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A Survey on Electric Power Consumption Prediction Techniques

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Abstract

Prediction of electric power consumption has recently become one of the important domains, not only for the electrical utilities, but also for the consumers of the electricity. In the recent time, the demand of accurate electric power consumption prediction has been increased and is considered as an integral part for electric utility in planning and scheduling of electricity distribution from the power system. Accurate prediction enabled to better manage of electric usage. A review of the recent electric consumption prediction techniques will be presented in this paper in the context of different power consumption prediction applications. This study focusses a comprehensive survey of the existing methods employed for power consumption prediction process and a comparative study has been performed on different models based on the three methods. The predicted results of the models are evaluated by using the performance metrics such as Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) metric.

I. INTRODUCTION

Electricity consumption prediction for household plays a vital role in the energy planning such as power generation and distribution. Due to nonlinearity and uncertainty of various factors like consumer's behavior, weather condition, economic variables, geographical factors or other random effects, electric power consumption prediction is still a challenging task. Consumption prediction has great impact on the smart grid applications as a large scale of relevant information can be recorded with the help of advanced smart meter technology. Various methods have been proposed for the accurate prediction of power consumption on hourly, daily, weekly, monthly, and yearly time-based scales, from simple regression models to complex artificial neural network models.

The prediction process of electric power consumption is divided into three categories based on time period of prediction. They are short-term prediction, medium-term prediction and long-term prediction [1, 2].

Short-term prediction: The time-period of short-term prediction takes for an hours to one-day ahead or a week. It aims at economic dispatch, optimal generator unit commitment, power distribution and load dispatching while addressing real-time control and security assessment.

Mid-term prediction: The time-period of mid-term prediction is few weeks to a few months. The purpose of this type of prediction is to maintain system, purchasing energy, and price settlement so that demand and generation is balanced.

Long-term prediction: The time-period of long-term prediction is a year to 10-20 years ahead. It aims at system expansion planning, i.e., generation, transmission and distribution. This prediction can also affect the purchase of new generating units.

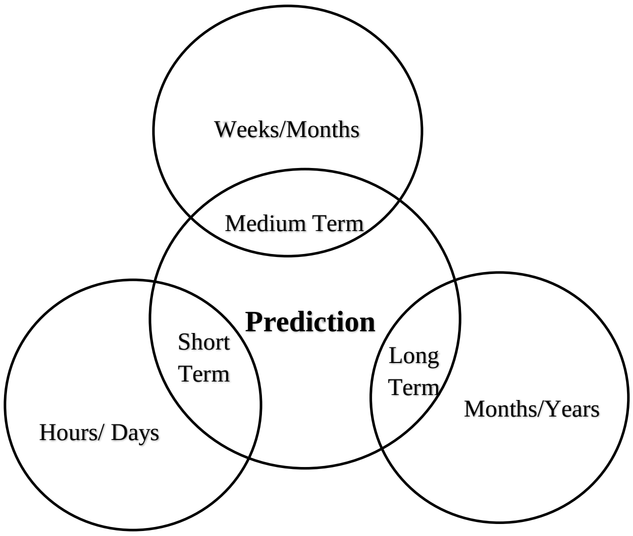

Fig 1.2: Types of prediction

A large variety of prediction models have been developed and used to generate these three different types of predictions for different purposes. The method suitable for short term prediction cannot produce accurate result for mid-term as well as long-term predictions. The limitations of each method needs to be understood before applying predictive analysis.

Based on the above mentioned prediction categories, prediction of electric power consumption can be done by using three methods:

- Statistical-based methods (ARIMA, SARIMA, SVR, VAR)

- Machine Learning methods (LR, DT, RF, MLP,) and
- Deep Learning methods (RNN, LSTM, CNN, DLNN, DELM)

Initially, statistical techniques such as regression analysis and time series analysis, were applied to short term prediction. Then, there was a rise in the prevalence of Artificial Intelligence based techniques like artificial neural network (ANN), fuzzy logic, support vector machine, multilayer perceptron etc. After that machine learning methods were applied and extensive literature studies have reported ML based approach to prediction analysis. However, in recent times, most of the researchers have demonstrated deep learning-based models for accurate prediction of electricity consumption.

The following section sheds light on the various works as demonstrated by different authors for prediction of electricity consumption. All their approaches are based on the above mentioned three methods.

II. PREDICTION MODELS ON STATISTICAL-BASED METHODS

Numerous studies have been conducted in the analysis and energy usage prediction with the help of statistical-based method. Statistical methods are designed to infer about the relationships between variables of the input dataset and to create a model that is able to predict future values.

Hung Nguyen *et. al.* (2017) [3] introduced ARIMA and SARIMA models for short term load forecasting using historical data of electricity load for past 14 years. The objective of this analysis was to separate the time series random components from deterministic components like trend, seasonality and cyclicality of the dataset and apply the ARMA processes to construct the models. In the study, SARIMA model provide a better fit to time series data as it allows randomness in the seasonal pattern. For accuracy measurement Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD) and Mean Squared Deviation (MSD) statistics were calculated for different length of input data and recorded as 9.13% of MAPE for ARIMA and 4.36% MAPE for SARIMA model.

A comparative study of load forecasting approaches using three different methods for occupancy prediction and context-driven control of a smart building's appliances was reported by S. **Hadri *et.al.* (2019)** [4]. The proposed methods were ARIMA and SARIMA, which were based on statistical method, while XGBoost and Random Forest (RF) are based on machine learning method and LSTM is based on deep learning method. This study also investigated the performance of the prediction results of the five methods by evaluating the error metrics. It was reported that the XGBoost model gives better performance in terms of execution time and also better accuracy for short term load forecasting and occupancy prediction.

Electricity consumption profile using a statistical analysis was demonstrated by **A. Sauhats *et. al.* (2015)** [5], wherein probability theory was used to predict daily electricity consumption of household consumers. The research group analyzed historical consumption data of 500 consumers which were segmented into 6 groups by average monthly electrical consumption. In the study, integral and differential characteristics were evaluated to extract the irregularities of daily consumption pattern and compare the hourly consumption values with different priced products. The result indicated that consumption profile varies greatly among consumer group, working and weekend day as well as seasonally.

N. Demba *et. al.* (2011) [6] developed a regression model to predict the electricity consumption of housing units in Oshawa (Ontario, Canada). They performed a conditional demand analysis of 59 predictor variables using the regression model to obtain only 9 predictor variables that gave a coefficient of determination of 0.784. The 9 predictors were number of occupants, house status (owned or rented), average number of weeks of vacation taken away from the house each year, type of fuel for the pool heater, type of fuel for the heating system, type of fuel for the domestic hot water heater, availability of air conditioning system, type of an air conditioning system, and number of air changes per hour at 50 Pa. The data was collected based on three methods: survey, site audits, and audit of smart meters information

S. Mirasgedis *et.al.* (2006) [7] developed two statistical models of multiple regression models with incorporating autoregressive structures for daily and monthly electricity demand predictions. It estimated medium term demand up to 12 months ahead by using primitive (relative humidity) and derived (heating and cooling degree-days) meteorological parameters. Both the models showed a high predictive value with adjusted R2 above 96%. The findings indicate that the electricity demand of a particular day can be predicted by taking a note of the temperature of the two previous days. Also, the RH is the most important weather parameter that affects electricity consumption.

The regression model for prediction of monthly energy consumption patterns and implemented the model using Monte Carlo simulation technique was developed by **Q. Khalid *et. al.* (2010)** [8]. The input independent and dependent variables used in the model were outside temperature, daylight sensitivity and power consumption value per month respectively. It was observed that the time sensitivity variable depends on the three variables namely change in population, change in power consuming machines and implementation of energy conservation techniques for power consumption prediction.

In one of the studies, **M. Ghofrani *et. al.* (2011)** [9] reported smart meter-based short-term prediction for residential consumption by considering the weather-dependent component and the lifestyle component using a Kalman filter. In the study, the researcher used spectral analysis and fitted a Gauss-Markov process model to the random components of the residential load data. Prediction have been done for different sampling periods and forecasting horizons and it was observed that a faster sampling rate improves the accuracy of the load prediction.

P. Lusis (2017) [10] performed statistical analysis using regression tree, Support Vector Regression techniques for short term residential load forecasting. The forecasting methods were applied on 30-min interval household consumption data for a period 3 years. The load predictors were categorized as per the input data such as weather features, historical load features, and calendar effects. RMSE and normalized RMSE were used as forecast error metrics. The result of forecasting was that the performance of the regression trees technique was better than the other techniques. Support vector regression technique had the lowest NRMSE value showing a better overall ability to predict the household consumption for the next 24 hours.

III. PREDICTION MODELS ON MACHINE LEARNING METHODS

The generation of accurate prediction results machine learning methods have been used in order to understand the electricity consumption prediction.

A study by **F. Rodrigues *et. al.* (2014)** [11] introduced ANN method to forecast hourly and daily electricity consumption based in a feed forward ANN and Levenberg-Marquardt algorithm by using 18 months long comprehensive dataset of 93 households. The input parameters fed to the model were apartment area, number of occupants, electrical appliance consumption and Boolean inputs as hourly metering system. The performance of the adopted model was analyzed by calculating Mean Absolute Percentage Error (MAPE) and Standard Deviation (SDE) as 4.2% and 2.06 respectively for daily average consumption prediction and 18.1% and 8.25 respectively for daily maximum consumption prediction. Good performance results have been found in the hourly prediction of electricity consumption analysis for first 3 days of the 3rd week of one randomly selected household.

M. R. Braun *et. al.* (2014) [12] studied the Multiple Linear Regression (MLR) analysis based on electricity and gas data for 2012 of a supermarkets in northern England. The two generated equations form MLR analysis were used to estimate the consumption for the base period (1961-1990) and then compared it with actual values for consumption prediction of future period (2030-2059). To measure the accuracy of prediction, two error statistics namely NMBE and CVRMSE have been calculated. It was observed that NMBE as -2.6%, indicating that the estimated values were slightly low and 3.8% of CVRMSE indicated the accurate estimation. The overall findings indicate that the outside temperature has a great influence on the consumption and electricity consumption will increase by 2.1% and gas consumption will decrease by about 13% for the future predicted period.

R. Aras et. al. (2017) [13] provided prediction of the energy consumption of urban buildings using two types of neural network methods- a MLP and ResNet. They created a building energy model for 22 buildings to generate the inputs to the neural networks, consisting of 15-minute time interval energy usage data as well as hourly weather data including solar radiation, outdoor dry-bulb temperature and relative humidity features collected from the location of the study. The outputs of the network are the measured 15-minute time interval energy usage data for 22 buildings for two years. MLP network model consists of three layers: one input, one hidden and one output in which each layer consists of 64 neurons and is designed with a ReLU nonlinearity activation function. The accuracy of the results of all models were evaluated using MSE. The research group compared the error rates of prediction of both the models to the traditional error rates used in building energy modelling to select the best model. The result showed that deep residual network with 2 convolutions per block and 128 output channels were the most effective in estimating building energy consumption with 74.7% improvement in prediction ability.

S. Devi *et. al.* (2015) [15] focused on the demand side energy management to improve consumer's electricity consumption without compromising on their demand using short term load forecasting. Their study was based on ANN technique for load prediction. The system model was designed by collecting hourly consumption load data for three weeks and average consumption and load factor was calculated for 13 devices in 1-hour time interval. Load factor of consumer is the ratio of average energy consumption over a period to the peak energy consumption in that period. Increasing the value of load factor means decreasing the cost per unit generated. It was observed that the maximum load factor is 44% at 5 PM and minimum load factor is 11% at 1 AM.

The two models using artificial neural network for predicting the heating and cooling loads for building was proposed by **N. I. Nwulu *et. al.* (2017)** [16] The proposed model designed with a dataset having eight input attributes and the Back-Propagation Learning Algorithm (BPLA) was used to train the model.

J. Y. Kim *et. al.* (2019) [17] demonstrated a deep learning method based on an autoencoder to predict energy demand for 15, 30, 45 and 60 minutes for a month by using one household electric power consumption data for five years. The proposed model consisted of a projector and a predictor where the predictor used the output value of each time-step as the input of the next step. The performance of the proposed model was examined by using evaluation metrics such as MSE, MAE and MRE and compared the error values with four conventional machine learning methods like LR, DT, RF and MLP and three deep learning methods like LSTM, Stacked LSTM and the Autoencoder method proposed by Li et. al. [18]. The result of comparison showed that the proposed model outperforms other models.

T. Zufferey *et. al.* (2016) [19] focused on the use of ANN for accurate short-term load and PV predictions of SM profiles of both commercial and industrial consumers. Other predicted algorithm like SVM or more sophisticated ANNs like RNN and LSTM were also used for different sorts of smart meter data. According to the study, in order to improve the efficiency of work, aggregation of diverse smart meter information and dividing in light of time proved to be beneficial. The NRMSE and MAPE error metrics were used to measure the execution of forecasting algorithm.

B. Vincenzo *et. al.* (2013) [20] developed simple and multiple regression models to forecast electricity consumption using annual electricity consumption data of residential and non-residential consumers for a period of 37 years in Italy. The study was carried out by using historical electricity consumption data, GDP, GDP per capita, and population. The results showed that the selected predictor variables are strongly correlated to the electricity consumption.

W. J. Lee *et.al.* (2015) [21] developed a hybrid model based on dynamic and fuzzy time series for mid-term prediction applied on actual load data from the Seoul metropolitan area and then compared the predicted result with the Koyck and ARIMA models. The proposed hybrid model provided better forecasts than the Koyck and ARIMA models. It was observed that the index of agreement 'd' of the hybrid model was close to 1, and the MAPE of the total load forecast was less than 3% for consecutive four-month load forecasting. This indicated that the hybrid model produces a less forecasting error and can be used for mid-term forecasting along with observed air temperature data.

IV. PREDICTION MODELS ON DEEP LEARNING METHODS

Deep learning methods have been recently investigated for time series analysis of electricity consumption prediction to achieve the highest possible closest accuracy.

Tae-Young Kim *et. al. (2018)* [22] focused on predicting household power consumption using a CNN-LSTM hybrid network that linearly connects CNN and LSTM. The dataset used in the proposed model comprised of one generation of power consumption having 9 attributes among which the active power variable was used for power demand forecasting. Power consumption which was multivariate time series, included spatial and temporal information. Therefore, the CNN-LSTM hybrid neural network could extract the space time feature of the power consumption variables to predict household power consumption. The proposed CNN-LSTM method reduced the spectrum of time series data by using the convolution and pooling layer. The output of CNN layer was passed as an input to the LSTM layer and the output of the LSTM model was used as an input to the Deep Neural Network (DNN) layer to generate time series that predicts power demand. The operation of the model was confirmed through internal visualization and performance was compared with different machine learning methods. Root Mean Square error was used as an evaluation metric of the learning model. The predictive results visually confirmed that an excellent prediction performance was achieved even in situation where periodicity was not observed.

Recently, a hybrid CNN with a LSTM-AE model for energy prediction in residential and commercial buildings was developed by **Z. Ahmed Khan *et. al.* (2020)** [23]. The CNN model was used to extract features from the input power consumption data in France between 2006 and 2010. This was followed by feeding to the LSTM-AE model to generate encoded sequences and then decoded through another LSTM model to produce the output prediction of energy consumption. The result of the model was evaluated in terms of different performance metrics such as MSE, MAE, RMSE and MAPE and then compared with some other models like ARMA, SVM. It was reported that the proposed model recorded the smallest error rates for hourly and daily energy consumption dataset.

M. Fayaz *et. al.* (2018) [24] proposed a model of Deep Extreme Learning Machine (DELM) for energy consumption prediction of one week and one month in residential consumers. The proposed model comprises of four stages namely data acquisition, data preprocessing, prediction and performance evaluation. The predicted result of the proposed model was compared with the two other machine learning algorithms namely ANN and ANFIS by applying the same dataset. Different statistical measures have been calculated in the performance evaluation stage for the three algorithms and the values of the statistical measures indicated that the performance of DELM method was far better than ANN and ANFIS methods.

G. M. Ud Din *et. al.* (2017) [25] presented Feed-forward Deep Neural Networks (FF-DNN) and Recurrent Deep Neural Networks (R-DNN) models to predict short term electricity load by using 4 years dataset having date, hour, price of electricity, Dry bulb temperature, Dewpoint and load (MWh) as input parameters. The features of input parameters were analyzed on time and frequency domain represented temperature effect, time effect and lagged load effect for accurate prediction. The dataset was trained and tested for the two models and calculated the prediction errors MAPE, RMSE and MAE for four different seasons. Based on two case studies it was observed that highest errors found in summer season because of high temperature and more social events and predictions errors were less for R-DNN model in comparison with FF-DNN model. It was also presented that the weather, time, holidays, lagged load and data distribution over the period were found to be the most dominant factors in the prediction process.

A. Nugaliyadde, *et. al.* (2019) [26] demonstrated two approaches with one using a Recurrent Neural Network (RNN) and the other one using a LSTM network. It considered the previous electricity consumption of smart meter data for an individual house and a block of houses to predict the future electricity consumption. The predictions were done for daily, trimester and 13 months period which covered short term, mid-term and long-term predictions. Both the RNN and the LSTM network achieved an average Root Mean Square error of 0.1. The predicted results were compared with ARIMA, ANN, and DNN models. The findings indicated that ARIMA model performed well only for short term predictions. RNN and LSTM models performed at par with ARIMA model for short term predictions but outperformed all the other models in mid-term and long-term predictions for electricity consumption.

In one of the study **H. Shi *et. al.* (2017)** [27] had discussed a novel pooling-based deep recurrent neural network which batches a group of customers load profiles into a pool of inputs. The developed model was implemented on Tensor Flow deep learning platform and tested on 920 smart metered consumers from Ireland. The proposed method was compared with the state-of-the-art techniques in household load forecasting and it outperformed ARIMA by 19.5%, SVR by 13.1% and classical deep RNN by 6.5% in terms of RMSE.

In K. Yan *et. al.* (2019) [28] study, a hybrid deep learning model was generated by combining an ensembled LSTM neural network with the SWT technique to improve the accuracy of forecasting. Verification experiments were performed based on a real-world energy consumption of 5 households for the whole year of 2015. The performance of the forecasting model was evaluated using three error metrics that are RMSE, MAPE and MBE with different step lengths. The forecasting accuracy is compared to the state-of-art methods, including SVR, LSTM and CNN-LSTM. The proposed SWT-LSTM framework produces the most accurate forecasting results with time steps including 5, 10, 20 and 30 minutes.

H. Wan (2017) [29] proposed a novel Deep Neural Network architecture for short term prediction of the day ahead hourly consumption by using weather, timing and holiday information of the historical hourly loads data of about 3 years. The study utilized Convolutional Neural Network components to learn the deep representation and extract rich features from the input data use Recurrent Neural Network Components to model the implicit dynamics. Prediction accuracy was determined by the error metrics MAPE and MAE and the proposed method achieved was about 5% relative reduction of both the error values in comparison with CNN, CNN-RNN and SVR method.

V. SUMMARY OF REVIEWED PAPERS

A summary of the techniques used in the reviewed papers and the different techniques used in each time frame is represented in the Table 1.

Table 1: The three types of prediction methods for power consumption

Method	Techniques	Time Frame		
		Short-Term	Mid-Term	Long-Term
Statistical	ARIMA & SARIMA	[3]		
	Probability theory	[5]		
	LR	[6]		
	MR		[7]	
	Regression using Monte Carlo			[8]
	Gauss-Markov	[9]		
	SVR	[10]		
Machine learning	ANN	[11]		
	MLR			[12]
	MLP & ResNET	[13]		
	ANN	[15]		
	Autoencoder	[17]		
	SVM	[19]		
	Fuzzy logic		[21]	
Deep-learning	CNN-LSTM			[22]
	CNN & LSTM-AE	[23]		
	DELM, ANN & ANFIS		[24]	
	FF-DNN & R-DNN	[25]		
	RNN & LSTM	[26]	[26]	[26]
	DRNN based on pooling	[27]		
	SWT-LSTM	[28]		
	DNN	[29]		

From this survey, it is cleared that most of the prediction techniques are developed for short-term prediction process. Mid-term and long-term predictions are more complex than short-term prediction and it requires more information about the factors that affects the consumer's behavior. The statistical model ARIMA provides prediction with improved accuracy and reliability. This model is suitable for short term prediction process and the non-linear patterns of the time series data are not fully captured. Artificial Neural Network model performed well for non-linear time series data and it has the ability to exactly map input and output relationships. This model depends on the identification of the weight which is done by training the model with input data. Neural network methods are easy to implement but it is quite challenging to compute exact number of nearest neighbours. Deep learning techniques and hybrid models, which is a combination of two or more machine learning techniques are usually used as the prediction method to achieve more accuracy in the result. LSTM model is suitable for mid-term and long-term prediction process and gives best result for time series prediction.

A study on the advantages and disadvantages of various electricity prediction techniques is presented in following table.

Table 2: Comparison of various prediction techniques

Techniques	**Pros**	**Cons**
ARIMA	Reliability in prediction process	Not suitable for long-term prediction
ANN	Reduce the computation time and increase the prediction accuracy	Overfitting occurs and difficult to generalise
Regression	Useful to analyse the relationships among the input variables	Not fit for real-world applications
Fuzzy logic	Suitable for solving uncertainties in prediction process	Lack of stability and computational complexity
DNN	Efficient training process, Increase accuracy	Large volume of data is needed
CNN	High accuracy in prediction results	More suitable to analyse image data, Needs lot of training data
LSTM	High accuracy	Need more time to train the model, Not suitable for short-term prediction
Hybrid	Improve performance of the model	High model complexity

VI. EVALUATION METRICS

The performance of power prediction results of all models is evaluated by performance metrics. The values of the error metrics computes the error between the actual and predicted consumption values. Different models used different metrics to measure the performance of power prediction. Table 3 represents the formulations of mostly used error metrics for electricity consumption prediction.

Table 3: Error metrics used in electric power consumption prediction [30, 31].

Performance metrics	**Equations**
Mean Squared Error (MSE)	$\frac{1}{N}\sum_{i=1}^{N}(A_i - P_i)$
RMSE	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - P_i)^2}$
MAE	$\frac{1}{N}\sum_{i=1}^{N}\lvert A_i - P_i\rvert$
MAPE	$\frac{1}{N}\sum_{i=1}^{N}\frac{\lvert A_i - P_i\rvert}{A_i}\times 100$
NRMSE	$\frac{RMSE}{\sqrt{\frac{\sum_{i=1}^{N}(P_i - P_{avg})^2}{N-1}}}$

VII. CONCLUSIONS

Electric power consumption prediction is one of the domains of smart grid data analysis and recent research in this area was investigated in this study. The time frame for consumption prediction is an important factor that affects the techniques used in the prediction method. Different types of predictions have different outcomes. Short term prediction is useful for proper power system policies, while mid-term and long-term predictions are suitable for planning and finance of the electrical utility. Designing more accurate prediction methodology leads to the smooth operation of the power system. So for improving the accuracy of prediction methods techniques like grouping, classifying etc. are to be incorporated and the determinant factors which reflects the consumer's behavior are needs to be understand.

The prediction is done by following a number of steps. Initially, data is collected, cleaned and selected and then prediction algorithm is deployed in the dataset. The algorithm used in the prediction stage vary in the literature and can be categorized into statistical, machine learning and deep learning methods. In the last stage, the performance of the algorithm is measured by the evaluation metrics.

In the conclusion, it is investigated that the large volume of dataset leads for intelligent method and performance of algorithm is generally assessed by evaluation metrics such as Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) etc.

Conflicts of Interest: The authors declare no conflict of interest.

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