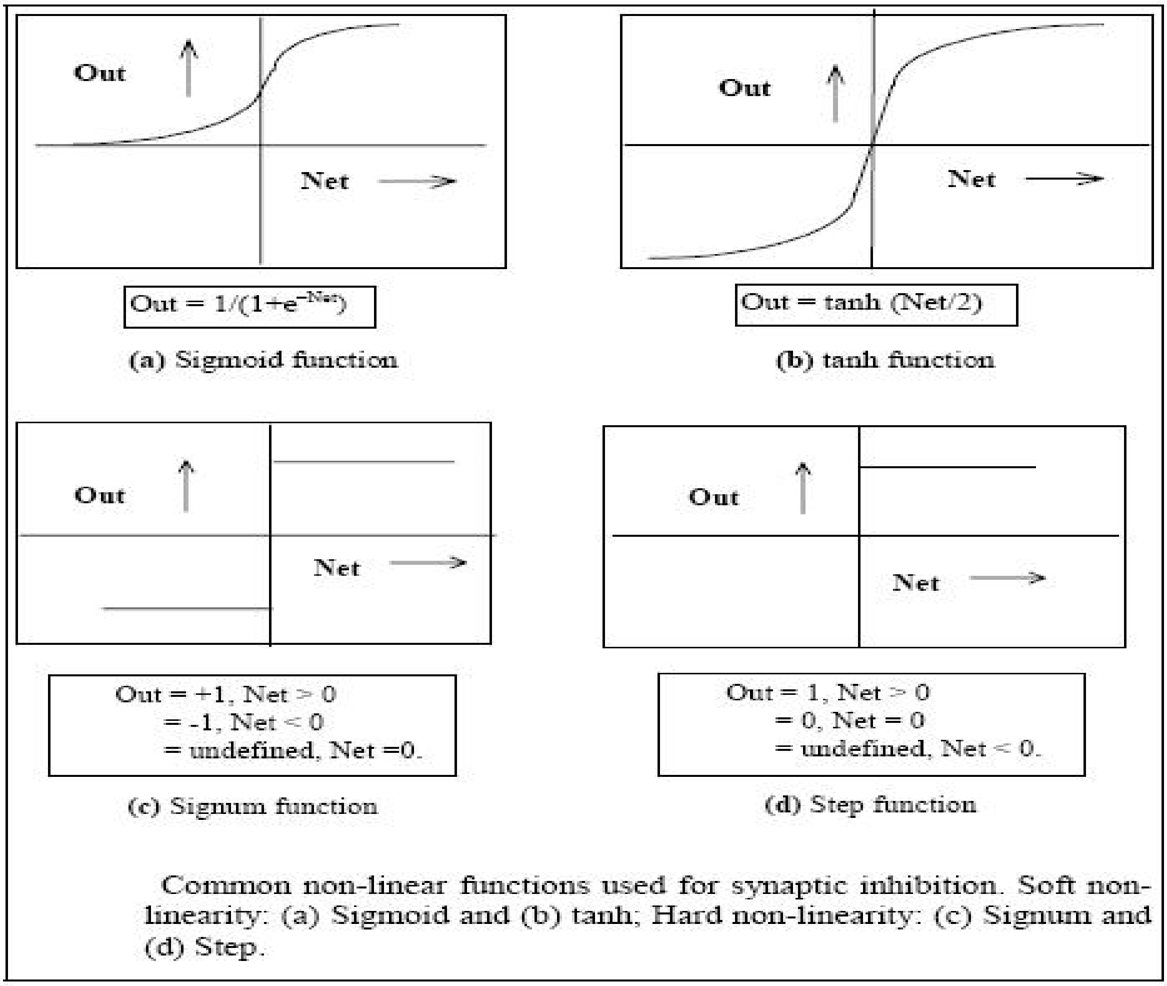

Fig. 2.11 Non Linear Functions

Input variables include historical hourly load data, temperature, and the day of the week. The model can forecast load profiles from one to seven days.

The effects of humidity and wind speed are considered through a linear transformation of temperature. As reported in [23], ANNSTLF was being used by 35 utilities across the USA and Canada. Chen *et al.* [22] developed a three layer fully connected feed forward neural network and the back propagation algorithm was used as the training method. Their ANN though considers the electricity price as one of the main characteristics of the system load.

Advantages

1. A neural network can perform tasks that a linear program can not.
2. When an element of the neural network fails, it can continue without any problem by their parallel nature.
3. A neural network learns and does not need to be reprogrammed.
4. It can be implemented in any application.
5. It can be implemented without any problem.

Disadvantages

1. The neural network needs training to operate hence more processing time.
2. Selection of the architecture of a neural network

2.3.2.4 Genetic Algorithm

Genetic algorithm is a stochastic optimization technique. More specifically, they are parameter search procedures based upon the mechanics of natural genetics. They combine a Darwinian survival-of-the-fittest strategy with a random, yet structured information exchange among a population of artificial "chromosomes".

Learning: GA are the best known and widely used global search techniques with an ability to explore and exploit a given operating space using available performance (or learning) measures.

Generic Code Structure: GA operates on an encoded parameter string and not directly on the parameters. This enables the user to treat any aspect of the problem as an optimizable variable.

Optimality of the solutions: In many problems, there is no guarantee of smoothness and unimodality. GA is known to be capable of finding near optimal solutions in complex search spaces.

Advanced Operators: This includes techniques such as niching (for discovering multiple solutions), combinations of Neural, Fuzzy, and chaos theory.

- **Genetic Terms**

Following are the term which are related to genetic algorithm

Chromosomes: Symbols from some finite alphabet in the form of strings. In case of binary alphabet (0, 1) the chromosomes are binary strings and in the case of real alphabet (0-9) the chromosomes are decimal strings.

Genes: The symbols that form the chromosomes are known as genes.

Population: A set of solutions represented by chromosomes.

Fitness Function: The criteria of goodness expressed in terms of an objective function to find the best alternative solution is called fitness function.

Fitness Value: It is the figure of merit, which is to be either maximized or minimized.

- **Genetic Operators**

Reproduction: Reproduction also known as selection operator is used to select the best chromosomes for parents from the population into the mating pool to cross over and produce offspring.

Cross over: Cross over is a recombination operator applied to the mating pool, proceeds in three steps. First, the reproduction operator selects at random a pair of two individual strings for mating. Then a cross-site is selected at random along the string length and the position values are swapped between two strings following the cross site.

Mutation: Mutation operator involves flipping a bit in the string from 0 to 1 and vice versa.

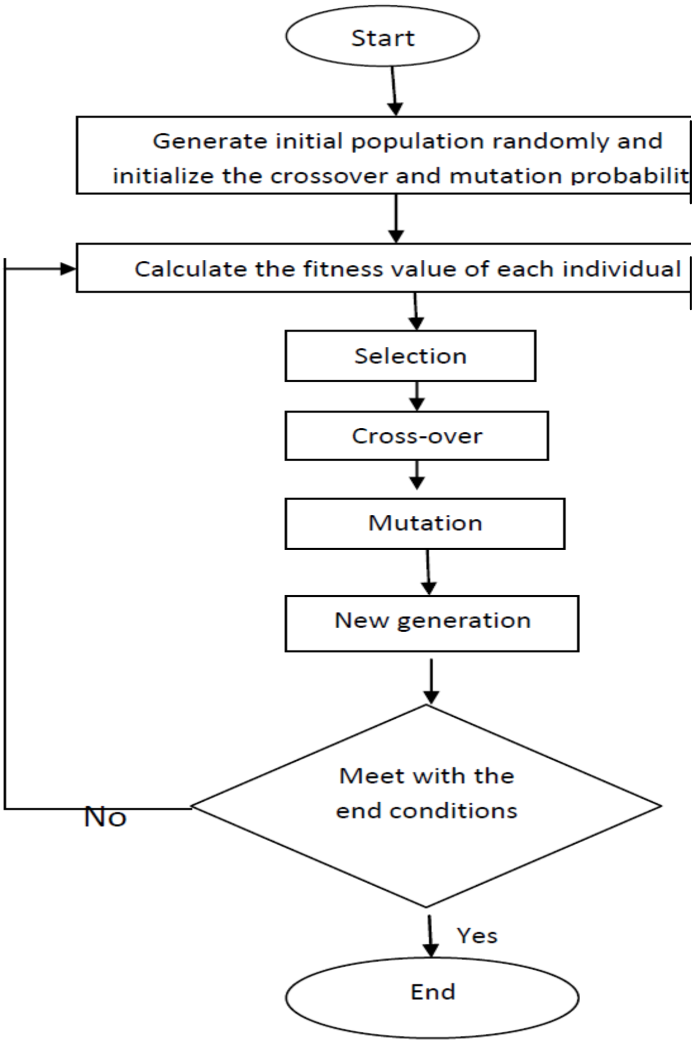

Fig 2.12 Flow Chart of Genetic Algorithm

CHAPTER 3
PARTICLE SWARM OPTIMIZATION

3.1 Introduction

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling [24]. The original objective of their research was to graphically simulate the social behavior of bird flocks and fish schools. The particle swarm concept originated as a simulation of simplified social system. The original intent was to graphically simulate the choreography of bird of a bird block or fish school. However, it was found that particle swarm model can be used as an optimizer.

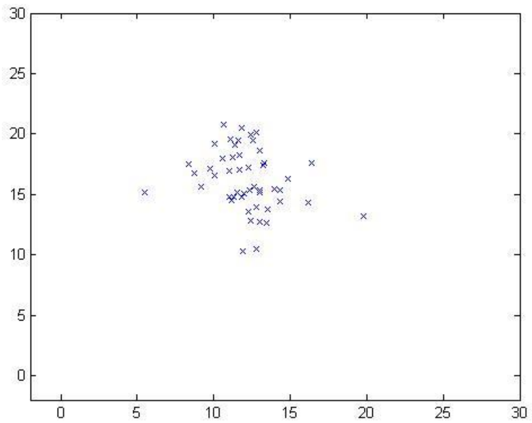

Fig 3.1 Particles Searching for the Minima of a Simple Function

Particle swarm optimization shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike Genetic Algorithm, Particle Swarm Optimization has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles.

Particle swarm optimization is a random set of population called particles. Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called *pbest*. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbors of the particle [25]. When a particle takes all the population as its topological neighbors, the best value is a global best and is called *gbest*. The particle swarm optimization concept consists of, at each time step, changing the velocity of (accelerating) each particle toward its p*best*. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward *pbest* location. Conceptually, figure 3.2 reflects the working of PSO.

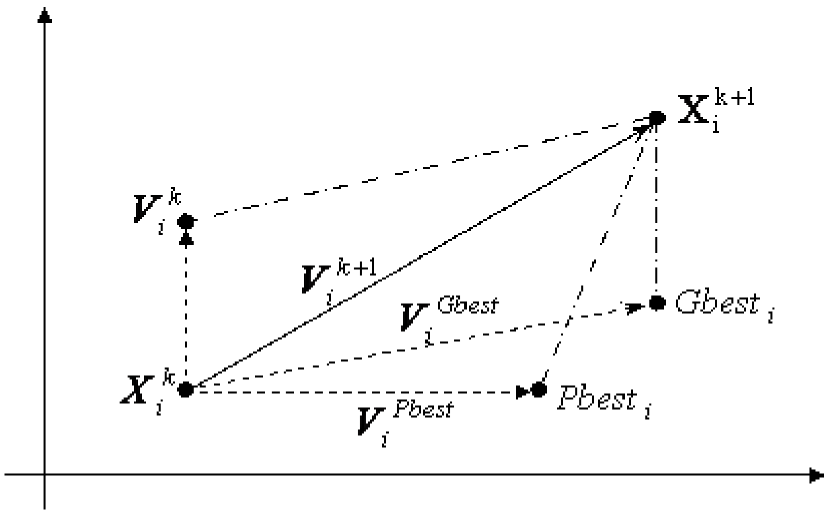

Figure 3.2 Concept of Searching Point by PSO

where

X^k: current position,

X^{k+} : modified position,

V^k: current velocity,

V^{k+1}: modified velocity,

V^{Pbest}: velocity based on *Pbest*,

V^{Gbest}: velocity based on *Gbest*

It is demonstrated that PSO gets better results in a faster, cheaper way compared with other methods. Another reason that PSO is attractive is that there are few parameters to adjust. Particle swarm optimization has been used for approaches that can be used across a wide range of applications, as well as for specific applications focused on a specific requirement.

3.2 Advantages

PSO has many key advantages over other optimization techniques like:

1. It is a derivative-free algorithm unlike many conventional techniques.
2. It has the flexibility to be integrated with other optimization techniques to form a hybrid tool.

3. It is less sensitive to the nature of the objective function, i.e. convexity or continuity.
4. It has less parameter to adjust unlike many other competing evolutionary techniques.
5. It has the ability to escape local minima.
6. It is easy to implement and program with basic mathematical and logic operations.
7. It can handle objective functions with stochastic nature.
8. It does not require a good initial solution to start its iteration process.

PSO is a population-based search algorithm (i.e., PSO has implicit parallelism).This property ensures PSO to be less susceptible in being trapped on local minima. Particle swarm optimization uses payoff (performance index or objective function) information to guide the search in the problem space. Therefore, Particle swarm optimization can easily deal with non-differentiable objective functions. PSO uses probabilistic transition rules and not deterministic rules. Hence, PSO is a kind of stochastic optimization algorithm that can search a complicated and uncertain area. Unlike Genetic Algorithm (GA) and other heuristic algorithms, PSO has the flexibility to control the balance between the global and local exploration of the search space. This unique feature of a PSO overcomes the premature convergence problem.

3.3 Algorithm

PSO learned from the scenario and used it to solve the optimization problems. In PSO, each single solution is particle in the search space. All of particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles.

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called gbest. When a particle takes part of the population as its topological neighbours, the best value is a local best.

After finding the two best values, the particle updates its velocity and positions with following equation (3.1) and (3.2).

$$v_{ij}^{r+1} = w * v_{ij}^{r} + C_1 * R_1 * \left(Xb_{ij}^{r} - X_{ij}^{r}\right) + C_2 * R_2 \, * \left(G_j^{r} - X_{ij}^{r}\right) \tag{3.1}$$

$$(i = 1,2 \ldots., NP; j = 1,2 \ldots NG)$$

$$X_{ij}^{r+1} = X_{ij}^{r} + v_{ij}^{r+1} \quad (i = 1,2 \ldots\ldots, NP; \;\; j = 1,2 \ldots\ldots, NG) \qquad (3.2)$$

where

NP is the number of particles in a group

NG is the number of members in a particle

R is the pointer of iterations

w is the inertia weight factor

C_1 and C_2 are the acceleration constants

R_1 is the uniform random values in the range [0, 1].

R_2 is the uniform random values in the range [0, 1]

v_{ij}^{r} is the velocity of j^{th} member of the i^{th} particle at r^{th} iteration, $V_j^{min} \leq v_{ij}^{r} \leq V_j^{max}$

P_{ij}^{r} is the current position of j^{th} member of i^{th} particle at r^{th} iteration

The inertia weights set according to the following equations:

$$w = w^{max} - \frac{w^{max} - w^{min}}{IT^{max}} * IT \qquad (3.3)$$

where

IT_{max} is the maximum number of iterations

IT is the current number of iterations

Particles' velocities on each dimension are clamped to a maximum velocity V_{max}. If the sum of accelerations would cause the velocity on that dimension to exceed V_{max}, which is a parameter specified by the user. Then the velocity on that dimension is limited to V_{max}.

The algorithm structure of the PSO procedure is as follows

```
For each decision variable
    Initialize particle
End
DO
    For each particle
        Calculate fitness value
      If the fitness value is better than the best fitness value (pbest) in history
            set current value as the new pbest
    End
Choose the particle with the best fitness value of all the particles as the gbest
    For each particle
        Calculate particle velocity according equation (3.1)
```

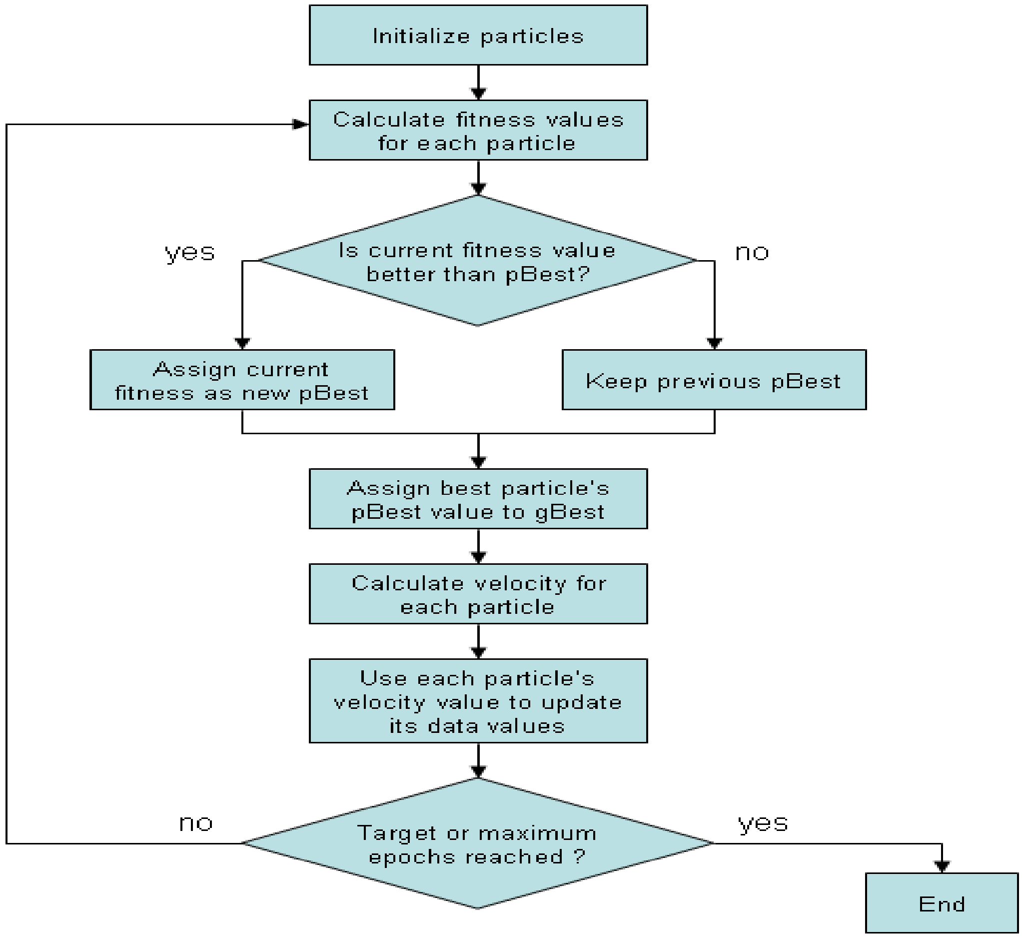

Fig 3.3 Flow chart of Particle Swarm Optimization

3.3 Comparisons between Artificial Neural Network, Genetic Algorithm and Particle Swarm Optimization

Most of the random population based techniques have the following procedure:

1. Random generation of an initial population
2. Reckoning of a fitness value for each subject. It will directly depend on the distance to the optimum.
3. Reproduction of the population based on fitness values.
4. If requirements are met, then stop. Otherwise go back to 2.

From the procedure, we can learn that PSO shares many common points with GA. Both algorithms start with a group of a randomly generated population, both have fitness values to evaluate the population. Both update the population and search for the optimum with random techniques. Both systems do not guarantee success. However, PSO does not have genetic operators like crossover and mutation. Particles update themselves with the internal velocity. They also have memory, which is important to the algorithm.

Compared with genetic algorithms (GAs), the information sharing mechanism in PSO is significantly different. In GAs, chromosomes share information with each other. So the whole population moves like a one group towards an optimal area. In PSO, only gbest gives out the information to others. It is a one -way information sharing mechanism. The evolution only looks for the best solution. Compared with GA, all the particles tend to converge to the best solution quickly even in the local version in most cases [26].

An artificial neural network (ANN) is an analysis paradigm that is a simple model of the brain and the back-propagation algorithm is the one of the most popular method to train the artificial neural network. Recently there have been significant research efforts to apply evolutionary computation (EC) techniques for the purposes of evolving one or more aspects of artificial neural networks.

PSO is a promising method to train ANN. It is faster and gets better results in most cases. It also avoids some of the problems GA met.

3.4 Particle Swarm Optimization (PSO) Parameter Control

It is learnt that there are two key steps when applying PSO to optimization problems: the representation of the solution and the fitness function. One of the advantages of PSO is that PSO take real numbers as particles. It is not like GA, which needs to change to binary encoding, or special genetic operators have to be used. The searching is a repeat process, and the stop criteria are that the maximum iteration number is reached or the minimum error condition is satisfied [27].

There are not many parameter need to be tuned in PSO. Here is a list of the parameters and their typical values.

Number of particles: The typical range is 20-40. For some difficult or special problems, one can try 100 or 200 particles as well.

Dimension of particles: It is determined by the problem to be optimized,

Range of particles: It is also determined by the problem to be optimized, you can specify different ranges for different dimension of particles.

V_{max}: It determines the maximum change one particle can take during one iteration. Usually we set the range of the particle as the V_{max}

Learning factors: c_1 and c_2 usually equal to 2. But usually c_1 equals to c_2 and ranges between [0, 4]

Termination condition: The maximum number of iterations the PSO execute and the minimum error requirement. This stop condition depends on the problem to be optimized.

3.5 Least Error square method

The term least squares describes a frequently used approach to solving over determined or inexactly specified systems of equations in an approximate sense. Instead of solving the equations exactly, we seek only to minimize the sum of the squares of the residuals.

The method of least squares is a standard approach to the approximate solution of overdetermined systems, i.e., sets of equations in which there are more equations than unknowns. "Least squares" means that the overall solution minimizes the sum of the squares of the errors made in solving every single equation.

Least squares problems fall into two categories: linear or ordinary least squares and non-linear least squares, depending on whether or not the residuals are linear in all unknowns. The linear least-squares problem occurs in statistical regression analysis; it has a closed-form solution. The non-linear problem has no closed-form solution and is usually solved by iterative refinement; at each iteration the system is approximated by a linear one, thus the core calculation is similar in both cases.

The method of least squares assumes that the best-fit curve of a given type is the curve that has the minimal sum of the deviations squared (least square error) from a given set of data.

Suppose that the data points are (x_1, y_1), (x_2, y_2), ..., (x_n, y_n) where x is the independent variable and y is the dependent variable. The fitting curve $f(x)$ has the deviation (error) d from each data point, i.e., $d_1 = y_1 - f(x_1)$, $d_2 = y_2 - f(x_2)$, ..., $d_n = y_n - f(x_n)$. According to the method of least squares, the best fitting curve has the property that:

$$\Pi = d_1^2 + d_2^2 + \ldots + d_n^2 = \sum_{i=1}^{n} d_i^2 = \sum_{i=1}^{n} [y_i - f(x_i)]^2 = \text{a minimum}$$

CHAPTER 4

Problem Formulation And Results

Particle swarm optimization approach to parameter estimation for short term load forecasting is proposed in this thesis work. The hourly peak load data from Punjab State Transmission Corporation Limited (PSTCL) for a week and from state load dispatch centre, Rajasthan is used for peak load forecasting. PSTCL data is the complete load demand of Punjab taken from State Load Dispatch Centre, Ablowal (Patiala). The forecasted load is compared with the actual peak load and percentage error is also calculated. The general identification process is composed of

1. Order Determination.
2. Parameter Estimation.

4.1 Mathematical Formulation

Coefficients of the load forecasting model are identified and are used to predict the future loads by extrapolating the relationship to desired lead time. Final accuracy of the forecast process depends on the selected model and accuracy of the estimated parameters.

Regression analysis or trend analysis is the study of the behavior of a time series or process in the past and its mathematical modeling so that future behavior can be extrapolated from it [17]. A time variant event such as power system load can be broken down into five components, basic, trends, seasonal variations, cyclic variations and random variations. Regression curves used in power system load forecasting are: linear, polynomial, exponential In general, a multi-variable regression model can be related to (n + 1) independent variables and can be written as follows:

$$P(t) = a_0 + \sum_{i=1}^{n} a_i t^i + r(t) \tag{4.1}$$

where P(t) is the peak load demand at time t, a_o, a_i are the regression coefficients relating the load P(t) to time t. The last term, r(t), is the residual load at year t.

Another type of regression technique involves nonlinear regression models that are nonlinear in terms of the parameters and cannot be made so by any transformation. The following models are nonlinear [30]:

$$P(t) = a_0 e^{a_1 t} + r(t) \tag{4.2a}$$

$$P(t) = a_0 + a_1 e^{a_1 t} + r(t) \qquad (4.2b)$$

$$P(t) = \frac{a_0}{1 + a_1 e^{a_2 t}} + r(t) \qquad (4.2c)$$

In order to build a proper forecasting process, one must construct the model, select the forecasting method and finally evaluate the results. As mentioned before, the regression technique is the most widely used one mainly because of its simplicity and ease of use. Therefore, this technique is considered for modeling. It is very important to emphasize that the primary objective of this thesis is to present the application of PSO technique in estimating the parameters of load forecasting models and evaluate the results obtained.

For many years, generation planners have used regression techniques as tools in predicting annual peak system demands. Peak electricity demands are known to be influenced by weather conditions, number and type of consumers and general economic conditions.

In order to identify the most adequate model for forecasting application among all available linear and nonlinear regression models, different types of graphs must be examined. Graphical visual inspection of a graph of a given observation against time can often reveal both obvious and less apparent data characteristics.

Data used in this work are taken from Punjab State Transmission Corporation Limited (PSTCL) and state load dispatch center, Rajasthan. The data has been tested and appropriate models have been chosen. In this work two models are considered, i.e. linear (i=1) and quadratic (i=2) models. Given the peak load (P) at each day *t*, an equation just like equation 4.1 can be written for each load. If the data consists of m sets of days and peak loads, then there will be (m) equations with (n) unknowns. This system of equation is an over determined system (m>n). Then for m days, a discrete system of equations in

$$P(t) = H(t)X + r(t) \qquad (4.3)$$

where

P (t) is the load demand vector;

X is the parameter vector to be estimated;

r (*t*) is the error vector associated with *P*(*t*) ;

H (*t*) is a row vector that relates *P* (*t*) to *X*

In this study following two models are used ;

Model 1: Linear model (i=1)

$H(t) = [T \quad 1]$

$T = 1,2, \ldots . m \ and \ X = [a_0 \quad a_1]^T$

Model 2: Quadratic model (i=2)

$H(t) = [T^2 \quad T \quad 1]$,

$T = 1,2, \dots m \; and \; X = [a_0 \quad a_1 \quad a_2]^T$

Now, the problem is to find an estimate of parameters vector X for any model that minimizes the error vector r (t).

4.2 Order determination

In this study, two types of orders are determined. One is linear order and the other is the quadratic order. Both are compared and better results are obtained from quadratic model.

4.3 Parameter Estimation

Parameters a_0 a_1 and a_2 are calculated for least error square method and particle swarm optimization.

4.4 Algorithm:

The procedure of proposed method for parameter estimation from peak load data is as mentioned below:

1. Read Input data:, Peak load demand of 'L' days of the period under consideration P_{Di} (i= 1,2---- L), population size NP, Maximum number of iterations IT_{max}, convergence tolerance error ERR, scaling factor β, acceleration constants, inertia weights, minimum and maximum values of decision variables $a_{j(min)}$ *and* $a_{j(max)}$;(j=1,2---D), D is order of polynomial chosen for modeling, minimum and maximum values of velocities.
2. Initialize randomly the individual population for decision variables i.e. curve coefficients as a_i *(i=1,2, --D)* according to the limits, searching points, velocities v_i
3. Initialize an array of dimensions (NP*D) of uniform random numbers.
4. Set particle counter i=0

   DO
5. Increment particle counter i=i+1
6. Set generation counter j=0

   DO
7. Increment generation counter j=j+1
8. Generate the position of particle X_{ij} and velocity of particle v_{ij}
9. Initialize $X_{ij}^{best} = X_{ij}$

   WHILE j<L
10. Compute fitness function f_i *using equation (4.1)*
11. Initialize $f_i^{best} = f_i$

WHILE (i<NP)

12. Set particle counter i=1 and $f_i^{global} = f_i^{best}$
13. Increment particle counter i=i+1
14. IF ($f_i^{best} < f_i^{global}$)THEN set $f_i^{global} = f_i^{best}$ *and* $G_j^{best+} = X_{ij}^{best}$ *(j=1,2—L)*

WHILE (i<NP)

15. Set iteration counter IT=0

DO

16. Increment iteration counter IT=IT+1
17. Compute $w = w_{max} - [(w_{max} - w_{min})/IT_{max}]*IT$
18. Initialize an array of dimensions (2NP*D) of uniform random numbers.
19. Set particle counter i=0

DO

20. Increment particle counter i=i+1
21. Set generation counter j=0

DO

22. Increment generation counter j=j+1
23. Calculate velocity of particle $v_{ij(new)}$
24. IF ($v_{ij(new)} > V_{j(max)}$) THEN update $v_{ij(new)} = V_{j(max)}$
25. IF ($v_{ij(new)} < V_{j(min)}$) THEN update $v_{ij(new)} = V_{j(min)}$
26. Calculate $X_{ij(new)} = X_{ij} + v_{ij(new)}$

WHILE (j<L)

27. Compute new fitness function $f_{i(new)}$
28. IF ($f_i^{new} < f_i^{best}$) THEN set $f_i^{best} = f_i^{new}$ and $X_{ij}^{best} = X_{ij}^{new}$ (j=1,2,…..L)

WHILE (i<NP)

29. Set particle counter i=1, $f^{min} = f_i^{best}$

DO

30. Increment particle counter, j=j+1
31. IF ($f_i^{best} < f^{min}$) THEN set $f^{min} = f_i^{best}$ and $X_j^{min} = X_{ij}^{best}$ (j=1,2,…L)

WHILE (i<NP)

32. IF $|f^{min} - f^{global}| \le ERR$; THEN GO TO step 40.
33. Set particle counter, i=0

DO

34. Increment particle counter , i=i+1
35. Set generation counter, j=0

DO

36. Increment generation counter, j=j+1
37. Set $v_{ij} = V_{ij}^{new}$

WHILE (j<L)

38. IF ($f^{min} < f^{global}$) THEN set $f^{global} = f^{min}$
39. Check termination criteria i.e number of maximum iterations IT_{max} If satisfied GO TO step 40 otherwise go to step 16.
40. END

4.5 Results

Real peak demands of State load dispatch centre are used in this study. The data set is used to establish an over determined system of equations. This system of equations is solved using the proposed PSO technique to find the optimal parameters for different forecasting models. Key parameters of PSO algorithm used in this study are presented in Table 1. Both linear and nonlinear models are used in the given test system and results obtained using PSO are compared with those of LES method.

Table 4.1 PSO Parameters

Parameter	Value
Population size (NP)	10 particles
Stop Criterion (IT_{max})	100 Iterations
Velocity	V_{max}=2.0, V_{min} =0
Acceleration Constants	C_1=3, C_2=3
Inertia Weights	w_{max}=0.9, w_{min}=0.4

4.5.1 Case Study-1

Peak demands of Punjab power network during 25th April 2011 to 1st May 2011 are used to estimate the parameters of both linear and nonlinear short term forecasting models.

Particle swarm optimization and least error square method are used to estimate models parameters for the same time horizon and the computed parameters are tabulated in Table 4.2. The corresponding forecasted demands based on the estimated parameters of linear and quadratic models are shown in Tables 4.3 and 4.4 respectively.

Calculated estimation errors are given in Table 4.5. This table reveals that PSO on average performed better than LES in minimizing the error associated with the estimation process.

Table 4.2 Estimated Parameters based on PSO and LES

Coefficients	Linear Model		Quadratic Model	
	PSO	LES	PSO	LES
a_0	37.072	51.429	-34.262	-30.69
a_1	5380.91	5370.4	321.95	296.95
a_2	--	--	4987.9	5002.1

Table 4.3 Performance of linear forecast model

Day/Date (25th April 2011 to 1st May 2011)	Actual Peak Load (MW)	Linear Model	
		PSO	LES
		Forecasted Peak Load (MW)	Forecasted Peak Load (MW)
Monday	5265	5417.982	5421.9
Tuesday	5546	5455.054	5473.29
Wednesday	5473	5492.126	5524.71
Thursday	5734	5529.198	5576.1
Friday	5801	5566.27	5627.6
Saturday	5643	5603.342	5679
Sunday	5571	5640.414	5730.4

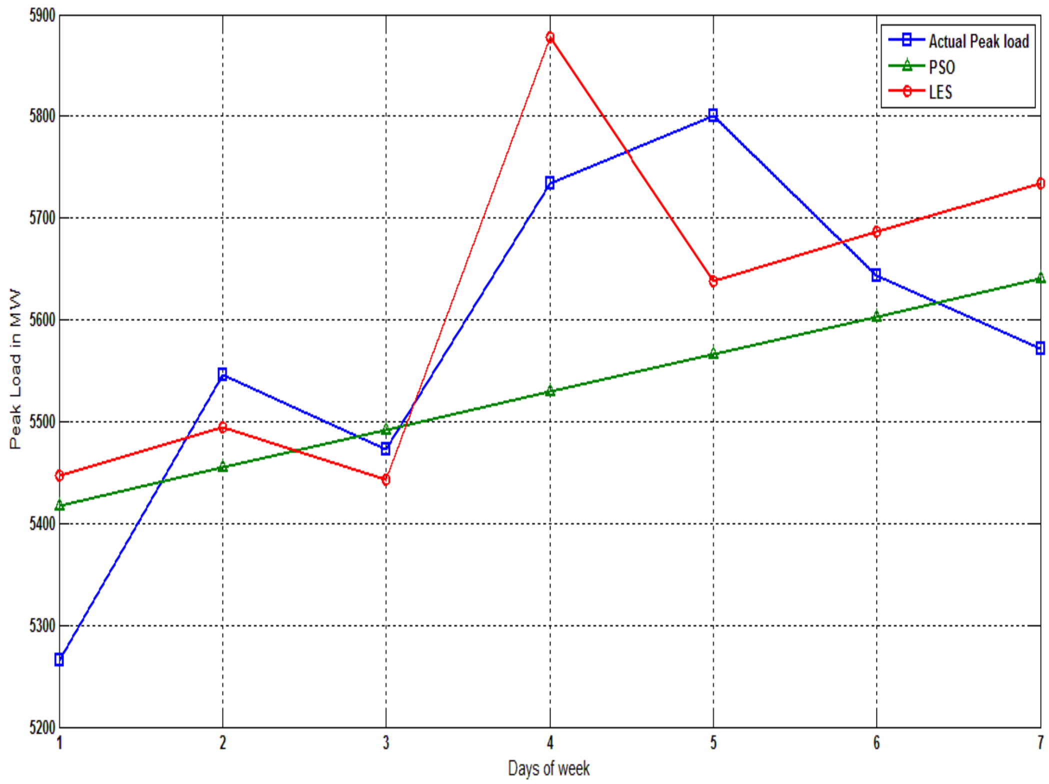

Fig 4.1 Characteristics of Linear Model

Table 4.4 Performance of quadratic forecast model

Day/Date (25th April 2011 to 1st May 2011)	Actual Peak Load (MW)	Quadratic Model	
		PSO	LES
		Forecasted Peak Load (MW)	Forecasted Peak Load (MW)
Monday	5265	5275.6	5268.40
Tuesday	5546	5494.8	5473.29
Wednesday	5473	5645.4	5616.8
Thursday	5734	5727.7	5698.9
Friday	5801	5741.1	5719.64
Saturday	5643	5686.2	5679
Sunday	5571	5562.7	5576.97

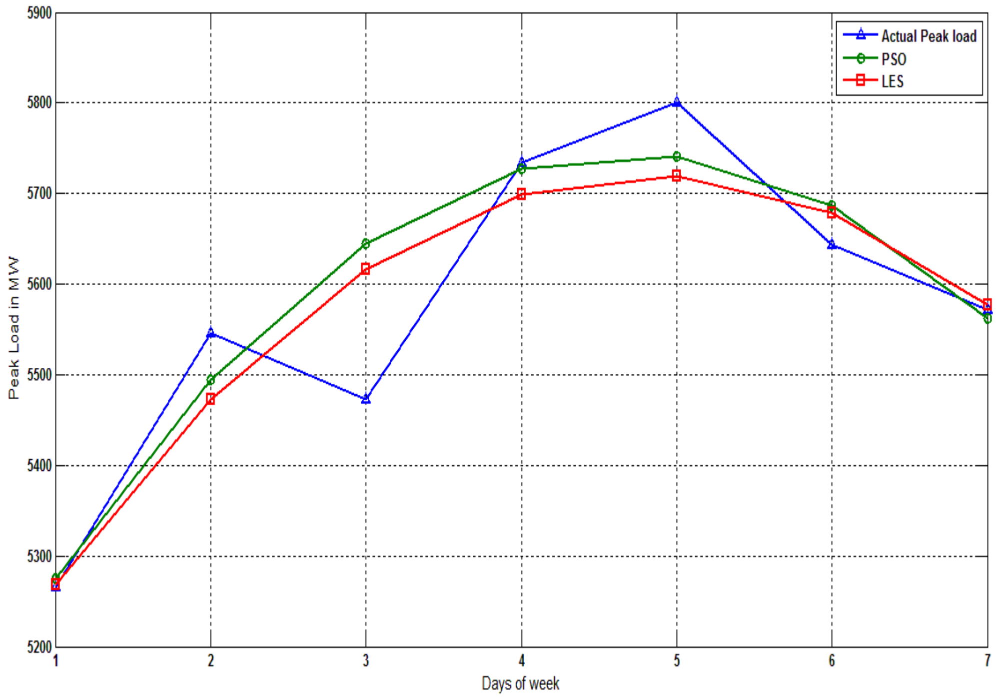

Fig 4.2 Characteristics of Quadratic Model

Table 4.5 Absolute Error Associated with PSO and LES

Day/date	Actual Peak Load (MW)	Linear Model		Quadratic Model	
		PSO	LES	PSO	LES
		% Error	% Error	% Error	% Error
Monday	5265	2.9056	2.980	.2010	.0646
Tuesday	5546	1.6398	1.311	.879	1.3110
Wednesday	5473	0.3494	0.944	3.150	2.627
Thursday	5734	2.0166	2.753	.1133	0.6121
Friday	5801	4.046	2.989	1.032	1.4025
Saturday	5643	0.7026	0.6379	.7650	0.6379
Sunday	5571	1.2459	2.8612	.1480	1.072
Absolute Average % error		**1.843**	**2.068**	**.89832**	**.9660**

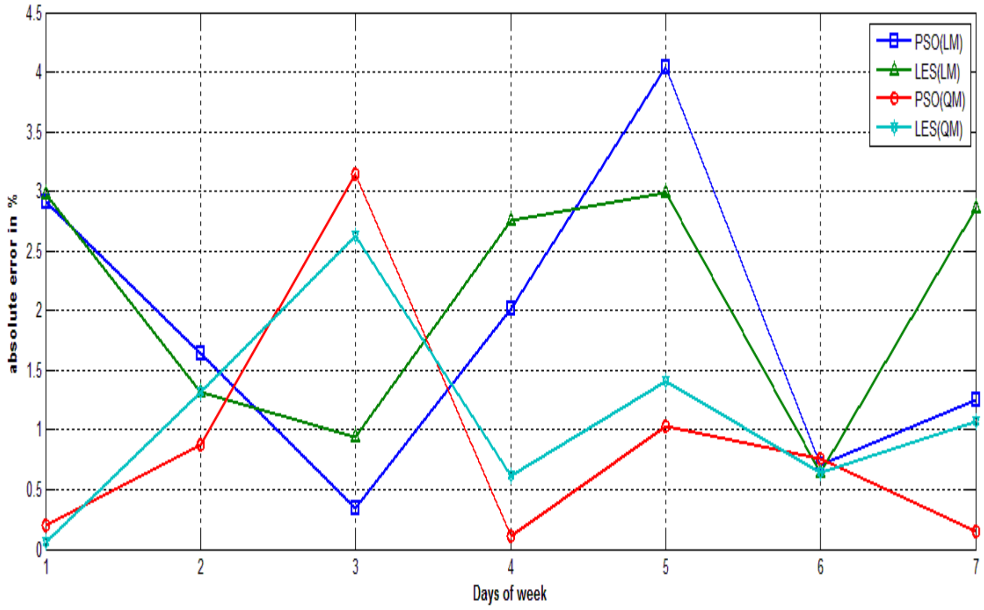

Fig 4.3 Characteristic of Errors associated with PSO and LES

This graph shows the errors associated with the linear and quadratic model with respect to particle swarm optimization and least error square method.

4.5.2 Case Study-2

Peak demands of Rajasthan power network during 1st January 2011 to 15th January 2011 are used to estimate the parameters of both linear and nonlinear short term forecasting models. PSO and LES techniques are used to estimate models parameters for the same time horizon and the computed parameters are tabulated in Table 4.6. The corresponding forecasted demands based on the estimated parameters of linear and quadratic models are shown in Tables 4.7 and 4.8 respectively. Calculated estimation errors are given in Table 4.9. This table reveals that PSO on average performed better than LES in minimizing the error associated with the estimation process

Table 4.6 Estimated Parameters based on PSO and LES

Coefficients	Linear Model		Quadratic Model	
	PSO	LES	PSO	LES
a_0	-15.61	-12.732	-.44	-.232
a_1	6269.13	6237.8	1.13	-9.0153
a_2	---	---	6171.2	6227.3

Table 4.7 Performance of linear forecast model

Day/Date (1st Jan,2011 to 15th Jan 2011)	Actual Peak Load (MW)	Linear Model	
		PSO	LES
		Forecasted Peak Load (MW)	Forecasted Peak Load (MW)
Saturday	6419	6171.9	6218
Sunday	6476	6171.7	6208.3
Monday	5661	6170.6	6198.1
Tuesday	6062	6168.7	6187.5
Wednesday	6024	6158.8	6176.4
Thursday	6324	6162.1	6164.8
Friday	6226	6157.6	6152.77
Saturday	6134	6152.1	6140.27
Sunday	6218	6145.7	6127.31
Monday	6094	6138.5	6113.88
Tuesday	6233	6130.4	6366
Wednesday	6319	6121.4	6552.4
Thursday	5799	6111.5	6070.8
Friday	6003	6100.8	6055.51
Saturday	6047	6089.1	6039.762

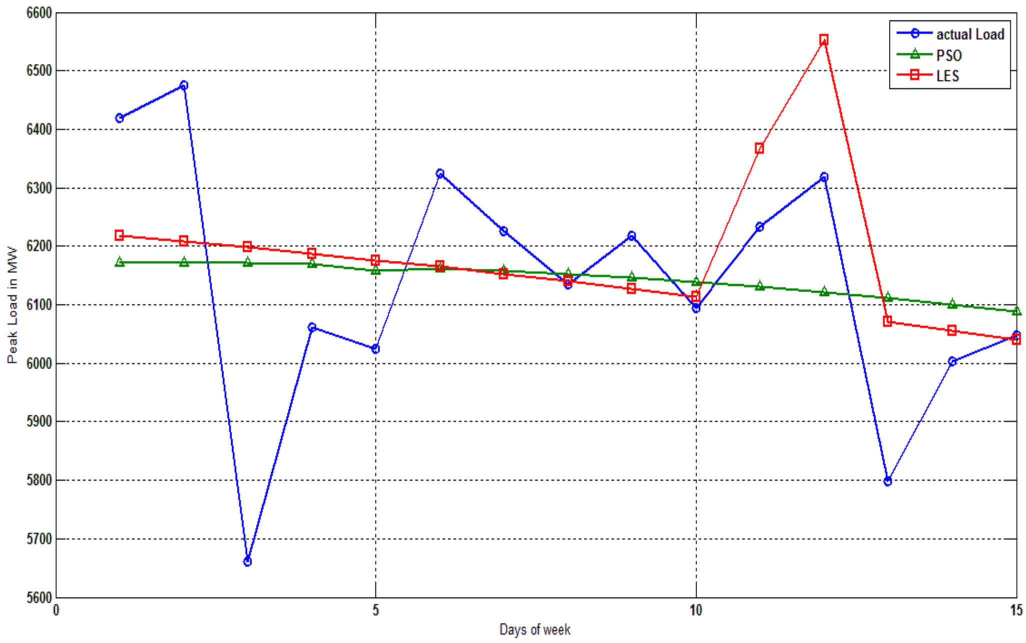

Fig 4.4 Characteristics of Linear Model

Table 4.8 Performance of Quadratic forecast model

Day/Date (1st Jan,2011 to 15th Jan 2011)	Actual Peak Load (MW)	Quadratic Model	
		PSO	LES
		Forecasted Peak Load (MW)	Forecasted Peak Load (MW)
Saturday	6419	6253.52	6225.1
Sunday	6476	6237.91	6212.3
Monday	5661	6222.3	6199.6
Tuesday	6062	6206.69	6186.9
Wednesday	6024	6191.08	6174.1
Thursday	6324	6175.47	6161.4
Friday	6226	6159.86	6148.67
Saturday	6134	6144.25	6135.933
Sunday	6218	6128.64	6123.2
Monday	6094	6113.03	6110.47

Tuesday	6233	6097.42	6097.7
Wednesday	6319	6081.81	6085
Thursday	5799	6066.2	6072.3
Friday	6003	6050.59	6059.54
Saturday	6047	6034.98	6046.8083

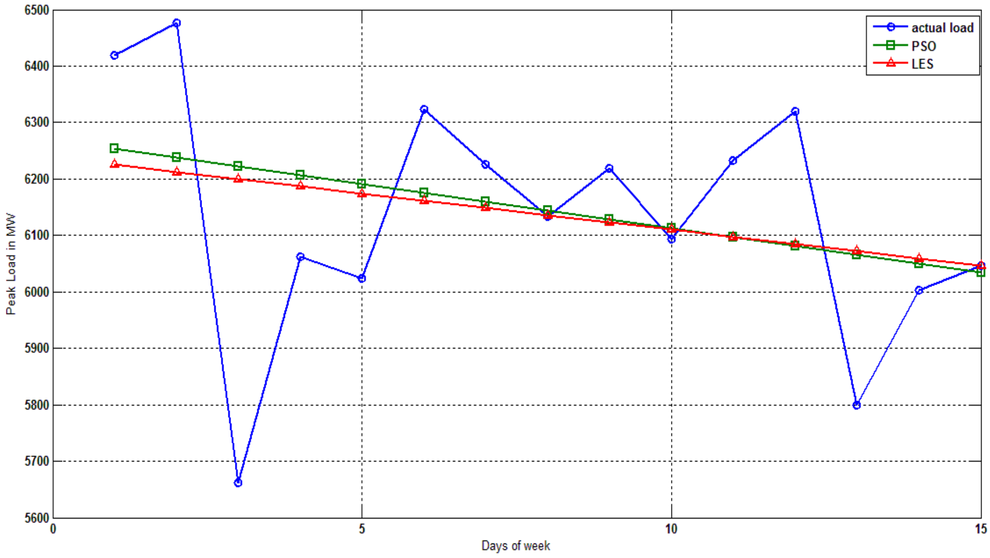

Fig 4.5 Characteristics of Quadratic Model

Table 4.9 Absolute Error Associated with PSO and LES

Day/Date (1st Jan,2011 to 15th Jan 2011)	Actual Peak Load (MW)	Linear Model		Quadratic Model	
		PSO	LES	PSO	LES
		% Error	% Error	% Error	% Error
Saturday	6419	2.577	3.020	3.863	3.131
Sunday	6476	3.676	4.071	4.709	4.133
Monday	5661	9.915	9.515	8.991	9.480
Tuesday	6062	2.386	2.069	1.748	2.070
Wednesday	6024	3.773	2.591	2.340	2.529
Thursday	6324	2.348	3.571	2.561	3.517
Friday	6226	1.062	2.242	1.108	1.176
Saturday	6134	0.167	0.031	0.293	0.102
Sunday	6218	1.437	1.524	1.174	1.568
Monday	6094	0.3122	.290	0.722	0.326
Tuesday	6233	2.275	2.270	1.652	2.133
Wednesday	6319	3.853	3.703	3.127	4.693
Thursday	5799	4.607	4.712	4.388	4.687
Friday	6003	0.792	0.949	1.629	0.874
Saturday	6047	0.198	.003	0.694	0.119
Absolute average % error		**2.625**	**2.709**	**2.597**	**2.702**

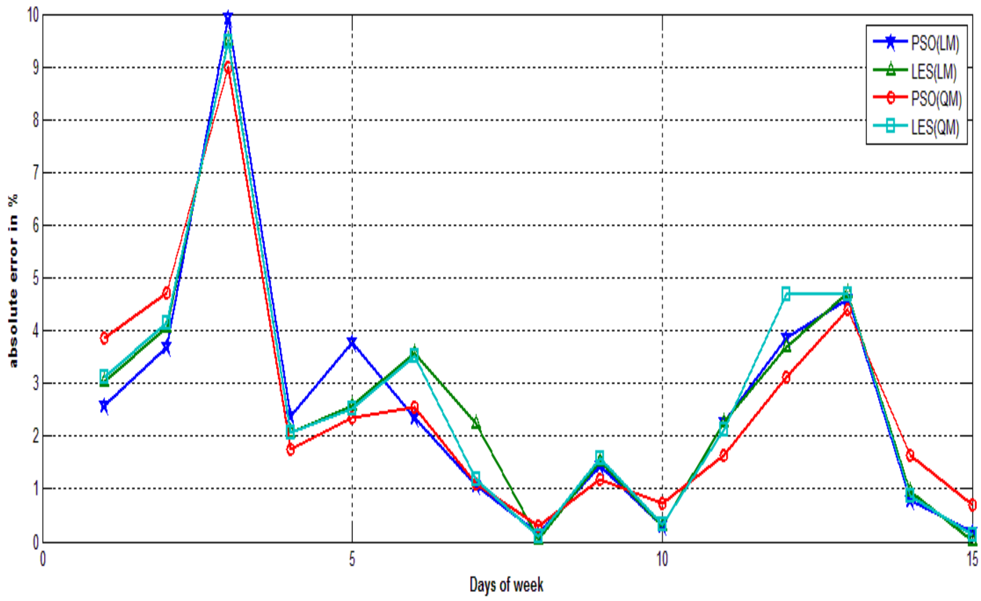

Fig 4.6 Characteristic of Errors associated with PSO and LES

This graph shows the absolute errors associated with the linear and quadratic model with respect to particle swarm optimization and least error square method.

From both the case studies, error is calculated and graph is plotted for particle swarm optimization and least error square method. The graph shows the percentage of absolute error of actual peak load and estimated load with respect to days of week. With the help of graph, we say that quadratic model and particle swarm optimization technique is best.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

This thesis presents an application of Particle Swarm Optimization algorithm for peak load forecasting in power systems. The estimation problem is formulated as an optimization one. The solution framework is implemented and tested using actual recorded data. Real demands data are used to validate the performance of the proposed approach and test its potential. Two different models are used and the quadratic model is proven to more suitable for representing the available data in terms of absolute average error. Forecasting using the PSO method has been compared with that obtained using the LES method. From total error point of view, it is found that PSO method has produced better estimates than the LES method. This indicates that the PSO approach is quite promising and deserves serious attention as a new tool for parameter estimation.

5.2 Future Scope of Work

After carrying thesis work in Short Term Load Forecasting, the following guidelines seem to be worth pursuing in this area:

1. Based on the weather conditions, parameters can also be determined.
2. Sensitivity analysis of control parameters of particle swarm optimisation algorithm can be done for improvement in results.
3. A hybrid optimization method based on evolutionary algorithm and particle swarm optimization to identify the parameters of ARMAX model for short-term load forecasting can be proposed and it may take advantage of evolutionary strategy to speed up the convergence of Particle Swarm Optimization.

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