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Analysis and Evaluation of Short-Term Load Forecasting Techniques

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Abstract- **To supply electric power and energy to every customer in an economical and secure manner, all the electric companies faces several technical and economic challenges. The short-term load forecasting is the most crucial field of research, has become the most priority operations for reliable and efficient power supply system. It plays a very substantial role in the contingency analysis, scheduling, planning, maintenance, and load flow analysis of the entire power system in a specific region. Considering the electricity as a consumable product, it contains very distinctive characteristics when compared with any other product. For example, electricity as energy cannot be, in any way, stored like other products. It needs to be generated the moment when the demand for electricity is required. Therefore, forecasting the load demand remains the central and integral part of the entire system for planning, arranging and delivering periodical operations at regular intervals, with continuous growth in the electricity sector. The pattern of demand formation is a very complicated process, and forecasting a particular electricity network of a region is a complex task because of the total deregulation of the electricity sector and energy markets. Many forecasting models were developed, but none has generalized as an accurate method for every electricity demand pattern. This review paper explores realistic situations.**

Keywords — Electric load forecasting, demand load forecasting, load forecasting techniques, future electricity load, neural networks, short-term load forecasting

I. INTRODUCTION

The future load forecasting is an integral and major process in the operation and planning of the entire electric applications and utilities. The prime task is to accurately predict the needs of electric utility load demand at all times, particularly for short-term in our case [1].

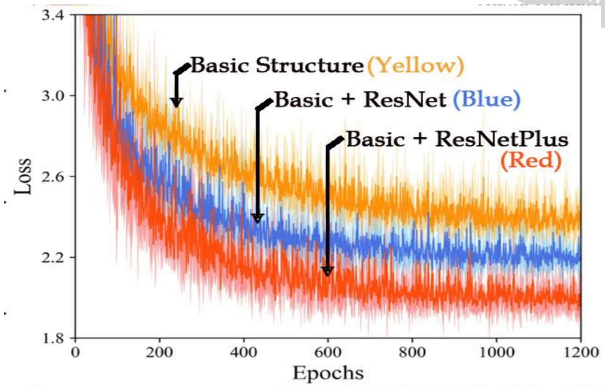

Figure 1: STLF- Short-term load forecasting applying artificial neural networks [2]

In the figure 1 neural network test losses having the Basic Structure (Yellow) model, Deep Residual Network showed as Blue- (Basic + Res. Net), and the modify model of Deep Residual Network shown as Red- (Basic + Res. Net Plus). Every model is 5 times trained using shuffled weight. The solid each color line indicates average losses and the deviation is below and above the part of average losses.

The basic function of the electrical power supply load system is to supply all customers, with both large and small customers, electrical energy as reliable and as economically feasible as possible. The exact load forecasting facilitates the formation of electric unit commitment, selection, the capability to scale back spinning reserves and in scheduling device maintenance to associate properly [3].

One additional function and responsibility of the power utility system is to recognize the customer's needs concerning the demand and supply of requisite energies. Due to several limitations and restrictions on energy generation resources over and above environmental factors, the use of the electric energy should be done more efficiently, by installing more effective and resourceful power plants, laying systematic transmission lines at all locations [4].

A. Objectives of Short-term Load Forecasting

- The commitment of operational unit design and economic delivery calculations
- Formation and maintenance of proper planning program
- Operational design method for getting accuracy in on-line load flows
- Spinning reserves and their calculations

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- Short-run interchange scheduling considering neighboring system
- Systems for security analysis
- Planning of stressful storage units
- Load planning and management [5]

B. Electric Load Forecasting Benefits

The short-term electrical load forecasting imparts several benefits and advantages for the electric company, for their business needs [6].

- For the purchase and production of electric power;
- To transmit, transfer and distribute electric power;
- To manage and maintain the sources of electric power;
- To manage the demand for daily electric load;
- For the planning of economic structure and marketing.

Therefore, the electric load forecasting is a specifically defined methodology to forecast electric of s specific time period and duration/horizon [7].

C. Classification of Load Forecasting

Table: 1 Load Forecasting Classifications [8]

Business Needs/	Climate factors	Economics	Land Use	Updating Cycle	Horizon
Load Forecast	Optional	Optional	Optional	< = 1 Hour	1 Day
ST Load Forecast	Required	Optional	Optional	1 Day	2 Weeks
Medium Load Forecast	Simulated	Required	Optional	1 Month	3 Years
Long Term Forecast	Simulated	Simulated	Required	3 Years	30 Years

II. FIVE SHORT-TERM LOAD FORECASTING TECHNIQUES

The electricity load demand pattern is the most complicated because of the energy market deregulation. A brief review and discussion of every technique, together with the relevant equations, is offered. The algorithm of load forecasting techniques and their implementation are programmed, so as to apply to the similar database to conduct for direct comparison of these various techniques. The comparison summary of these results is provided to understand several inherent difficulties arising at every level of each technique together with their performance.

For short load forecasting assumptions, several factors are involved, such as weather information, time factors, and doable customer's category [9]. Several approaches and techniques have been assessed and investigated to manage this electricity load forecasting problems in the last twenty years.

The forecasting of the Short-term load is developed to generate requisite info to facilitate system management with a unified commitment for regular operations. The forecasting prediction time or time-period for short load forecasting is always week-by-week, day-by-day, hour-by-hour, to facilitate utilities beyond the knowledge of normal load demand of (a) Condition of the Peak load for during a day system; (b) System load assessment at various intervals of a day, hour and half an hour; (c) Energy needs on an hourly basis of time unit; (d) Prediction of an individual busload; (e) Forecasting the utility system for several minutes to several hours ahead to help manage and dispatch load economically with security assessment [10]. Based on this, many techniques can be applied for short load forecasting, and they can be classified.

III. SHORT-TERM LOAD FORECASTING METHODS & TECHNIQUES

The objective of this methodology is to offer stable and safe electricity as per the market demand of the end user. Therefore, EPLF - Electric Power method of Load Forecasting is a valuable procedure by planning of all the operations of electric power system [11]. The accuracy in forecasting saves maintenance and operating costs, increases power supply reliability and delivery process, to take precise decisions for forthcoming developments. This EPLF methodology is to forecast and analyze the pattern of future electric load without restricting to short, or medium, or long duration term length [12].

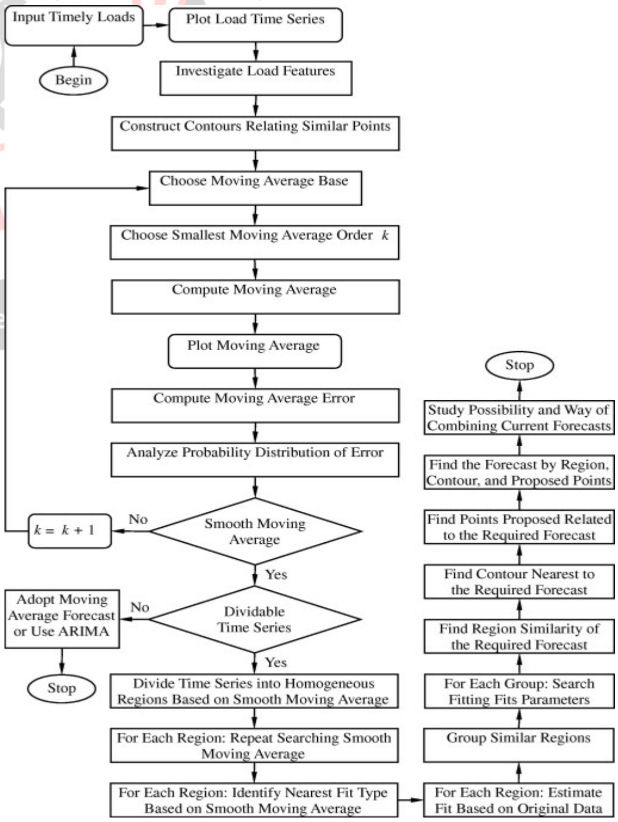

Figure 2: EPLF Methodology Flowchart [12]

The forecasting methodology and performance can be evaluated by many statistical metrics. However, the useful and reasonable is known to be MAPE - *Mean Absolute Percentage Error*. It means:

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$$\mathrm{MAPE} + \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|y(t) - \hat{y}(t)|}{y(t)}\right)$$

Where; *y (t)* and yˆ (t) are Load Estimated and Load Actual values at a t = time; the n = data number used. Fewer value of MAPE indicates more precise estimate. The metric suitability, performance depends on load time series [13].

In figure 3 daily loads is the real recorded data in MWh, obtained between 2006 and 2008 from the Kuwaiti electric network and is analyzed.

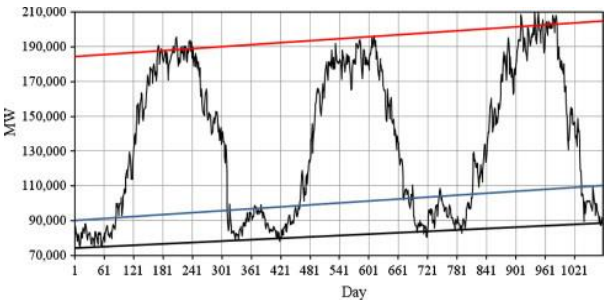

Figure 3: Daily load network between 2006 and 2008 [13]

In figure 4 illustrated as the load meshed plot for three years and it can applied to load weighting.

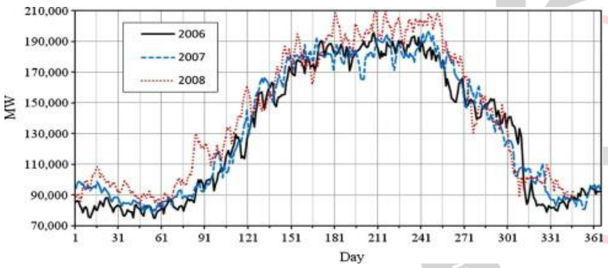

Figure 4: Plot of daily mesh load between 2006 and 2008 [13]

The moving average process is applied for filtering data, and observed the moving average for 7 days, as shown in the figure 5, showing close to the average error value = 30.55 MW; and MAPE = 0.0384 [14].

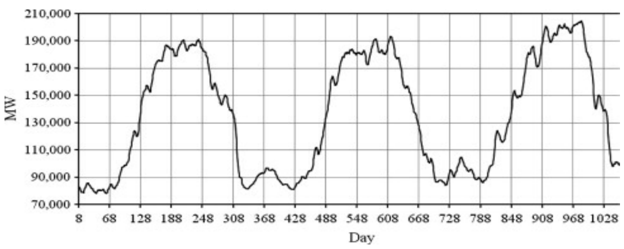

Figure 5: 7 day load moving average between 2006 and 2008 [14]

The error shown in figure 6 depends on the moving average. The hypothesis does not prove that the noise level is generally distributed due to evident odd values. The moving average is enough to locate the time series regional homogeneity, while more smoothing cannot yield the level of actual noise due to distortion in the main load [15].

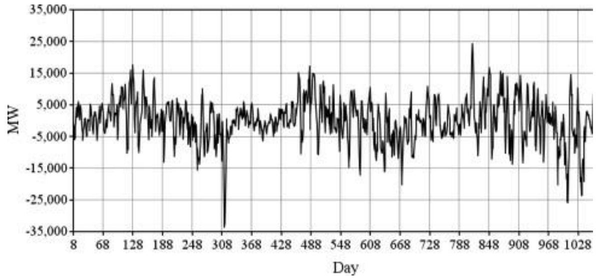

Figure 6: 7 day noise moving average for load between 2006 and 2008 [15]

In figure 7 shows the moving average for 30 days, provides homogeneity value mean error = 174.47 MW, which is not noise.

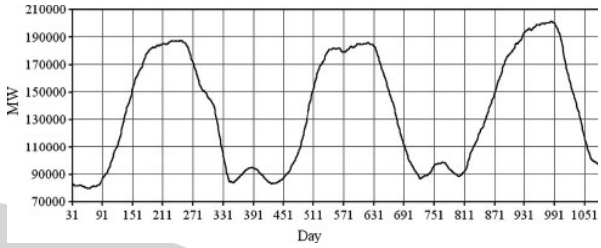

Figure 7: Moving average load for 30 days between 2006 and 2008 [15]

The third polynomial order was fitted as indicated in the figure 8 and 9 for the year 2006. The first group = first region, has the particularly similarity, and the second group = second regions carry another similarity [16].

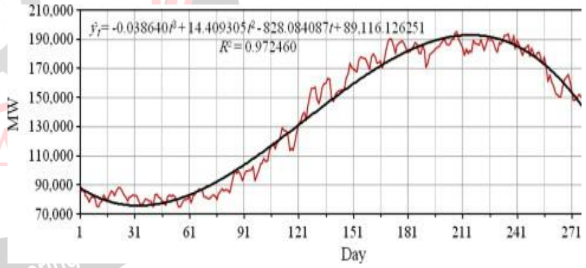

Figure 8: First region Trend of 2006 [16]

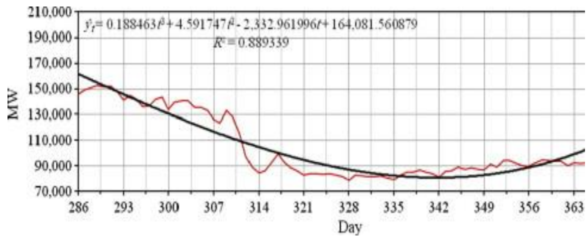

Figure 9: Second region Trend of 2006 [16]

Every group, with polynomial parameter indicates a different trend. The figure 9 shows the Probability Plot, to test the noise probability and distribution hypothesis on the basis of the polynomial estimated trend. The noise to time series is expected to be normally distributed having mean zero value [17].

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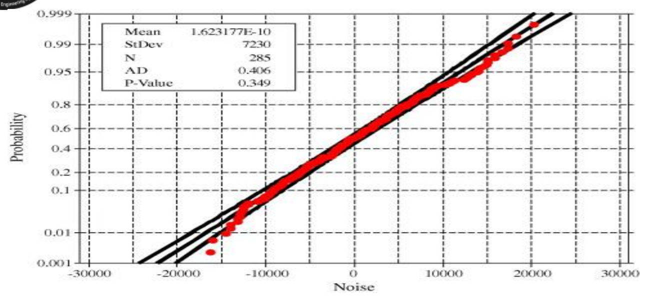

Figure 10: Noise of first region probability plot of 2006 [17]

Hence, the estimated forecast value is attained with a definite confidence level, as indicated in the figure 11. Every region is to forecast the future load on a daily basis with little amendment to their trend parameters.

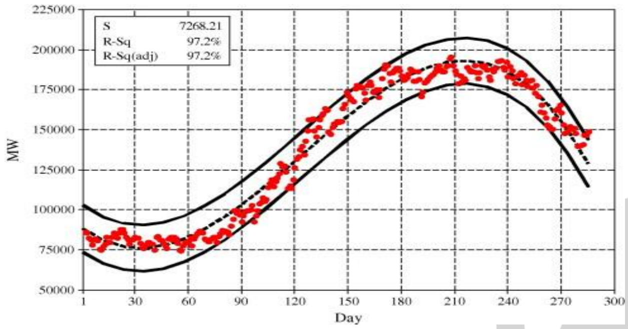

Figure 11: Confidence polynomial plot fitted for the 1st region with 95% in 2006 [17]

In conclusion of this methodology, the forecasting of the Electricity demand performs the major task to plan the production of electricity. Because, it decides the needed resources for the functioning of electricity plants and the daily fuel consumption needed [18]. The algorithm proposed offers substantial computational efficiency enhancement due to:

- The decoupling in the AC-network due to dimensionality reduction and the formulation by exploiting variable active-reactive reduction;
- Meager matrix techniques available in selecting and generating the needed sensitivities; and
- The effective strategy format that slows down all inactive and idle constraints. The help of the computer was taken to perform and obtain results to prove the algorithm efficiency [19].

The research analysis has used the algorithms to acquire hourly load forecast details, for one complete day of 24 hours, during the summer and winter peak seasons. The methodology of five forecasting techniques is used in the same database, and the performances are right away compared. The analyses of forecast errors are also tabulated for the two seasons, winter and summer. These results are by forecasting two whole days, specifically for the comparison purpose. Certain appealing observations were prepared to regard the results produced [20].

IV. TECHNIQUES FOR LOAD PREDICTION IN THE ELECTRICITY-SUPPLY INDUSTRY

EPLF - Electric Power Load Forecasting is a very important procedure in scheduling, planning, and development of electricity in the industry for the accurate electric power system operation [21]. Accurate forecasting can help in economic considerations and leads to significant savings in the overall costs of operation and maintenance, helps increase reliability and consistency of power generation, supply, and delivery method, and provide an accurate guide for future development [22]. The demand pattern of electricity gets affected by many factors that include time, economic, environmental, and social factors by which the pattern will form various complicated variations [23].

A. One set of methodology

There are often various application methods with different engineering matters and significances, considering proper economic analyses and measures. By analysis and evaluation, the review paper has explored several sets of methods and compared Five Short-term Load Forecasting Methods and Techniques for electricity generation, transmission and distribution facilities, and they are:

- Multiple Linear Regression
- Stochastic Time Series
- General Exponential Smoothing
- State Space Method
- Knowledge-based Approach [24].

B. The second set of methodology

- Simplistic Benchmarking Method
- Modeling of Seasonal ARMA
- Periodic Modeling of AR
- Holt-Winters, Double Seasonal, Exponential Smoothing
- PCA-Derived Method [25].

C. The third set of methodology

Similar Day methodology for short-term load forecasting is predicted based on the historical knowledge and data support available for one, two, and three days, a few months with identical characteristics to the assessed forecast day. The same characteristics adopt weather details, specific day of that week, as well as the date. The load values are considered on the same day, only after considering the weather forecast. Instead of the identical day load, the forecast is always taken as a linear regression or combination process, which considers several identical days of the week. The scanning of the trend constant is used for those identical days of the previous few months [5].

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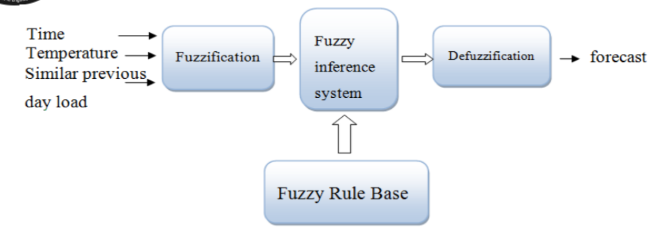

Figure 12: Flow Chart & Block Diagram, Fuzzy logic, Similar Day methodology for forecasting short-term electrical load [26]

The following figure of PLF - probabilistic load forecasting is to generate daily and hourly measures of PDF - Probability Density Function taking into account an annual hourly power load using less than one-year information. The whole process of PLF is summarized in figure 13. It shows the process with five basic steps: (1) Outliers detection; (2) Trend analysis; (3) Data normalization; (4) Training of Probabilistic Forecasting model; and (5) Combination of dual uncertainty - Load deviation & Temperature variation.

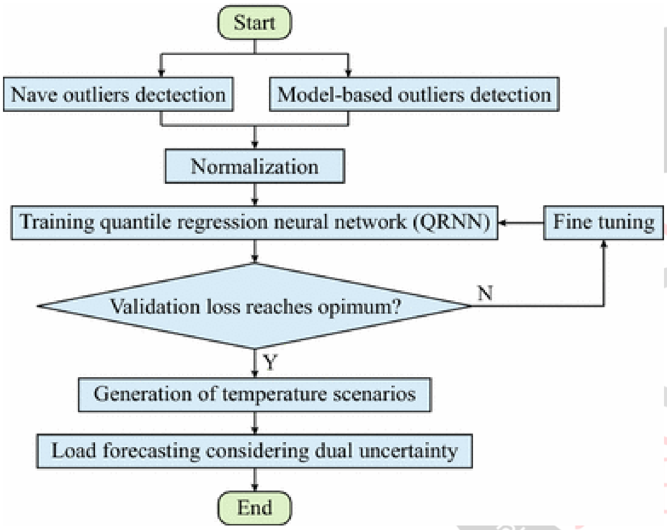

Figure 13: PLF - Probabilistic load forecasting process Flowchart of Short-term load forecasting methodology [27]

D. Regression methodology

It employs a regression strategy after considering the load consumption link and various other factors, such as weather, and a specific day of the week for short-term load forecasting. The regression strategy purposefully correlates load demand to various competitive, economic, or weather variables related to the estimated equation, which mistreat the smallest quantity of squares techniques. The multivariate scrutiny involves the necessity of mistreated judgment in correlation with applied mathematical investigations. The Regression process involves time series information and facts and unremarkably utilized to apply in various utilities where the requisite performance measures of the week, month or three-month basis is evaluated and they are used to obtain the load model and analyzed [28].

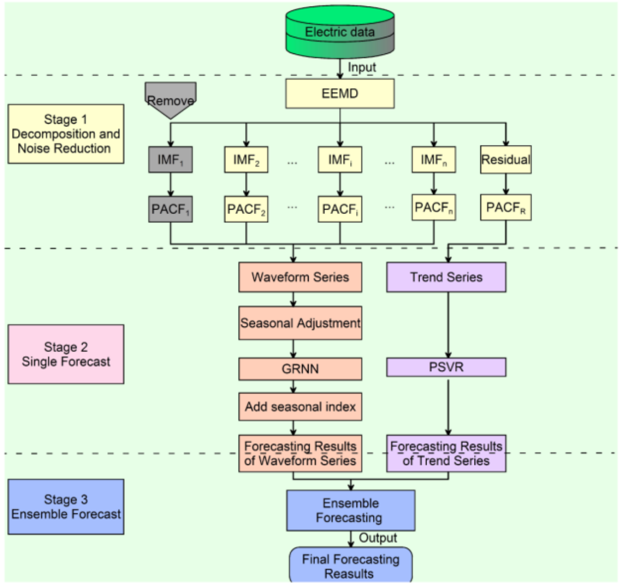

Figure 14: The flowchart combines IMF: Intrinsic mode of function; EEMD – Electrical Empirical mode & decomposition; PACF - Partial autocorrelation & function; PSVR: Particle swarm optimized algorithm, the support vector of regression machine [29]

Quantile regression neural network (QRNN): The conventional NN can raise one single output at one time, which remains incompatible with probabilistic forecast load. Hence, NN is proposed for probabilistic forecasting depending on the fundamental ANN structure, and it is called QRNN model with an intention of QRNN to develop quantile vectors of PDF based on hourly load and by regulating definite loss functioning parameters [30].

E. The Time series methodology

It uses short load forecasting strategies on the concept that the knowledge and information on load demand are based on their internal structure and for instance, the normal trend, auto-correlation, and seasonal variations. The statistical forecasting strategy identifies and explores this type of structure. These statistics are applied for several years in specific fields like digital signal processing, social science, apart from the electrical load anticipating and forecasting. (1) ARMA - Auto Regressive Movement of Average; (2) ARIMA - Auto Regressive Integration and Moving Average; (3) ARMAX - Auto-Regressive Moving Average along with exogenous variables; and (4) ARIMAX - Auto-Regressive Integrated Moving Average together with exogenous variables; they are the classical primary statistical methods for forecasting and anticipating a short load time. At the same time ARMA model, at times, applied to stationary procedures, while ARIMA is related ARMA extension used for non-stationary procedures. ARMA with ARIMA is then utilized with time and cargo, solely due to their input parameters. The load habitually based on the time and weather conditions of the day, while ARIMAX is largely a natural tool for forecasting short duration load among all other classical and statistical models [31].

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F. Artificial Neural Network (ANN)

This methodology is the most popular and highly applied for forecasting short-term electrical load. The ANN network is a non-linear circuit having the incontestable capacity to attempt, struggle and perform non-linear curve specific fittings. The man-made outputs of the ANN have certain linear and non-linear input functions. The inputs relate to outputs of other components of the network, apart from the authentic network inputs.

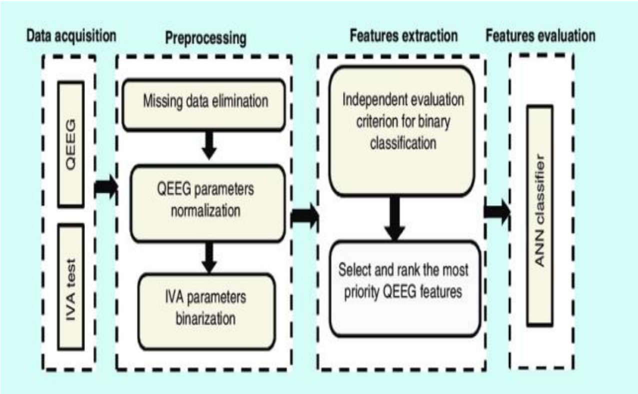

Figure 15: Artificial neural network (ANN) Flowchart Integrated auditory and visual [32]

QEEG: Quantitative Electro Encephalography
IVA – Integrated Visual and Auditory

Continuous Performance Test (CPT) is a processing and screening tool applied in combination different diagnostic procedures, like a teacher with the parent and their rating scale of behavior to help screen individuals to ascertain Attention Deficit Hyperactivity Disorder (ADHD) [33], while QEEG - Quantitative Electro Encephalography is related to the electroencephalography data and its numerical analysis associated with behavioral patterns.

The network components are structured at the time of less range of linked component layers within the inputs and outputs of the network. Sometimes, the feedback methods are applied. The ANN has been successful in several grid applications; for instance, fault diagnosing, security analysis, analysis, planning, load predictions and forecasting, and protection. The ANN has the mapping ability to perform in intricate non-linear correlations and is accountable for its increasing range of applications in short-term load forecasting. ANN is considered the most fashionable and best available application model for short load prediction and forecasting, as the Back-propagation neural pattern, which uses endless and valued functions with monitored and supervised learning methods.

The neural network, a fuzzy version called Fuzzy BP - a network of Fuzzy Back Propagation is developed for the prediction of short-term electrical load [35].

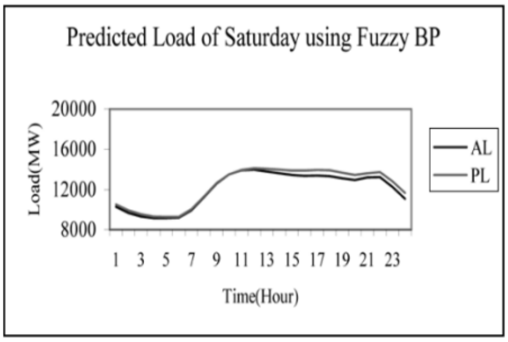

Figure 16: Using Fuzzy Method. Actual Comparison of predicted loads on 25, Saturday, by applying 5-24 patterns on Saturday for training. The % error maximum = 4.25%, and MAPE=2.48%.

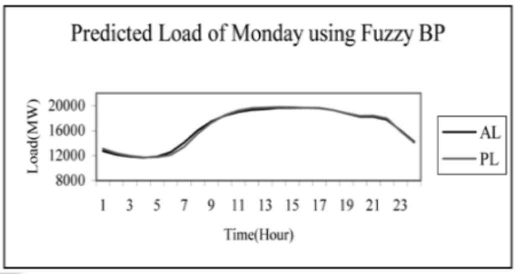

Figure 17: Using Fuzzy Method. Actual Comparison of predicted loads on 30, Monday, by applying 10-29 patterns for training. The % error maximum = 3.35%, and MAPE=1.24% [35]

The below figure 18 produces a set of data is a historical hourly load table and temperature conditions observed from ISO New England between the years 2004 and 2008. The information on the weather involves the temperature of dry bulb and also the dew point. The data set is obtained from the Access database applying the auto-generated operation of fetch DB Load Data.

The below figure 18 are to differentiate the predicted load with the actual load and thereafter to compute the estimated error. It is also to quantify the performance of the estimated values using metrics like MAE - Mean Absolute Error, MAPE - Mean Absolute Percent Error along with DFPE - Daily Forecast Peak Error. They provide the visual picture of Actual Load (Blue Color) as Compared with Forecast Load (Red Color).

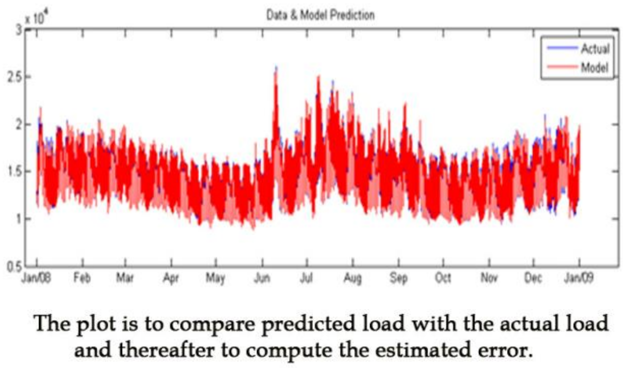

Figure 18: Artificial Neural Network for forecasting short-term electrical load. It reads: MAPE Daily Peak: 1.63%; MAE - Mean Absolute Error 243.18 MWh; & MAPE - Mean Absolute Peak Error: 1.61% [35]

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Within the administered and organized learning, there are specific numerical weights allocated to their partial inputs and they are decided by identical past data and historical information like time and weather, with specific outputs of historical facts of loads, at the time of pre-operational session of training. The PNN - Perennial neural network methodology along with FFBP – Feed of forwarding, back propagation of the methodology of NN - Neural network are deployed to forecast the load height. The RBFN - Radial height based operating network method is used for rapid coaching and more after the valleys of peak-loads [5].

G. *Expert System methodology*

It mainly derives rules which are normally heuristic in practice for an accurate load forecasting. The systems incorporate procedures and rules employed by expertise within the load forecasting field to feed into the computer system to unable to create a forecast mechanically without human help. The expert system used the short load forecasting methodology starting from 1960 for geological applications. The knowledgeable systems worked well-developing computer code with accurate data fed by the expert system in computer code. This expert data is applicable and can be codified into the rules of computer codes [36].

The most important Fuzzy logical method and management systems basically are ruled by the system collected by the fuzzy-rules representing a sway calling mechanism that regulates the bound stimulation consequences. Fuzzy logic can be generalized into a standard symbolic logical mode and applied in the digital circuit designing method. For instance, the load of the electrical device can be High, Medium, and Low. The Fuzzy logic permits the consumer to apply logic to obtain the output from fuzzy input. The mathematical and logical techniques can be applied to correctly mapping all the inputs to convert into outputs [37].

Support Vector Machining methodology (SVM) supports the SRM - structural risk minimization principle, rather than ERM - Empirical risk minimization principle conducted by the standard NN - Neural Network model. The SVM is the recent development with a robust technique for the short load forecasting and is useful to classify for regression issues.

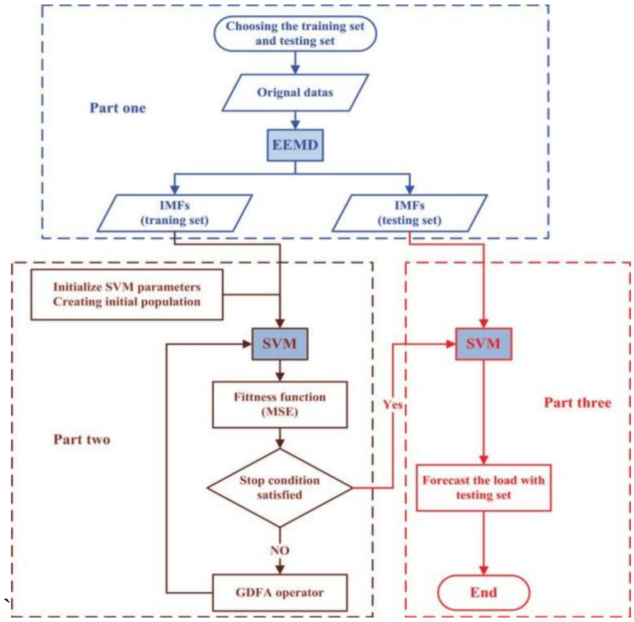

Figure 19: SVM work methods [38]

EEMD- Ensemble Empirical Mode Decomposition, a signal processing system applied to analyze nonlinear and non stationary signals
IMF– Intrinsic Mode Function
SVD– Singular Value Decomposition
CMSE- Consecutive Mean Square Error
MSE– Mean Squared Error in Computing & Networking;
GDFA- Generic Data Flow Analyzer

Unlike ANN, which tries to sketch the complex functions of the input house feature, they support vector machines carry out a non-linear plot by mistreating kernel functions of the data and information to utilize in high dimensional space features. The SVM uses the clear linear function to structure the linear cell outline inside the new house. The work of choosing the associate architect for the NN is therefore replaced by the selecting tasks for an appropriate kernel to help develop an SVM methodology [38].

V. CONCLUSION

For the short term load prediction, many models were explored and studied in this work. While taking the measures of these approaches, it was observed a transparent tendency and inclination towards stochastic, new, and robust prediction techniques. There are several research tendencies to evaluate the neural network techniques, which offers a new approach and hope during in the direction of study and analysis. Because this kind of network is very efficient and dynamic while predicting future demands. Such data for load forecasting was obtained from the Electricity Board grid of Chhattisgarh and the data was collected from the Danganiya, Raipur, Chhattisgarh Load Dispatch Centre, by proceeding with the research and the analysis, giving the ANN-based load forecasting with the results of the grid [5].

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This review paper has also explored several electric load forecasting models for the short term of a day and one week demand for electricity forecasting. The prime innovative idea is to forecast various waveform components and trend components so as to substitute completely to forecast the basic and original demand for electricity. Our study has explored certain advanced methods and techniques to assess the load demand model, containing white noise; cyclic adjustment is also considered taking into account the seasonal factor using the waveform module and trends. By combining the predicted results, we can get the eventual predicted electric demand with more accurate results than the direct forecasting model, by adjusting non seasonal models, and decomposing model.

These experiments significantly enhanced the stability and accuracy of prediction. The model can be utilized to schedule the demand forecasting of electric energy in the electrical market. Moreover, these models also can be used to measure wind speed, electric price, tourism demand, and several other electricity demands. Apparently complex, the datasets of experiment results indicate that the models do not solve the over-fitting problems. Otherwise, this model performs strongly, with certain shortcomings to overcome. For example, using the forecast method of electric demand, additional time is required in relation to other simple models. These models are sophisticated, using an extended memory space as can be seen by computing. By increasing the computing ability, the new hybrid models can be quickly implemented to cover all the problems [38].

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