Short-Term Load Forecasting Methods: A Review

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***Abstract*—For decision makers in the electricity sector, the decision process is complex with several different levels that have to be taken into consideration. These comprise for instance the planning of facilities and an optimal day-to-day operation of the power plant. These decisions address widely different time-horizons and aspects of the system. For accomplishing these tasks load forecasts are very important. This paper presents a comprehensive survey of the short term load forecasting. It also reviews various methodologies for short term load forecasting (STLF). Authors strongly believe that this survey article shall be very much helpful to the researchers working in the field of short term load forecasting for finding out the appropriate references and future work.**

Keywords: STLF, Statistical Technique, Artificial Intelligent (AI) Technique, Knowledge based Expert Systems, Hybrid Techniques

I. INTRODUCTION

The prediction of short term loads i.e. Short Term Load Forecasting (STLF) plays a key role in the formulation of economic, reliable, and secure operating strategies for the power system. Demand prediction is an important aspect in the development of any model for electricity planning, especially in today's reforming power system structure [1]. The form of the demand depends on the type of planning and accuracy that is required. With the introduction of competition and deregulation of the power markets, a new challenge has appeared. One of the merits of the deregulated power market is the load mutual sensitivity [2-4]. It turned out that even accurate load forecasts cannot guarantee profits. The market risk related to trading is considerable due to extreme volatility of electricity prices. Considering the uncertain nature of future prices in competitive electricity markets, price forecasts are used by market participants in their operation planning activities. In addition, to ensure the secure operation of the power system at some future time requires the study of its behavior under a variety of postulated contingency conditions. Important decisions depend on load forecast with lead times of minutes to months. Depending on the time zone of planning strategies the load forecasting can be divided in to following four categories [5].

Very short term load forecasting

Short term load forecasting

Mid term load forecasting

The estimated forecasts in this time range are important inputs for generating scheduling functions, power system security assessment and power system dispatcher. Owing to the importance of the load forecasting, numerous methods for STLF have been reported in the last few decades. These methods can be summarized in to deterministic, stochastic, knowledge based expert systems and artificial neural networks (ANN). Use of above methods with fuzzy interface is also reported in the literature.

The aim of this paper is to survey and classify electric load forecasting techniques published till date. In comparison with those earlier literature reviews, this survey not only covers recent papers, but also includes new categories that recent research trends. It also provides up-to-date brief verbal descriptions of each category. STLF forecasting techniques are classified into four 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 chronological order, the four categories of load forecasting techniques to be discussed are:

- Statistical Technique
- Artificial Intelligent (AI) Technique
- Knowledge Based Expert Systems
- Hybrid Techniques

The deterministic methods are classical causal model of load and weather variables. This includes curve fitting, data extrapolation and smoothing methods [1-5]. The stochastic methods model the load behavior in terms of stochastic process. Kalman filtering, autoregressive moving averages and time series approaches fall in this category. Knowledge based expert system have been successfully tried and have shown encouraging results [6]. These models are based on the knowledge acquired by an expert about the past load behavior. Fuzzy logic based inferences also find good application in such systems.

Application of ANN began in early 90's, since then, considerable amount of research work has gone into this area. The ANN based forecasters used various architectures based on both supervised as well as unsupervised mode of learning. Feed forward network is most widely used in form of both single layer and multilayer in fully connected or non-fully connected architecture. Recurrent networks have also come into existence due to dynamic modeling of load and have

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shown good results [7]. Kohnen network based day type identification and later forecasting with network based on supervised learning is reported. Fuzzy neural approach is also used where the fuzzy inferences are used for the neural network forecaster [8]. The above said networks require long training sessions. They also have problems of convergence/stability and therefore the learning and the momentum parameters have to be continuously monitored for the effective training of the network. Time factor, weather data, consumer class, load demanded by the area, growth of the region, amount of increased load etc., are the factors which play important role in calculating the load demand.

II. Short term Load Forcasting Methods

A variety of methods, which include the so-called similar day approach, various regression models, time series, neural networks, expert systems, fuzzy logic, and statistical learning algorithms, are used for short-term forecasting. The development, improvements, and investigation of the appropriate mathematical tools will lead to the development of more accurate load forecasting techniques.

A. Statistical Technique

Statistical approaches require an explicit mathematical model which gives the relationship between load and several input factors. Several classical models are applied for load forecasting, such as:

- Multiple regression method
- Exponential smoothing
- Iterative reweighted least square
- Adoptive load forecasting
- Stochastic time series

1) Multiple regression method

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 defined amount of historical data. Mbamalu and El-Hawary [9] used the following load model for applying this analysis:

$$Y_t = v_t \alpha_t + \varepsilon_t \tag{1}$$

where

t Sampling Time,

Y_t Measured system load

v_t Vector of adapted variable such as time, temperature, humidity etc.,

α_t Transposed vector of regression coefficients,

ε_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 [10] evaluated this model and compared it with other models for a 24-h load forecast. Barakat *et al.* [11] used the regression model to fit data and check seasonal variations. The model developed by Papalexopulos and Hesterberg [12] 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 [13] 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.* [14] 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 [15] used a least-squares approach to identify and quantify the different types of load at power lines and substations. Hyde and Hodnett [16] 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 [17] 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.* [18] 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.* [19] 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.* [20] 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 [21] presented a regression-based daily peak load forecasting method for a whole year including holidays. To forecast load precisely throughout a year,

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different seasonal factors that effect 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.

2) 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 [10], the load at time t, y…t†, is modelled using a fitting function and is expressed in the form:

$$y(t) = \beta(t)^T f(t) + \varepsilon(t) \quad (2)$$

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.* [11] 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.* [22] 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 [23] was based on optimal smoothing. This technique has been shown to compare favorably with conventional methods of load forecasting.

3) Iterative reweighted least square

Mbamalu and El-Hawary [9] 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 suboptimal model of the load dynamics. The weighting function, the tuning constants and the weighted sum of the squared residuals form a three-way decision variable in identifying an optimal model and the subsequent parameter estimates. Consider the parameter estimation problem involving the linear measurement equation:

$$Y = X\beta + \varepsilon \quad (3)$$

where Y is an *n x1* vector of observations, X is an *n x p* matrix of known coefficients (based on previous load data), β is a *p x 1* vector of the unknown parameters and ε is an *n x 1* vector of random errors. Results are more accurate when the errors are not Gaussian. β can be obtained by iterative methods (Mbamalu and El-Hawary [9]. Given an initial β, one can apply the Newton method. Alternatively, one can also use the Beaton and Turkey iterative reweighted least-square algorithm (IRLS). In a similar work, Mbamalu and El-Hawary [9] 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.

4) Adoptive 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.* [24] 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.* [25] 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.* [26] presented an adaptive-time series model, and simulated the effects of a direct load control strategy. Park *et al.* [27] 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 [28] presented a practical real-time implementation of weather

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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 [29] 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 [17] 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.* [30] 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.

5) Stochastic time series

Time series method has been most popular method although it has several draw backs such as complex to use, require more time and historical data for prediction but in today's most complex system and system of fast development in context of energy generation and demand method has difficulty to predict however it has been using for STLF. The remaining models of time series uses are:

a) Autoregressive (AR) model

b) Autoregressive moving-average (ARMA) model

c) Autoregressive integrated moving-average (ARIMA) model

a) 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.* [31] as:

$$L_k = -\sum_{i=1}^{m} \alpha_{ik} L_{k-i} + w_k \tag{4}$$

where, L_k is the predicted load at time k (min), w_k is a random load disturbance, α_i, $i = 1,\ldots\ldots\ldots,m$ 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 [9]. The algorithm presented by El-Keib *et al* [32] includes an adaptive autoregressive modelling technique enhanced with partial autocorrelation analysis. Huang [33] proposed an autoregressive model with an optimum threshold satisfaction 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.

B. 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),……*] and in terms of previous values of a white noise [*a(t), a(t-1)………*]. For an ARMA of order (p; q), the model is written as:

$$y(t) = \phi_1 y(t-1) + \ldots\ldots + \phi_p y(t-p) + a(t) - \theta_1 a(t-1) \\ - \ldots\ldots\ldots - \theta_q a(t-q). \tag{5}$$

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.* [11] 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 [28] used the WRLS (Weighted Recursive Least-Squares) algorithm to update the parameters of their adaptive ARMA model. Chen *et al.* [34] 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.

C. 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 ∇ operator, the series $\nabla y(t) = (1-B)y(t)$. For a series that needs to be differenced times and has orders p and q for the AR and MA components, i.e. ARIMA (p; d; q), the model is written as:

$$\phi(B)\nabla^d y(t) = \theta(B)a(t) \tag{6}$$

The procedure proposed by Elrazaz and Mazi [35] 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.* [11] used a seasonal ARIMA model on historical data to predict the load with seasonal variations. Juberias *et al.* [36] developed a real time load forecasting

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D. Artificial Intelligent (AI) Techniques

Computational intelligence is a relatively new research field. The expression computational intelligence is commonly used to refer to the fields of fuzzy systems, artificial neural networks (ANN), evolutionary computation, and swarm intelligence. Of these fields, neural networks are the subtype which is most often applied in load forecasting. In the following, we focus on Fuzzy Logic and Neural Network

1) 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 [37] observed that a fuzzy logic system has great capability in drawing similarities from huge data. The similarities in input data (L-i-L0) can be identified by different first order differences *(V_k)* and second-order differences *(A_k),* which are defined as:

$$V_k = \frac{L_k - L_{k-1}}{T}, A_k = \frac{V_k - V_{k-1}}{T} \quad (7)$$

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 [38] 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 [39] formulated a fuzzy linear programming model of the electric generation scheduling problem, representing uncertainties in forecast and input data using fuzzy set notation. The hybrid fuzzy-neural technique to forecasting load was later enhanced by Dash [40]. This hybrid approach can accurately forecast on weekdays, public holidays, and days before and after public holidays. Mori and Kobayashi [41] 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 [42] 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 [43] formulated a fuzzy model of the optimal planning problem of electric energy. Computer tests indicated that this approach outperforms classical deterministic models because it is able to represent the intrinsic uncertainty of the process. Chow and Tram [44] 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 [45] applied a fuzzy, multi-objective model to spatial load forecasting. The fuzzy logic approach proposed by Senjyu [46] 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 [47] 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 [88] proposed an alternative to the traditional trial and error method for determining of fuzzy membership functions. Automatic model identification is used, that utilizes analysis of variance, cluster estimation, and recursive least squares. Mastorocostas. [49] applied a two-phase STLF methodology that also uses orthogonal least squares (OSL) in fuzzy model identify cation. Padmakumari *et al.* [50] combined fuzzy logic with neural networks in a technique that reduces both errors and computational time. Srinivasan *et al.* [51] combined three techniques fuzzy logic, neural networks and expert systems in a highly automated hybrid STLF approach with unsupervised learning.

2) Neural networks

Neural networks are modeled after the basic working principle of human brains. They consist of several neurons. A neuron receives information over its input nodes and aggregates the information. Afterwards, it determines its activation and propagates its response over the output node to other neurons. Neural networks are very frequently applied for load forecasting (see e.g. Hippert *et al.* [52] for a survey). As stated in Hippert *et al.* [53], in 1998 a software based on neural networks technology was used by over 30 US electric utilities. Several subtypes of neural networks exist (see e.g. Bishop, [54]. In load forecasting, for example, radial basis function networks Ranaweera *et al.* [55], Gonzalez-Romera *et al.* [59], self-organizing maps Becalli *et al.* [56] for clustering and recurrent neural networks Senjyu *et al.* [57], Tran *et al.* [58] are used. However, feed-forward neural networks (or multilayer perceptron) are the subtype which is most often applied (Hippert *et al.* [52-53], Gonzalez-Romera *et al.* [59] Becalli *et al.* [56], Ringwood *et al.* [60]). A feed-forward network consists of several successive layers of neurons with one input layer, several hidden layers, and an output layer. The neurons are connected using weight vectors and neither feedback nor intralayer connections exist. A neuron i thus takes the output of its k input neurons, computes the weighted sum, subtracts a so-called bias θ_i and applies the activation function *a(), i.e.* $y_i = a(\sum_{k-1}^{n} w_{ik} x_k - \theta_i)$. The basic learning or weight-adjusting procedure is back-propagation (a form of steepest descent) which propagates the error backwards and adjusts the weights accordingly (Bishop, [54]). Frequently, only one hidden layer is used (see for instance Becalli *et al.* [56], Fidalgo *et al.* [61] and Hippert *et al.* [52]. Hippert *et al.* [53] provided a comparison of large neural networks (neural networks with a large number of neurons and weights) with several classical approaches. The classical approaches ranged from naive forecasting methods over smoothing filters and combination of smoothing filters with linear regression. Furthermore, hybrids of smoothing filters and neural networks were considered. The task was to forecast the 24 hours load profile based on data from a local utility in Rio de Janeiro. Used for building, testing, and validating the forecast model were the hourly loads and the temperature from April 1996 to December. Hippert *et al.* [53] found large neural networks to perform best–not only with the smallest MAPE (2.35–2.65%) but also with a lesser spreading of the errors. As they conclude, large artificial neural networks can be seen as competitive with other models as far as the forecasting of load profiles is concerned.

3) Genetic algorithms

Genetic algorithms (GAs) represent a powerful and robust approach for developing heuristics for large-scale combinatorial optimisation problems. The motivation underlying GAs can be expressed as follows: evolution has been remarkably successful in developing complex and well adapted species through relatively simple evolutionary mechanisms. A natural question is the following: what ideas can we adapt from our understanding of evolution theory so as to solve problems in other domains? This fundamental question has many different answers because of the richness of evolutionary phenomenon. Holland [62] and DeJong [63] provided the first answer to this question by introducing the concept of a GA as a general search technique that mimics biological evolution with the survival of the fittest individuals and a structured, yet randomised, information exchange, like in population genetics. In general, a GA encodes the problem into a set of strings, each of which is composed of several bits, then operates on the strings to simulate the process of evolution [64]. In the field of STELF, few GA based load forecasting methods have been reported, but encouraging results have appeared [64–66]. Recently, Srinivasan [67] used a GA to evolve the optimum neural network structure and connecting weights for the one day ahead electric load forecasting problem.

III. KNOWLEDGE BASED EXPERT SYSTEM

Expert systems are the result of advancement in Artificial Intelligence in last two decades. These are rule-based methods, which take decisions based on experience of experts. The forecaster is developed based on the knowledge gathered by the expert in the field. It is taken as a complementary method, useful when sudden or unpredictable changes take place in human behavior (festivals or public gathering etc.) and /or weather conditions where data driven approaches fail due to lack of data for such events. Knowledge based expert system can be viewed as a machine version of a human expert. This is based on the experts knowledge of the system load behavior which is written in the form of IF………THEN rules. S. Rahman *et al.* in their work [68] developed reference day load curve from the historical data. The reference load curve is then reshaped according to weather parameters for which rule base is designed by the human expert. K. L. Ho *et al.* [69] used similar technique to forecast a load of Taiwan Power Corporation. The authors observed that the forecast accuracy highly depend on hourly load patterns and daily peak and valley loads. Y. Y. Hsu *et al.* [69] incorporated a fuzzy inference process by processing the load and temperature data and utilized expert algorithm for forecasting. The work is performed offline and dependent on operator experience and observation. A decision making model for combination of short term load forecasting is given by Kang Chongqing *et al.* [59] which is a key feature of expert system.

IV. HYBRID TECHNIQUES

Hybrid approaches are also very common. Generally, these approaches combine two or more different approaches in order to overcome some drawbacks of the original methods. Frequently, combinations of CI-methods and classical methods or of several CI-methods can be observed. We already mentioned that particle swarm optimization (PSO) was used to determine the order and the coefficients of an ARMAX-model Huang *et al.*, [70]. Particle swarm optimization Eberhart and Kennedy, [71] is used also in combination with fuzzy neural networks Liao, [72], neural networks (Bashir and El-Hawary, [73], Niu *et al.* [74] and support vector machines (Wang *et al.* [75]. A particle swarm models the swarming behavior of a flock of birds or a school of fish. It consists of a

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population of several individuals, each representing a possible solution. The individuals update their position and velocity based on the memory of their best position and the best position in a neighborhood (or the whole swarm) (Engelbrecht, [76]. Frequently, genetic algorithms or other evolutionary algorithms are applied in combination with artificial neural networks (de Aquino *et al.* [77], El-Desouky *et al.* [78]; Liao and Tsao, [79]. In Huo *et al.* [80] genetic programming (see e.g. Eiben and Smith, [81] was used directly for load forecasting. In short, evolutionary algorithms mimic the natural evolution: they are population-based search or optimization heuristics that apply the principles of recombination, mutation, and selection to find good solutions. Since they are on the one hand population-based and on the other randomized algorithms, they are expected to be more robust against a convergence in local optima and towards noise Kyriakides and Polycarpou [82]. Furthermore, they do not require the same restrict assumptions as some classical approaches. Genetic programming is a specific evolutionary algorithm which evolves ‘‘programs” or functions directly. Apart from genetic programming, evolutionary algorithms and PSO appear to be applied mainly for determining an optimal setting of control parameters of the principal method.

V. Conclusion

Load forecasting is not only important to provide accurate estimates for the operating of the power system but also as a basis for energy transactions and decision making in energy markets. The accuracy of forecasts is a very crucial factor: A decision maker in the energy sector has the need of accurate forecasts since most of the decisions are necessarily based on forecasts of future demands. One of the first decisions to be made is therefore the selection of an appropriate model. This paper present review of the recent development in the area of Electrical load forecasting. Emphasis has been given to categorizing various short term load forecasting methods which is reported in the literature. Paper also presented salient feature of the various short term electrical load forecasting methods.

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