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A REVIEW ON DEEP LEARNING BASED LOAD DEMAND FORECASTING TECHNIQUES FOR SMART GRID

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Abstract: Electrical load forecasting plays a major role in planning an advanced power system such as smart grid. This context gives an overview on what is load forecasting, classification and requirement. On what external variables the load forecasting will depend and how the forecasting was already achieved in earlier days by using some conventional techniques like regression methods which also includes the history of load forecasting techniques.Load forecasting is a very complex process and it can be achieved by using AI (Artificial Intelligence) techniques. By using this AI methods very high degree of accuracy can be attained. This review gives a brief about the ANN (Artificial Neural Network) and the drawbacks faced by this method. Some deep learning techniques were introduced to overcome the drawbacks of ANN. Even by designing a complex system a lot of challenges need to be overcome for achieving an accurate result in load forecasting.

1. Introduction

Load forecasting is a central and integral process in the planning and operation of electric utilities. It involves the accurate prediction of both the magnitudes and geographical locations of electric load over the different periods (usually hours) of the planning horizon. The basic quantity of interest in load forecasting is typicallythe hourly total system load. However, according to Gross and Galiana (1987), load forecasting is also concerned with the prediction of hourly, daily, weekly and monthly values of the system load, peak system load and the system energy. Srinivasan and Lee (1995) classified load forecasting in terms of the planning horizon's duration: up to 1 day for short-term load forecasting (STLF), 1 day to 1 year for medium-term load forecasting (MTLF), and 1±10 years for long-term load forecasting (LTLF). Accurate load forecasting holds a great saving potential for electric utility corporations. According to Bunn and Farmer (1985), these savings are realised when load forecasting is used to control operations and decisions such as dispatch, unit commitmentfuelallocation and transmission line network analysis. The accuracy of load forecasts has a significant effect on power system operations, as economy of operations and control of power systems may be quite sensitive to forecasting errors. Haida and Muto (1994) observed that both positive and negative forecasting errors resulted in increased operating costs.

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Artificial Intelligence (AI) is a fundamental theme of future technology research and development. In many nations, smart grids are being developed to be an intelligent layer to improve power distribution, control, and generation [1]. The smart grids are being established with intelligent devices and sensors to computerize and improve various applications' productivity, including metering distribution.Machine learning, deep learning, and swarm intelligence are the common mechanisms of AI that are broadly used in smart grids for different purposes. Machine learning is being used for analysing big data in the smart grid and for security aspects of the Internet of Things (IoT) in the smart grid [6]In smart grids, different electrical power utilization data are aggregated in centralized cloud servers or cloud storage. Due to this large amount of data, the computation time for deep learning is high.

2.Load Demand Forecasting

Electrical load forecasting plays a vital role in order to achieve the concept of next generation powersystem such as smart grid, efficient energy management and better power system planning. As a result,high forecast accuracy is required for multiple time horizons that are associated with regulation,dispatching, scheduling and unit commitment of power grid.

Load forecasting is future load prediction, which plays a veryimportant role in the energy management system and better planning for the power system. In the proceeding years, a large number ofresearches have been published on accurate short term load forecasting (STLF) due to its impact on the reliable operation of power systemsand economy. It ensures the reliable operation ofpower system thatleads to uninterruptable power supply to the consumer [1]. Theoperations of power system,for example scheduling, maintenance,adjustment of tariff rates and contract evaluation can be convenientlycarried out by accurate load forecast. Energy policy makingdecision can be carried out based on accurate load forecast. Severaldecisions of power management system canbe carried out on thebasis of accurate load forecasting such as power system operation,maintenance and planning. Effective planning of power systemscan save millions of dollars, which plays a significant role in theeconomic growth of a country.There is a strong impact of weather variables on load demandsuch as temperature, relative humidity, dew point, dry bulbtemperature, wind speed, cloud cover and the human body index.The multiple loads consumed by individuals also creates enormousimpact on load forecasting. However, in order to achieve thehigher forecast results, there is need to accommodate all factorsaffecting on load demand as forecast model inputs such as;historical load and respective weather data. In this modern eraof technology, an accurate load forecast plays a vitalrole toimplement the

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concept of smart grids and smart buildings.

2.1 Classification of Load Demand Forecasting

Load forecasting is divided into three categories by most of researchers but some of them divided it into four categories [2]. Normally Load forecasting can be divided in three categories on the basis time interval.

1. Long term load forecast (1 year to 10 year ahead).
2. Medium term load forecast (1 month to 1 year ahead).
3. Short term load forecast (1 h to 1 day or 1 week ahead).

Long term load forecast is used for the long-term power systemplanning according to the future energy demand and energypolicy of the state. Medium term load forecast is being used forthe efficient operation and maintenance of the power system.

Literature shows that, mainly efforts are concentrated on shortterm load forecasting in preceding years. It is due to the importance of short-term load forecasting and it also play a vital role inoptimum unit commitment, control of spinning reserve, evaluation of sales/purchase contracts between various companies.

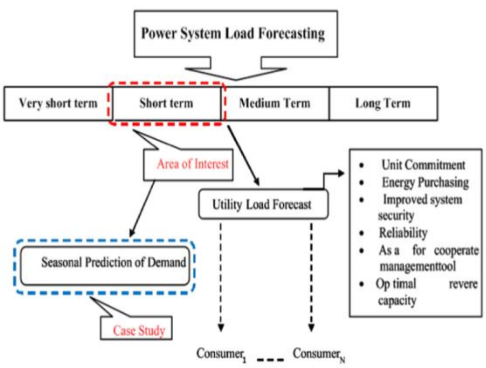

Fig. 1 Classification of Power system Load Forecasting

2.2 Short Term Load forecasting an it's importance

Literature review shows that, a large number of researches have been published on short term load forecasting for different load scenarios. Fig.1 illustrates that, the type of Load forecast andits application of short-term load forecast for reliable and efficientenergy management system. Fig.1 also depicts that, seasonal loadforecast scenario as STLF case studies to analyze the performanceof forecast model and utility perception for multiple consumers.The major objectives of accurate STLF are given below:

1. Generation scheduling of power system.
2. Secure and reliable operation of power plants.
3. Economic dispatch and reliability.

2.3 Different Load forecasting techniques that are present in the market

Different types of techniques for load forecasting are available. But not all them will give accurate results and used in the market. Some of the methods are best for the theoretical calculations and some are good for practical implementation.

1. Multiple regression
2. Exponential smoothing
3. Iterative reweighted least-squares
4. Adaptive load forecasting
5. Stochastic time series

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6. ARMAX models based on genetic algorithms
7. Fuzzy logic
8. Neural networks
9. Knowledge-based expert systems.

There are number of forcasting methods are present in theory but the above mentioned are the main forecasting domain methods that are present in the market. Among all the above-mentioned forecasting techniques a lot of them having a great difficulty in many accepts like lacking accuracy, having very high computational time, requires very high processing power, very difficult to find the relationship between the non-liner time variables.

2.4 The major functionalities of Load forecasting

The major functions and requirements for operation planning in each period are presented in Table 1. The aim of short-term load forecasts is to predict future electricity demands based, usually, on historical data and predicted weatherconditions [4,5]. The short-term load forecast is required for unit commitment, energy transfer scheduling and load dispatch. With the emergence of load management strategies, the short-term forecast is playing a broader role in utility operations. The development of an accurate, fast and robust short term load forecasting methodology is of importance to both the electric utility and its customers, thus introducing higher accuracy requirements. So far, a wide variety of STELF methods have been used .Traditionally, STELF techniques use conventional smoothing techniques, regression methods and statistical analysis. The statistical models used for STELF include peak load models and load shape models. The load shape models rely on time series analysis techniques. The autoregressive moving average model is among the most popular of the dynamic load shape models. Although these techniques and models are reliable, they are unable to adapt to unusual weather conditions and varied holiday activities, which form a highly non-linear relationship with the daily load. Hence, their load predictions in the presence of such events are not as satisfactory as desired, and consequently, more sophisticated means must be employed in order to map the correlation accurately between all the variables.

Table 1: Different Parameters in Load Forecasting

Forecast Problem	Short Term	Medium term	Long term
Time horizon	1/4–24 h	1 day - few weeks	Few months-year
Forecasting value	Load curves	Load Curves	Energy required
Accuracy	Exact load curves	Error<< Capacity	Exact enrgy

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Time Step	1/4–1 h	1 h	1h
Operation	Economic dispatch	Unit commitment	Reserve planning
Planning	Unit Commitment	Reserve planning	Capacity expansion

Apart from the above parameters there are different variations are present in differentiating the Load Forecasting Types.

2.4 Co-relation analysis between weather variables and load data

There is strongcorrelation between weather variables and load demand [3]. Generally, load demand of power is increases in summer season due to raisein temperature and lower in winter season. So, weather variable mustbe included as forecast model input in order to achieve acceptableforecast accuracy. The humanperception study shows that the dew point in the range of 40 F to 60 Fis suitable for humans. The load demand is low within this range ofdew point.

3. Integrations of Deep Learning in Load Forecasting

The utility industry has invested widely in smart grid (SG) over the past decade. They considered it the future electrical grid while the information and electricity are delivered in two-way flow. SG has many Artificial Intelligence (AI) applications such as Artificial Neural Network (ANN), Machine Learning (ML) and Deep Learning (DL). Recently, DL has been a hot topic for AI applications in many fields such as time series load forecasting. The common algorithms of DL in the literature applied to load forecasting problems in the SG and power systems. The main intention of this chapter is to explore the different applications of DL that are used in the power systems and smart grid load forecasting.

Deep learning (DL) is a type of machine learning that has deeper inner hidden layers cascaded into the network. Its goal is to make machines like computers think and understand as human thinks by mimicking the grid of the human brain connection.

3.1 Importance of Deep Learning in Load forecasting

Artificial Intelligence (AI) is a fundamental theme of future technology research and development. In many nations, smart grids are being developed to be an intelligent layer to improve power distribution, control, and generation [6]. The smart grids are being established with intelligent devices and sensors to computerize and improve various applications productivity, including metering distribution. The machine learning-based smart meter system contributes effectively to the Ambient Assistive Living (AAL) area for detecting daily living activities. Machine learning has been used with smart meters for improving end-user load modelling machine learning [7]. AI also combined with edge computing and edge analytics in smart power meters. At present, the smart grid, smart home, and smart meter success depend on AI

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and communication security. Machine learning, deep learning, and swarm intelligence are the common mechanisms of AI that are broadly used in smart grids for different purposes. Machine learning is being used for analyzing big data in the smart grid and for security aspects of the Internet of Things (IoT) in the smart grid [8]. Deep learning is a family of machine learning based on artificial neural networks (ANN) that are used in the smart grid for predicting load forecasting, price forecasting, solar forecasting, power quality, and other purposes.

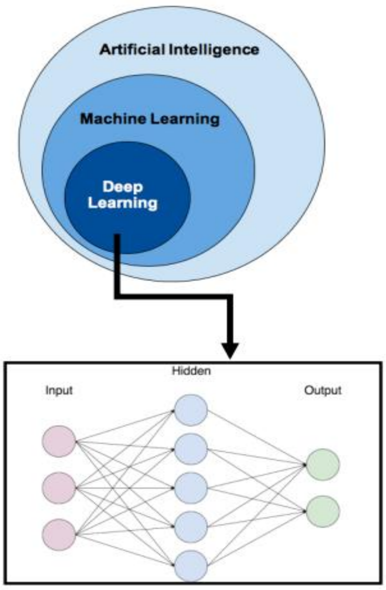

Fig. 2Deep Learning process contains Artificial Neural Network (ANN) mechanism

ANN mainly use the layered structure as shown above which mainly consists of input, output, and Hidden layers corresponding to precise weights.

3.2 Different Deep Learning Techniques in Load forecasting

Load forecasting is an essential outcome of a smart grid system. It predicts the short-term, medium-term, and long-term demand for electrical power to the users. Deep learning is widely used for load forecasting in smart grids [9]. Although a subset of machine learning, deep learning is more useful than other traditional machine learning algorithms. It also facilitates the use of other machine learning algorithms in conjunction with ANN for better results. For that reason, it is well known that it provides precise accuracy. Various techniques have been combined with ANN for smart grids, including Decision Tree, Random Forrest, Support Vector Machine, K-nearest Neighbor (KNN), and other machine learning algorithms, obtaining better outcomes for power management, load forecasting, and other purposes. Electrical power distribution companies will be particularly benefited from smart grids by determining better power distribution among the consumers or clients (home, industry, and corporate office). Currently, different electrical power utilization data are aggregated centrally. Deep learning performs load forecasting from this huge data, and hence the power distributors can predict the demand for electrical power distribution and provide power to different consumers accordingly. The process is shown in Figure 2 In smart grids, different electrical power utilization data are aggregated in centralized cloud servers or cloud storage. Due to this large amount of data, the computation time for deep learning is high [10]. Therefore, various machine learning techniques are being applied to deep learning to

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enhance computation time and efficiency. Distributed Machine Learning (DML) is one technique that is already being used to enhance computation time, so Distributed Deep Learning (DDL), a subset of DML, may also be applied to reduce the data being processed and may obtain useful and valid outputs compared to deep central learning. Smart grids are large-scale network systems consisting of physical power and an information network. When considering distributed storage and distribute power distribution control.

Distributed Smart Grid (DSG) appears to be a reasonable alternative to investigate in such systems. Distributed Artificial Intelligence or Decentralized Artificial Intelligence (DAI) can thus be employed in smart grids for obtaining effectual output.

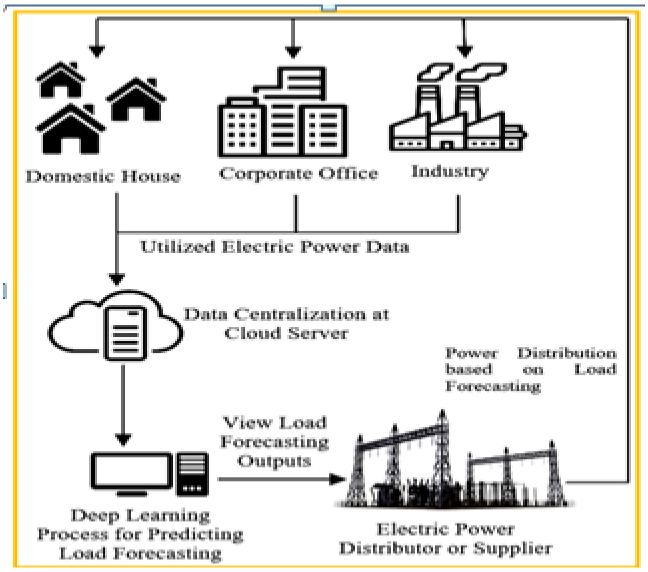

Fig 3 Load forecasting in Smart Grid Systems.[11]

DML is normally used in decentralized and distributedsystems such as IoT andwireless communication [11]. DDL has become common in computing the trainingprocesses ofmultiple devices by using ANN and other machine learningalgorithms[5]. Therefore, DDL has potential applications infuture smart grids for reducing ANN computation time anddecreasing huge data centralization dependency.At the same time, IoT is a very essential networkmechanism in the smart grid system. Cloud ofThings is a cloud layer of IoT used for monitoring, managing,and analysing data and information provided by using acloud server. A deep learning-based CoT model hasbeen implemented to identify the traffic in a heterogeneousnetwork. Therefore, DDL may be integrated with CoTfor better performance in a smart grid.

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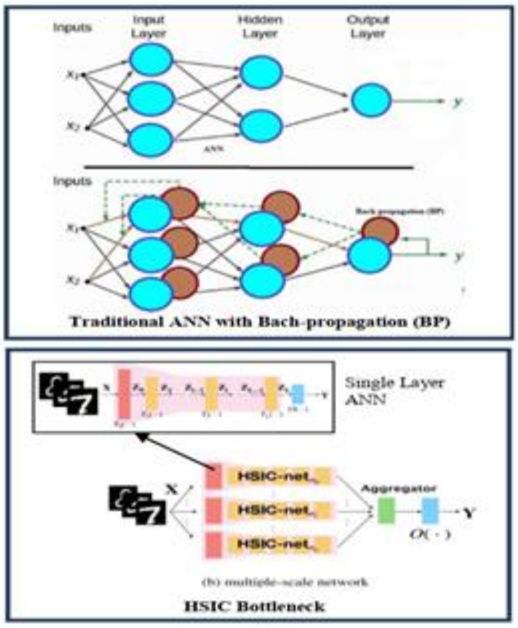

Fig 4 HSIC Bottleneck implementation in the ANN [11]

Typically, Back-Propagation (BP) method is used in deeplearning processes to find results with good accuracy. BP hassome disadvantages such as weight transport, update locking,vanishing gradients, and exploding gradients. In smart grids, BP takes additional computation time ontop of that caused by huge centralized data aggregates [6].So, it would be beneficial to reduce the computation timesfor load forecasting in the smart grid. Due to thedisadvantages of BP, non-BP based works have beenproposed for load forecasting. In otherapplication areas, alternative approaches to BP are also beinginvestigated [12][13]. The BP process withtraditional ANN has been illustrated in Figure 4.

3.4 Different ANN Techniques in Deep learning Based Load Forecasting

ANN is the primary and fundamental portion of deeplearning. For developing any deep learning process,researchers or developers need to integrate different kinds ofmachine learning algorithms with ANN structure. Table 2demonstrates different types of ANN that have been used inproposed load forecasting systems, along with theircharacteristics.

Table 2: Different types of ANNin Load Forecasting

ANN Type	Characteristics
FFNN	ANN without BP
BPNN	Combination of Multi-layer Perceptron (MPL) based FFNN with BP
DNN	ANN with multiple hidden layers
Distributed Neural Network	DDL based ANN where multiple parts of an ANN are distributed
RNN	Relationship between nodes like a graph

Feed-forward Neural Network (FFNN) is the basicconcept of ANN, FFNN isa forward propagation techniquewithout BP. FFNN has been used with GrasshopperOptimization Algorithm. BPNN is a version ofFFNN where BP is connected to aMulti-layer Perceptron(MLP) based FFNN. A low and medium voltage smart grid is an important matter for predicting accurate loadforecasting. BPNN is broadly used in low voltage gridsload shedding, and PV (Photovoltaic) generation.FFNN and BPNN based hybrid ANN have been proposed forpredicting MTLF and STLF in low voltage smart grid.BPNN with fuzzy logic has also been proposed for themedium voltage at self-optimized STLF. Deep NeuralNetwork (DNN) is a mechanism built upon FFNN wherethere are multiple hidden layers. Iterative ResBlocks (IRB)based DNN has been developed for individual residentialloads. BP algorithm has been utilized with DNN. From the review, most have combined differenttypes of ANN (hybrid ANN) for solving variouscomplex issues in load forecasting. A recentreview study ofload forecasting has been indicated the vital parts of deeplearning models with single and hybrid models. Singlelayer Perceptron (SLP), which has no hidden layer,as usedfor increasing SLTF speed in a hybrid SLP with RecurrentNeural Network (RNN), Encoder-Decoder Architecture. RNN is a directed graph-oriented ANN and hybrid RNN isbroadly used in various load forecasting processes for datacleaning, big data, computational time, highdimensional dataand other purposes. LSTM are techniques built upon RNN. LSTM was the most usedANN approach in load forecasting, demonstrating betterperformance in different complex situations such as low and high-frequency components, probabilistic loadforecasting, PV generation, CCHP (CombinedCooling, Heating, and Power) system, Hybrid energysystemsetc. A combination of three ANNs, namelyLSTM, BPNN, and DQN (Deep Q-Network), have beenused for establishing a similar day selection based STLFmodel. WNN (Wavelet Neural Network) with BPNNhas been used in MTLF to determine the reduction of theunavoidable stochastic part. Neuro-fuzzy is a fuzzylogic-based ANN technique and has been applied to RNN,LSTM, ELM (Extreme Learning Machine) in STLF, and other ANNs for improving some issues in loadforecasting. Table 3.1 presents various other types of ANN, RNN (Reinforced neural network), which have beenapplied for the various load forecasting model.

3.5 Updated Load Forecasting techniques only used for Short Term Load forecasting

The below mentioned table 3 gives an over view on different developing models corresponding to short term load forecasting, main focus area of the corresponding model and its major contribution.

Table 3: Different Forecasting models and their contributions

S.No.	Year	Developed Model	Focus Area	Major Contribution

1.	2020	Reinforcement Learning based similar day selection model in STLF algorithm	1) Similar day selection	Establishes a similardayselection basedSTLF model by using the reinforcement learning on the BPNN for Korea and other Northern States
2.	2020	Multi-layer ANN and GOA based load forecasting	1)Different hours and different days 2) Weather factors	The model canuseable to forecast loads at the daily and hourly over a month using GOA and Multi-layer ANN.
3.	2020	Advance BP based load forecasting	1) Load shedding 2) Cost saving	Predicts advance BP based loadforecasting on to reduce the load shedding, power loss and cost generation.
4.	2020	Fuzzy ARTMAP ANN and SSA based load forecasting process in disaggregated levels	1)Disaggregated levels 2) Cost saving (Computation cost)	Combining Fuzzy logic, ARTMAP and SSA in disaggregated levels of load forecasting for reducing computational costand data requirements.

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5.	2019	Bayesian Regularization and LevenbergMarquardt based ANN for VSTLF and STLF	1) Time horizon 2) Single building load forecasting	Integrating the ANN with Bayesian Regularization and Levenberg Marquardt for the single district buildings' load Forecasting
6.	2019	Terminal coding and fusion ANN based day-ahead load forecasting	1)Classification of similar load forecasting. 2) Day-ahead load	Classifying samegroup load forecasting and aggregating the load with various scales.

3.6 Different research works and contributions in Load Forecasting

For load forecasting, different researches focused on differentissues. Of these issues, much of the research has beendevoted to improving the speed and accuracy of loadforecasting, and so, as can be seen from Table 3.3 trainingand computational time,learning error and feature extractionhave received a large share of the attention fromresearchersin smart grids.Others have focused on improving accuracy by addingdata that are expected to be correlated with powerconsumption. Datasets used for loadforecasting includedsmart meter electric data, power loss data, temperature,weather, etc., depending on different power gridrequirements. For example, the weather has animpact onpower usage by consumers an important part of the smartgrid used meteorological data (temperature and humidity)Geographical, cultural, and income variances in differentplaces. Where it means that solutions for one area may notwork for another area of the world, so load forecastingmethods need to be reviewed for every locality.

Table 4: Major Utilization and different Problems faced by the corresponding Load Forecasting Types

Forecasting Type	Major Reason of Utilization	Technical Problem Facing
VSTLF	1) Load demand of residential buildings 2) PV generation and PV penetration 3) Single building load forecasting 4) Bus load forecasting	1) Over-fitting issue 2) Big data 3) High training andcomputationalTime 4) Feature extraction and selection related issue 5) Data requirement or limited data

	5) Thermal unit generation 6) Classification of similar load forecasting	6) High dimensional data related, problem 7) Noisy data 8) Data proliferation problem
STLF	1) Day-ahead load forecasting 2) Hourly load forecasting 3) Cost saving 4) Similar day load forecasting 5) PV generation and PV penetration 6) Wind generation 7) Load demand of residential buildings 8) Load demand ofdifferent hours andon different days 9) Individual residential electric load 10) Single building load forecasting 11) Peak load 12) Load demand ofdifferent hours anddifferent days 13) Load shedding 14) Probabilistic load forecasting	1) High training and computationalTime 2) Variance of load forecasting 3) Data requirement or limited data 4) Data and feature redundancy 5) High computational cost 6) Data discrimination 7) Low andhigh frequency components relatedissues 8) Time dependencies 9) Learning error and system accuracy 10) Big data 11) Over-fitting issue 12) Large time series 13) Nonenvironment friendly smart grid issue, 14) Unknown and identical distribution 15) Unnecessary hidden neurons 16) High dimensional data related Issue 17) Single and multipletimescale sequences 18) Highly volatile Period 19) Feature extraction and selection related issue 20) Noisy data 21) Data clustering related issue 22) Data proliferation problem
	1) Load demand of different hours anddifferent days 2) Load demand of residential buildings 3) Individual residential electric load	1) Over-fitting issue 2) Learning error and system accuracy 3) Big data 4) High training andcomputational time

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MTLF	4) Peak load 5) Maximum power load identification 6) PV generation and PV penetration 7) Probabilistic load forecasting	5) Large timeseries 6) Single and multiple time scalesequences 7) Feature extraction and selection related issue

The above given Table 4 is about the major reasons of Utilizations of different Load forecasting types and different technical problems were Faced during the developing, building and implementing of the techniques.

4.Conclusions

In present days, VSTLF, STLF, MTLF, and LTLF approaches are very important to estimate power suppliers required electrical load power demand. Among all the above approaches, STLF was widely concerned for reducing day-ahead and hourly ahead load forecasting related problems for many researchers and industrial applications. A very few of the researchers were interested in LTLF and VSTLF. After this STLF, many of the researchers was concerned about MTLF. Deep learning from a smart grid was greatly studied to the need of forecasting, and there are many ANN techniques and models in the market and in the industry.

Maximum researchers used the BP process at load forecasting is to obtain better accuracy, but it takes additional computational time. The load forecasting processtakes muchtime because there is a huge data aggregate at the cloudserver in the smart grid system. On the other hand, the BPprocess takes more additional processing time. For thatreason, few groups of researchers had developed the non-BPbased hybrid ANN. Very huge training time or computational time is the majorissue in load forecasting because the cloud server containsenormous data. Alongside computational time, learning error,big data, limited data, etc., are becoming a concern in theforecasting process. For reducing Big data related issue indemand forecasting, researchers have tried to developedlimited data based load forecasting with highaccuracy whereno need for massive data.After reviewing thecurrent challenges and positive aspects of the HSICbottleneck, we have realized that the Distributed NeuralNetwork-based DDL process becomes essential for reducingthe challenges. However,many current load forecasting proposals may suffer fromdata centralization, training time, and computational timeissues. Therefore,a DDL model for load forecasting may be proposed thatcould solve some of these issues. It is expected that thefindings of this survey and the proposed model will be ofbenefit to researchers, policymakers, in thisfield.

4.1 Future Research Scope

Althoughmany have focused on deep learning for load forecasting insmart grids, few have tried to apply distributed computingusing DML and

DDL. Therefore, thereduction of dataaggregation dependency is a barely-explored scope forpossible research scopes in load forecasting to reducecomputational time and learning error. Such work would beextremely beneficial as there are not many works onmitigation of data centralization and computation load oncentral servers, problems which decentralization anddistribution can help resolve. Some works have tried todemonstrate a reduction in training and computation timeusing limited database load forecasting [14] butthe use of DML and DDL is still open for stud**y.**

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