International Journal of Engineering & Technology, 9 (3) (2020) 842-869

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Electrical Load Forecasting: A methodological overview

Medhat A. Rostum[1*], Amr A.Zamel[2], Hassan M. Moustafa[1] and Ibrahim E. Ziedan[2]

[1] *Ministry of Electricity & Energy, Egypt*
[2] *Computer and Systems Engineering Department, Faculty of Engineering, Zagazig University, Egypt*
[*] *Corresponding author E-mail: medhatrostum@yahoo.com.sg*

Abstract

Electric load forecasting process plays an extensive role in forecasting future electric load demand and peak load by understanding the previous data. Several researchers proved that, the presence of load forecasting error leads to an increase in operating costs. Thus Accurate electric load forecast is needed for power system security and reliability. It also improves energy efficiency, revenues for the electrical companies and reliable operation of a power system.
In recent times, there are significant proliferations in the implementation of forecasting techniques. This survey aids readers to summarize and compare the latest predominant researches on electric load forecasting. Besides, it presents the most relevant studies on load forecasting over the last decade and discusses the different methods that are used in load prediction as well as the future directions in this field.

Keywords: *Load forecasting; load predictions; load demand*

1. Introduction

Due to population growth, industry development and rising living requirements; electricity consumption has increased. So power generating stations need to generate sufficient and reliable electricity to meet its consumption. So, in order to meet the electric load demand in the future, a load forecasting process should be used to predict what is the power generating stations need to generate sufficient and reliable electricity in the future by analyzing the historical data. The results of the load forecasting process can be used in power plants such as generator maintenance scheduling, security and reliable operation, purchasing of generating units and energy reservation.
Moreover, accurate load predictions lead to improve the energy efficiency, decrease the operating costs through making a proper planning and decision for development in the future, as well as increasing the revenues for the electric companies. Several researchers proved that a decrease in load forecasting error by 1% leads to save hundreds of thousands or even millions of dollars [1-2].
Due to the emergence of load forecasting importance, several prior surveys such as Hippert et al. [3] Alfares and Nazeeruddin [4] , Singh and Singh [5] , Metaxiotis et al. [6], Taylor et al. [7], Hahn et al. [8] and Hernandez et al. [9] have been published previously.
This paper presents a study of very short term, short term, medium term and long term load forecasting methods for the period from years 2011 to 2019. It introduces a comprehensive survey of 70 papers on electric load forecasting techniques. All of these papers were extracted from journals and conferences. Several academic research sources (such as Google Scholar or IEEE Explorer) were extensively searched with relevant keywords such as:"load forecasting" and "load predictions". The exploration was stopped in March 2019.
The remainder of this survey is arranged as following. In section 2, basic factors affecting the load forecasting are discussed. Section 3 explains the evaluation of performance metrics. In Section 4, dataset of load forecast is demonstrated. In section 5, classifications of load forecasting process according to the forecasting horizon are described. Section 6, explains the approaches of load forecasting. In Section 7, a comprehensive comparison of all the previous studies is provided. Finally, future trends of research are provided and concluded in Section 8.

2. Factors affecting electric load forecasting

The load consumption is influenced by several exogenous variables such as: weather-related variables (temperature, humidity, thunderstorms and precipitation) [10], time factors (seasonal, holidays, weekdays and weekends), economics (person income/year), random events (industrial operation shutdown, FIFA world cup and popular TV shows), population and price of electricity.

3. Evaluation of performance metrics

Several metrics are used to measure accuracy of prediction for each fitted model [11-12]. In each of the following definitions 'A_t': is the real value, 'P_t': is the predicted value, and 'S': is the size of the test data set.

1. Sum of Squared Error (SSE): is defined as sum of square errors and can obtained using the following equation

$$SSE = \sum_{t=1}^{S} (A_t - P_t)^2 \tag{1}$$

2. Mean of Squared Error (MSE): is measured as an average of square errors as shown in the following equation

$$MSE = \frac{SSE}{S} \tag{2}$$

3. Root Mean Square Error (RMSE): is estimated as root of calculated MSE

$$RMSE = \sqrt{MSE} \tag{3}$$

4. Mean Error (ME): is defined as average error values of observed minus forecast.

$$ME = \frac{\sum_{t=1}^{S}(A_t - P_t)}{S} \tag{4}$$

5. Mean Absolute Error (MAE): is defined as the average of absolute error values of observed minus forecasted data.

$$MAE = \frac{\sum_{t=1}^{S}|A_t - P_t|}{S} \tag{5}$$

6. Mean Percentage Error (MPE): is represented as the average of the PE values.

$$MPE = \frac{\sum_{t=1}^{S}\frac{A_t - P_t}{A_t}}{S} * 100 \tag{6}$$

7. Mean Absolute Percentage Error (MAPE): It expresses the forecast error in percentage terms.

$$MAPE = \frac{\sum_{t=1}^{S}|\frac{A_t - P_t}{A_t}|}{S} * 100 \tag{7}$$

4. Dataset of load forecasting

In order to fit a model can be employed in load forecasting process, the historical data such as electric load, weather conditions and price of electricity must be available. In this matter, the access to public databases facilitates process of constructing suitable models.
Descriptions of load forecasting databases which have been presented in this review are elucidated in Table 1. This table contains the area (country, city or smart building) from which the data have been obtained, data description (amount of data, the periods in which the data were collected, as well as data partitioning into training, validation and test set) and URLs from which databases can be accessed.

Table 1: Description of load forecasting databases

No.	Authors [Reference]	Area	Data description	URL
1.	Guan et al. [13]	ISO New England (ISO-NE)	Electrical load data. Training set: 1st January 2007 to 31st December 2007. Validation set: 1st January 2008 to 30th June 2008. Test set: 1st July 2008 to 31st December 2009.	-
2.	Hsiao [14]	Taiwan	Weather, economic, calendar and meter load data from 31st October 2010 to 1st March 2012. 80% of the days were selected randomly to construct the model and 20% to test the model.	Weather data http://www.cwb.gov.tw Calendar data http://www.dgpa.gov.tw
3.	Laouafi et al. [15]	French power system	Load data from 7th April 2013 to 31st January 2015.	www.rte-france.com
		New South Wales (NSW), Australia	Load data between 2006 and 2007.	www.aemo.com.au
4.	Penya et al. [16]	University of Deusto, Basque Country.	Electrical load data First records date: February 2009.	-
5.	Koo et al. [17]	Korea	Hourly electrical load data from 2008 to 2011.	-
6.	Khwaja et al. [18]	England Pool region	Hourly temperatures and load data. Training set: 2004 to 2007. Test set: 2008 and 2009.	-
7.	Khwaja et al. [19]	England Pool region	Hourly temperatures and load data. Training set: 2004 to 2007. Test set: 2008 and 2009.	-
8.	Hong [20]	Northeastern China	Monthly load data from 2004 to 2009. Training set: December 2004 to July 2007. validation set: August 2007 to September 2008. Test set: October 2008 to April 2009.	-
9.	Hong et al. [21]	Northeastern China	Monthly load data from 2004 to 2009. Training set: December 2004 to July 2007. validation set: August 2007 to September 2008. Test set: October 2008 to April 2009.	-
10.	Feilat & Bouzguenda [22]	Mazoon electricity distribution company, Oman.	Electrical load and weather data Training set: 2006 to 2009. Test set: 2010.	-
11.	Lee & Hong [23]	South Korea	Load and temperature data from January 2000 to October 2010. Test set: four months ahead.	-
12.	Al-Hamadi [24]	Liaoning Province	Electrical load data Training set: 1989 to 2004 Test set: 2005 to 2007.	-
13.	Li et al. [25]	China	Annual electrical load data from 1978 to 2011. Training set: 1981 to 2005. Test set: 2006 to 2011.	-
14.	Wang et al. [26]	Beijing city, China	Annual load data. Training set: 1984 to 2003. Test set: 2004 to 2008.	-

15.	Li et al. [27]	Beijing city, China	Annual load data from 1978 to 2010. Training set: 1981 to 2005. Test set: 2006 to 2010.	-
16.	Vu et al. [28]	Australia	Load and weather data from 1999 to 2000. Training set: year 1999. Test set: year 2000.	The electricity demand data http://www.aemo.com.au The climatic parameters http://www.bom.gov.au
17.	Dudek [29]	Polish power system	Hourly load data from 2002 to 2004. Test set: January 2004 and July 2004. Hourly load data from 2012 to 2014. Test set: 2014 except for 14 atypical days.	http://gdudek.el.pcz.pl/varia/stlf-data
		French power system	Half-hourly load data from 2007 to 2009. Test set: 2009 except for 21 atypical days.	-
		British power system	Half-hourly load data from 2007 to 2009. Test set: 2009 except for 81 atypical days.	-
		Victoria, Australia.	Half-hourly load data from 2006 to 2008. Test set: 2008 except for 12 atypical days.	-
18.	Taylor [30]	French and British load data	Half-hourly load data Training set: 2007-2008. Test set: 2009.	-
19.	Lee & Ko [32]	Taipower Company	Hourly load data for year 2007.	-
20.	He et al. [33]	China	Hourly and quarter-hourly load data of July 2011.	-
21.	Matsila & Bokoro [34]	Johannesburg, South Africa	Electrical load data over a period of three months. Training set: 45 days. Test set: 20 days.	-
22.	Alberg & Last [35]	Israeli city	Hourly load data from 1st December 2012 to 31st March 2014.	http://www.powercom.co.il
23.	Almeshaiei & Soltan [36]	Kuwaiti electric network	Daily loads data from 2006 to 2008.	-
24.	Fan & Hyndman [37]	Australian Energy Market Operator (AEMO)	Half-hourly load and temperature data. Training set: 2004 to 2008. Test set: January 2009.	-
25.	Goude et al. [38]	French grid	Electrical load data. Training set: 1st January 2006 to 31st December 2010. Test set : 1st January 2011 to 31st December 2011.	-
26.	Ding et al. [39]	French distribution networks.	Load and temperature data from 9th September 2009 to 27th October 2010. 117 days for training set, whereas 297 days for test set.	-
27.	Khosravi et al. [40]	Iran national power system	Hourly load data for three years 80% for Training set and 20% for Test set.	-
28.	Mukhopadhyay et al. [41]	Eastern region load dispatch centre and area load dispatch centre.	Electrical load, temperature and humidity from 27th June 2017 to 26th July 2017.	Temperature and humidity are collected from https://www.timeanddate.com

29.	Hernandez et al. [42]	Spain	Electrical load data from 1st January 2008 to 31st December 2010. 70% of data for training set, whereas 30% for validation and test set.	-
30.	Webberley & Gao [43]	Public database of the global energy forecasting competition 2012.	Hourly load data from nineteen different zones: 1st January 2004 to 30th June 2008 along with ten sets of temperature in the same time frame.	http://www.kaggle.com/c/GEF2012-wind-forecasting
31.	Rodrigues et al. [44]	93 households, in Lisbon, Portugal.	Daily load data from February 2000 to July 2001, containing both weekend and weekdays.	-
32.	Zjavka & Snášel [45]	National Grid, U.K. Electricity Transmission.	Test set: 18th February 2013 to 3rd March 2013.	http://www2.nationalgrid.com/UK/Industry-information/Electricity-transmission-operational-data/Data-explorer/
		Canadian detached houses	Test set: 25th January 1994 to 7th February 1994.	-
33.	Warrior et al. [46]	Power consumption data	Hourly load data for year 2016	-
34.	Ertugrul [47]	Portugal	Electrical load data from 2011 to 2014.	-
35.	Houimli et al. [48]	Tunisia	Half-hourly load data from 2000 to 2008. Training and validation sets: 2000 to 2007. Test set: 2008.	-
36.	Ryu et al. [50]	Korea	Hourly load data from KEPCO and weather data from NCDSS between 2012 and 2014.	-
37.	Zheng et al. [51]	An airline passengers data set and an electrical load data set of the school's engineering building- State University of New York at Binghamton.	Airline passengers data set comprises 144 observations for twelve years. Electrical load data of the past ten days is used to predict the electricity consumption of a day ahead.	-
38.	Narayan & Hipel [52]	Province of Ontario, Canada.	Hourly load data from 2006 to 2016. 70% for training set. 30% for validation and test sets.	http://www.ieso.ca/Pages/Power-Data/Demand.aspx
39.	Liu et al. [53]	Elia grid load, Belgium.	Load data was recorded every week from Monday to Sunday at 60 minutes, over a whole year.	-
40.	Kong et al. [54]	Smart grid smart city, Australia.	Electrical load data Training set: 1st June 2012 to 5th August 2013. Validation set: 6th August 2013 to 22th August 2013. Test set: 23th August 2013 to 31st August 2013.	-
41.	Kong et al. [55]	Canada	The dataset records the minutely current readings for a full year.	-
42.	Shi et al. [56]	Ireland	Half-hourly electrical load data from 1st July 2009 to 31st December 2010.	-
43.	Zhang & Ye [58]	China	Load output, load imports, load exports and GDP. Training set from 1995 to 2008. Test set from 2009 to 2013.	-
44.	Thokala et al. [59]	Three office buildings; from three cities in India.	Eight months of electrical load and temperature data.	-

45.	Nie et al. [60]	Electric power company in Heilongjiang of China	Days of the week, electrical load and weather data from 1st March 1999 to 31st March 1999.	-
46.	Ebrahimi & Moshari [61]	Isfahan grid, Iran	Electrical load data for all the holidays between March 2002 and March 2006. Training set: 3 years and Test set: 1 year.	-
47.	Dudek [62]	Polish power system	Hourly load data from 2002 to 2004. Test set: next day in July 2004.	http://gdudek.el.pcz.pl/varia/stlf-data
48.	Li et al. [63]	ISO-NE	Load and temperature data. Case1: Test set are January 2010 and July 2010. Case2: Training set from March 2003 to December 2005 and Test set from 1st January 2006 to 31st December 2006. Case3: Test set from 1st July 2008 to 31st July 2008. Case4: Training set from 2004 to 2009 and Test set from 2010 to 2011. Case5: 1st January 1988 to 12th October 1992. Case6: Training set from 1985 to 1989 and Test set: year 1990.	-
49.	Bantugon & Gallano [64]	Philippines	Hourly load data from the beginning of year 2013 to 10th November 2013.	-
50.	Qiu et al. [65]	AEMO	Half-hourly electrical load data from AEMO.	http://www.aemo.com.au
51.	Akarslan & Hocaoglu [66]	Cay vocational high school of Afyon kocatepe university.	Electrical Load data Training set: 1st April 2016 to 1st April 2017. Test set: 2nd April 2017 to 27th December 2017.	-
52.	Liu & Wang [67]	Institutional micro-grid and UK national grid.	Load data of institutional micro-grid. Training set: 1st February 2013 to 4th March 2013. Test set: two weeks after 5th March 2013. Load data of UK national grid. Training set: 4th June 2012 to 4th July 2012. Test set: two weeks beginning from 5th July 2012.	-
53.	Xiao et al. [68]	Australia	Half-hourly electrical load data from August 2006 to 2008 in Victoria (VIC), November 2006 to 2008 in Queensland (QLD) and February 2006 to 2009 in NSW.	-
54.	L.Xiao & Xiao [69]	Victoria in Australia	Half-hourly electrical load data on Wednesday in February from 2006 to 2009.	-
55.	Ghayekhloo et al. [70]	England	Electrical load data from 2008 to 2013. 80% for training set and 20% for test set.	-
56.	Liang et al. [71]	Langfang in China	Hourly load data from 1st August 2017 to 31st October 2017.	-
57.	Ahmad et al. [72]	EKPC (Kentucky, USA) and DAYTOWN (Ohio, USA).	Electrical load and temperature data. Training set: January to December 2014. Test set: January to December 2015.	www.pjm.com

58.	Gao et al. [73]	Australia's market in NSW	Historical data of load, price and temperature for year 2010.	http://www.aemo.com.au/Electricity/Data/Price-and-Demand
		new England market	Historical data of load, price and temperature for year 2009.	http://www.energy-uk.org.uk/energy-industry/the-energy-market.html
		North American	Collected data from 1st January 1988 to 23rd October 1992.	-
59.	Singh et al. [74]	New England Power Pool	Hourly electrical load data Training set: 2004 to 2007, Test set: 2008 and 2009.	-
		Australia	Load data for two years from AEMO.	-
60.	Ko & Lee [75]	Taipower Company	Electrical load data in the year of 2007	-
61.	Ceperic et al. [76]	ISO-NE	Load and temperature data. Training set from March 2003 to January 2006. Validation set: 60 days prior to the test set. Test set: 1st January 2006 to 31st December 2006.	-
		North-American Utility	Hourly load and temperature data set from January 1988 to 12th October 1992. Validation set: 365 days prior to the test period. Test set: hourly loads for the two-year period prior to 12th October 1992.	http://fkeynia.googlepages.com/loaddata
62.	Barman & Choudhury[77]	Assam, India	Electrical load data for year 2016.	-
63.	Kavousi-Fard et al. [78]	Fars in Iran	Daily load data. Training set: 21st March 2007 to 20th January 2010. Test set: 21st January 2010 to 20th February 2010.	-
64.	Selakov et al. [79]	City of Burbank utility, USA	load and temperature data from 2009 to 2011.	-
65.	Yang et al. [80]	Australia	Electrical load data from 1st April 2015 to 23rd June 2015 in VIC, 1st June 2015 to 23rd August 2015 in QLD and 1st August 2015 to 23rd October 2015 in NSW.	-
66.	Bahrami et al. [81]	Iran	Load and weather data in 2010.	-
		New York network	Electrical load and weather data. 52 days ago were utilized to predict the load on 1st July 2004.	-
67.	Ray et al. [82]	New Delhi	Load and weather data from 1st December to 28th February.	-
68.	Li et al. [83]	ISO-NE	Load and temperature data. From March 2003 to 31st December 2006. From 1st July 2008 to 31st July 2008. From November 2009 to December 2010.	-
		North American electric utility	Load and temperature from 1st January 1988 to 12th October 1992.	http://sites.google.com/site/fkeynia/loaddata
69.	Ziel [84]	Germany and neighbouring countries.	Load and temperature data from 1st January 2009 to 30th September 2014.	The load data of all countries is taken from ENTSO-E https://www.entsoe.eu Hourly temperature in Germany http://www.dwd.de/
70.	Zeng et al. [85]	Ningde City, China	Load data from January to June in 2010.	-

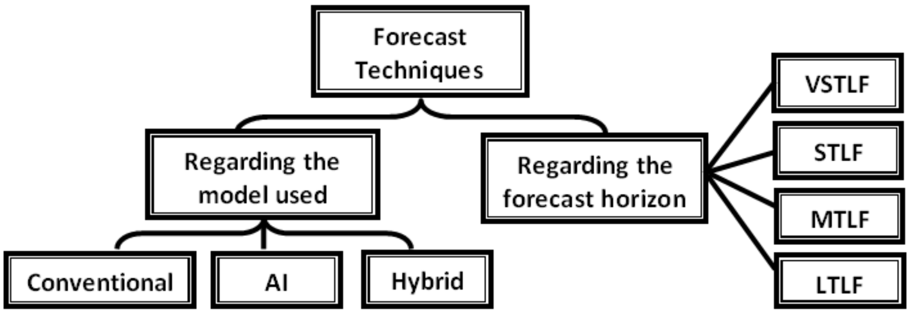

Figure 1: Classifications of load forecasting according to the forecasting horizon and modeling techniques.

5. Classification of load forecasting based on forecasting horizon

The load forecasting can be classified according to the time interval of the prediction (this called forecasting horizon) or modeling techniques as appeared in Figure 1. In this section, the load forecasting process is classified from the opinion of the forecasting horizon. In the next section, the states of the art for the modeling techniques of the load forecasting process are investigated.

Based on the forecasting horizon, the load forecasting process can be classified into four categories: very short term, short term, medium term and long term load forecasting [9].

1. Very Short-Term Load Forecasting (VSTLF):
   VSTLF predicts the load demand from several minutes to a few hours ahead. It is useful in automatic generation control and resource dispatch. In the following some of new proposed methods on VSTLF are investigated.
   Guan et al. [13] proposed a wavelet neural networks (WNN) and data pre-filtering technique. The wavelet technique is employed to decompose the filtered load into various frequency components. Each load component is fed with date and time indices as inputs to a separate neural network. A twelve dedicated WNN are employed to execute moving forecasting every five minutes. Hsiao [14] carried out a VSTLF for individual household load based on user schedule analysis and context information. The inter-cluster classification and the intra-cluster prediction were applied to forecast the electric load.
   An online load forecasting method, namely hampel filter-based forecast combination method (HFCM), is introduced by Laouafi et al. in [15] for VSTLF under normal and anomalous daily load conditions. The aim of this method is to improve the forecasting performance, guarantee low computation time and avoid large prediction errors.
2. Short-Term Load Forecasting (STLF):
   STLF predicts the load demand from hours to a few weeks ahead. It is used in the daily operations of power stations such as unit start-up, scheduling of generation capacity, scheduling of fuel and coal purchases, etc. So with accurate STLF, electric utility would be able to operate in a reliable and secure manner. Next, some papers on STLF are introduced.
   Penya et al. [16] presented a methodology to STLF in non-residential buildings. This methodology classified the day load according to the work day schedule then adjusted hourly consumption curve using several statistical and artificial intelligence methods. Koo et al. [17] apply k-NN classification and K-mean clustering to classify the load data. Then discrete wavelet transform (DWT) is applied to the clustering data and feed as inputs to artificial neural network (ANN), group method of data handling (GMDH) and Holt-Winters method to predict the electric load.
   Two different merged NNs is pressed by Khwaja et al. [18-19], are named bagged neural networks (BaNNs) and boosted neural networks (BooNN), for STLF. The BaNNs combined several ANNs on different data set that randomly sample from the training data. The final result is obtained by averaged the ANNs output. But, the BooNN includes several ANNs trained iteratively. Each ANN is trained using the error predicated from the previous one. The final predication result in BooNN is obtained by the weighted summing of ANNs output. Khwaja et al. [19] claimed that BooNN outperformed the BaNNs in time consummation and accuracy terms.
3. Medium-Term Load Forecasting (MTLF):
   MTLF predicts the load demand from a month to one year ahead, and it can be used in scheduling maintenance for devices and equipment. In the following, several papers are introduced for MTLF.
   Hong [20] presented a hybrid method, namely SRSVRCABC, based on the combination of support vector regression (SVR) and chaotic artificial bee colony (CABC) algorithm to enhance the prediction accuracy. SRSVRCABC employs CABC for parameters estimation of the SVR to avoid premature local minimum. Hong et al. in [21] also presented other approach based on SVR to model the cyclic nature and seasonal load demand prediction. This approach applies chaotic immune algorithm (CIA) and seasonal adjustment mechanism, namely SSVRCIA, to optimize support vector machine (SVM) parameters.
   ANN model based on back-propagation neural network (BPNN) is used by Feilat and Bouzguenda [22] to carry out a MTLF. Their model takes into account the variation in both of the weather data and the monthly peak load. Lee and Hong [23] introduced a hybrid method based on dynamic model in combination with fuzzy time series. The dynamic model depends on the relationship between electric load and the meteorology, whereas the uncertainties due to several socioeconomic factors are presented to fuzzy time series.
4. Long-Term Load Forecasting (LTLF):
   LTLF predicts the load demand for a period longer than a year up to several years ahead. It is used in the planning. Several papers are introduced for LTLF as following:
   A Fuzzy linear regression method is presented by Al-Hamadi in [24] for LTLF. factors affecting load prediction such as annual growth factors, population and load are fed as inputs to this method. Li et al. [25] introduced another technique based on least squares support vector machine (LSSVM) method. The fruit fly optimization (FOA) algorithm is used to automatically estimate the proper values of LSSVM parameters.
   A hybrid method is presented by Wang et al. [26], namely DESVR, based on SVR with differential evolution (DE) algorithm. DE

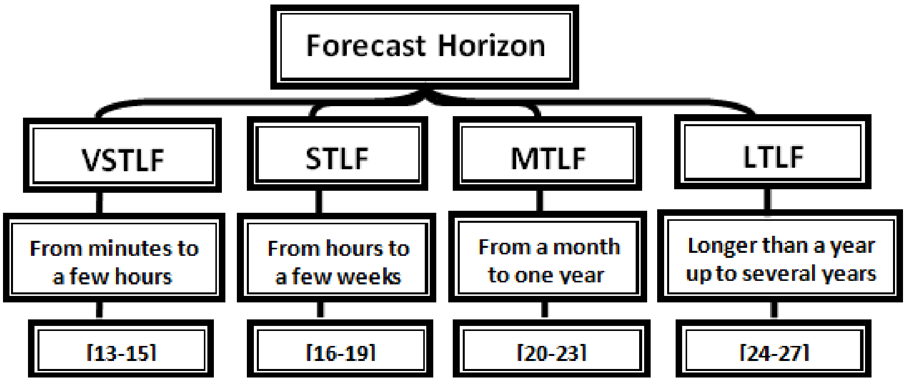

Figure 2: Classification of load forecasting according to the forecasting horizon.

is used to get optimal SVR parameters. Another hybrid method is proposed by Li et al. [27], namely FOAGRNN, based on FOA algorithm with generalized regression neural network (GRNN). The FOA is used to get optimal parameters of GRNN.
Figure 2 summarizes the classifications of load prediction based on the forecast horizon. Reference numbers of the papers that are mentioned in this section have been included.

6. Classify load forecasting based on modeling techniques

In the following subsection, several papers are investigated according to different modeling techniques. A variety of methods have been developed for load forecasting. These methods can be divided into conventional, Artificial Intelligence (AI) and hybrid methods.

6.1. Conventional methods

Conventional methods are statistical models based on the historical data of the electric load and some affecting factors such as temperature and population to predict future electric load demand. These methods include the following approaches:

6.1.1. Regression method

Regression is one of the most widely used statistical methods. It based on the average relationship between previous load and other affecting factors for predicting future load. The coefficients of regression are estimated using least-squares method [28-29].
Regression based moving window method is presented by Vu et al. in [28] for STLF. A moving window is exploited to trace the pattern of load based on the historical load and weather data. Then, the regression model parameters are estimated by using least square method. Dudek [29] introduced another usage of linear regression (LR) method to create a univariate model for STLF based on patterns of daily cycles of load time series.

6.1.2. Time Series method

A time series is defined as a sequential collection of observations, are taken at regular intervals of time. This series is decomposed into trend, cycle, seasonality and residual components. Time series method uses the previous observations to predict future ones. Exponential smoothing (ES) and Box-Jenkins' autoregressive integrated moving average (ARIMA) methods are amongst the most widely utilized methods in the time series approach.

- *Exponential Smoothing method*

ES method is used to forecast future values of the electric load based on the previous data. The exogenous variables cannot be fed as inputs into this method. HWT method is one of the most widely utilized methods in ES approach [30].
Taylor [30] carried out a STLF using several exponentially weighted methods as well as discount weighted regression (DWR), singular value decomposition (SVD) and cubic splines methods. In addition, a new SVD method is executed on the intraweek cycle and this leads to a more simpler and efficient model formulation. The new SVD showed some potential, but the exponential smoothing method was the best method.

- *ARIMA Method*

ARIMA is one of the most popular time series methods. It is introduced by Box and Jenkins principle [31]. This method exploits the previous data to predict future load. ARIMA is formed by combination of three partitions, the autoregressive (AR) model, the moving average (MA) model, and the differencing process. It is defined for stationary time series. If the series is non-stationary, then ARIMA should differential the data until the series becomes stationary.
Ko and Lee [32] carried out a STLF by integrating a lifting scheme with ARIMA. the historical load data is decomposed into several subseries at different levels using the lifting scheme. These subseries are then predicted using ARIMA. At the end, the inverse lifting scheme reconstructs the results of prediction at different levels to create the original load forecasting. He et al. in [33] introduced a high frequency forecast technique for STLF based on ARIMA to measure the relationship between load demand and several variables. This model is utilized to predict quarter-hourly and hourly load for few days ahead.
Matsila and Bokoro in [34] also presented a statistical time series method based on seasonal ARIMA (SARIMA) to predict electric load of a hospital in South Africa. Alberg and Last in [35] proposed two seasonal and two non-seasonal sliding window-based ARIMA methods for STLF in smart meters. These methods are integrated with the online information network(OLIN) methodology.

- *Other Time Series methods*

Various papers introduced another time series methods for load forecasting and described as follow:
A pragmatic methodology based on the load time series decomposition and segmentation is proposed by Almeshaiei and Soltan [36]. The methodology is used as a good guide to build load forecasting models. Several statistical analyses are used to analyze the load pattern and prediction accuracy. Fan and Hyndman [37], and Goude et al. [38] presented a statistical methodology based on a semi-parametric additive method. The additive method deals with the nonlinear relationships between electric load and the exogenous variables.
An additive time series method is introduced by Ding et al. in [39] to improve the load forecasting accuracy on the medium/low voltage substation level. This method decomposes the analysis into cyclic, trend, and random error components. Cyclic and trend are formed with dummy variable regression methods, whereas random error component is tested after the estimated method to guarantee a good method performance. The results of prediction are obtained by summing the prediction results of both trend and cyclic methods.
The advantage of conventional methods is that they are more simple but their main drawback is that most of them are not suitable for non-linear relationships between variables.

6.2. AI Methods

The research direction has shifted towards AI methods to overcome the limitation of conventional methods to deal with non-linear relationships between variables. AI methods include the following approaches:

6.2.1. Fuzzy Logic

Fuzzy (IF-THEN rules) logic was designed to deal with uncertainty and vagueness problems. This method has the ability to deal with incomplete, inaccurate or ambiguous information. In fuzzy logic, the variables are divided into subsets in which the membership degree is exploited for each subset [40-41].
Khosravi et al. [40] carried out a STLF using interval type-2 fuzzy logic systems (IT2 FLSs), which allow handling uncertainties and enhancing the accuracy of prediction. Takagi-Sugeno-Kang (TSK) fuzzy inference systems are utilized to improve IT2 TSK FLSs models. Test results show that IT2 TSK FLSs outperform the other two (traditional T1 TSK FLSs and feed-forward neural networks) methods. Mukhopadhyay et al. in [41] presented a development method using fuzzy logic system to include the weather parameters for STLF.

6.2.2. Artificial Neural Networks

ANNs methods have emerged since the second half of the 80's. These methods have the capability of learning non linear relationships between variables. ANNs try to recognize patterns in the input data that learn from experience and then give results depending on the previous knowledge. The basic idea of ANNs was inspired by the simulation of human brain. ANNs building unit is a neuron. It is a node in the network which houses either a function or values. The structure of ANNs comprises three layers: an input layer, hidden layer and output layer. Adjusting the network structure and finding optimal parameters are very important to decrease the forecast error in terms of training and test sets [42].
Hernandez et al. in [42] introduced an ANN method for STLF in a disaggregated environment based on simple multilayer perceptron (MLP) architecture. Webberley and Gao [43] presented a model to STLF using ANN, which consists of three layers feed-forward network. Two BPNN training algorithms are used. Firstly, Levenberg-Marquardt (LM) algorithm is used in each iteration of training the ANN to find the minimum point in the power system. Second, Bayesian Regularization algorithm takes longer where it searches among more iteration.
Rodrigues et al. [44] carried out a STLF using ANN to build a robust model for forecasting the electric load of a household. The authors claimed that LM algorithm and feed-forward ANN provided a superior performance. Zjavka and Snasel [45] presented a new neural network type, namely differential polynomial neural network (D-PNN), for STLF. D-PNN is used to decompose and solve the partial differential equation in which the searched function can be modeled on the bases of data samples.
Warrior et al. [46] compared NNs, conditional restricted Boltzmann machines (CRBMs) and decision trees (DT) for STLF. The authors concluded that NN outperforms DT in day-ahead prediction, whereas CRBM exhibits superior performance over NN and DT in hour-ahead prediction. Recurrent extreme learning machine (RELM) method is introduced by Ertugrul in [47]. A single hidden layer Jordan recurrent neural network (SHLRN) is trained by using RELM. The obtained results reveal that the recurrent types ANNs achieve better extraordinary success in predicting time-ordered datasets and dynamic systems than feed forward ANNs.
Houimli et al. [48] carried out a STLF using ANN model. The pattern search technique is exploited to obtain the optimal structure of ANN. Moreover, ANN is equipped with LM technique. Test results show that this model is a promising tool in predicting short-term load demand.
The advantage of ANNs methods is that they can deal with non-linear relationships between variables but their drawbacks are the time consuming and over-fitting risk in which the error in test phase starts to increase whereas the error in the training phase still decreases.

6.2.3. Deep Learning

The main difference between deep learning (DL) and standard ANN is that, DL architecture has deeper inner hidden layers and complex computations. There are several DL methods such as autoencoder, recurrent neural network (RNN), long short term memory (LSTM), convolution neural network (CNN), restricted Boltzmann machine (RBM), deep belief network (DBN) and deep Boltzmann machine (DBM) [49].
Ryu et al. [50] presented forecasting framework for STLF using deep neural networks (DNNs). Two ways are used to train the DNNs. Firstly, pre-training RBM which includes the hidden and visible layer only. Secondly, rectified linear unit without pre-training (ReLU) which needs less computational time and power. Zheng et al. [51], Narayan and Hipel [52], Liu et al. [53], Kong et al. [54-55] presented a LSTM based RNN method for STLF. RNN has the capability to deal with nonlinear mapping, while LSTM exploits the memory unit advantage for making abstract of long sequences. In LSTM-based RNN, the long term dependency in the load time series is utilized for prediction more accurately.
Shi et al. [56] presented a novel pooling-based deep recurrent neural network (PDRNN) method for STLF to improve the household load prediction accuracy. The pooling strategy was developed to tackle two challenges, the over fitting problem and the high uncertainty in

household load profiles. A group of households' load profiles were batched into a pool of inputs. PDRNN can learn information shared between interconnected households and hence enabling more learning layers before occurring the over fitting.

6.2.4. Support Vector Machine

SVM is a supervised machine learning algorithm for classification and regression problems based on statistical learning theory, which is introduced by Vapnik [57]. It is an appropriate algorithm, when the relationships between the response variable and its predictors are nonlinear. SVM employs the principle of structural risk minimization (SRM) instead of the principle of empirical risk minimization (ERM) to minimize a bound on the expected risk to guarantee good generalization to new testing data set. In SVM, a nonlinear transformation is executed to map the input data points into a higher dimensional space, and then builds a linear model in space. SVM has been expanded to solve nonlinear regression estimation problems with the presence of Vapnik's ε -insensitive loss function, so-called SVR [58].
Zhang and Ye [58] carried out a LTLF based on SVR. SVR is exploited to find the non-linear relationship between electric load and gross domestic product (GPD) to improve the prediction accuracy. Test results indicate that SVR outperforms LR and BPNN. Thokala et al. [59] introduced a nonlinear autoregressive method with exogenous input-neural network (NARX-NN) and SVR to predict the office buildings energy in India. The authors concluded that SVR performs better than NARX-NN by a thin margin.
The advantage of SVM is that it can avoid problems like over-fitting risk and local minimum, but there is a difficulty in the proper parameters selection.

6.3. Hybrid Methods

Nowadays, hybrid methods are used to overcome the drawbacks of an individual model and benefit from the advantages of each one. Hybrid methods can be classified into the following categories:

6.3.1. Two or more methods are combined together

A Combined technique between ARIMA and SVM is presented by NIE et al. in [60] for STLF. ARIMA is used to predict the daily load, whereas SVM is used to correct the former prediction deviation. Ebrahimi and Moshari [62] presented a model for holidays STLF based on modified similar day method (MSDM) with fuzzy expert system. Firstly, characteristics of the holidays load are extracted from similar days. After that, the holiday's load is predicted by integrating these characteristics. Then, fuzzy expert system is utilized to modify the results of MSDM.
A hybrid univariate cross-forecasting (C-F) model is presented by Dudek in [63] for STLF based on two neural methods. The daily pattern is fed as input to the first NN, while other one is fed by the weekly pattern. Both NN results are incorporated by averaging.
Li et al. [64] presented an ensemble model for STLF based on the integration between wavelet transform (WT), extreme learning machines (ELM) and partial least squares regression (PLSR). The WT is used to generate an ensemble of individual forecasters. A parallel forecast model including 24 ELMs is employed to forecast the hourly load of day ahead. The individual forecasts are associated by using PLSR in order to form the ensemble prediction. Bantugon and Gallano [65] compared HWT and ANN for S/LTLF. The results reveal that HWT outperforms the ANN in LTLF, whereas the HWT outperforms the ANN and vice versa in STLF. So, a combination method is created by associating the best results of HWT and ANN to improve the accuracy of prediction.
Qiu et al. [66] presented an ensemble method for V/STLF based on the combination of empirical mode decomposition (EMD) method and DL. Firstly, the original load data is decomposed into various intrinsic mode functions (IMFs). Then, each of the extracted IMFs is modeled by using DBN, thus the tendencies of these IMFs can be forecasted accurately. Finally, IMFs prediction results are incorporated by either unbiased or weighted summation to form an ensemble output for electric load demand. Akarslan and Hocaoglu [67] presented a novel approach for STLF based on adaptive neuro-fuzzy inference system (ANFIS) method, which allows the usage of NN together with fuzzy logic.

6.3.2. Using the developed algorithms with various methods

In past few years, several enhanced learning algorithms are used to adjust the structure and parameters of the AI models to improve the prediction accuracy. These algorithms were applied to ANN, SVM, and other techniques.

- *Combining ANN with various enhanced learning algorithms*

Several enhanced learning algorithms are used to improve the accuracy of ANN predication model.
A combination of chaotic search (CS) method and genetic algorithm (GA), namely chaotic genetic algorithm (CGA), is used by Liu and Wang [68] to find optimal parameters of radial basis function neural network (RBFNN). Also, the CS technique is used by Xiao et al. [71] to optimize the hybrid method weight coefficients. The hybrid method comprises BPNN, GRNN, RBFNN and GA optimized BPNN (GA-BPNN).
The particle swarm optimization (PSO) algorithm is used by L.Xiao and Xiao [69] to enhance the weight coefficients of the hybrid method which comprises the PSO, BPNN and GA-BPNN. The GA algorithm is employed by Ghayekhloo et al. [70] to optimize the prediction components coefficients of a wavelet-Bayesian neural network (BNN).
The FOA algorithm is exploited by Liang et al. [72] to enhance the smoothing factor for GRNN. Also, the minimal redundancy maximal relevance (mRMR) is used to get optimal features of decomposed IMFs. Then, a combination of EMD-mRMR and FOA-RNN are presented to get the final predicted load.
An optimization technique, namely modified version of enhanced differential evolution (mEDE), is exploited by Ahmad et al. in [73] to reduce the prediction errors of the hybrid ANN model. The mutual information (MI) technique is used in the forecasting model to eliminate irrelevant data samples. A sigmoid function is used to activate the ANN, whereas multivariate auto regressive algorithm (MARA) is used to train the ANN model.
An intelligent technique, namely enhanced shark smell optimization (ESSO), is used by Gao et al. [74] to optimize all the variables of

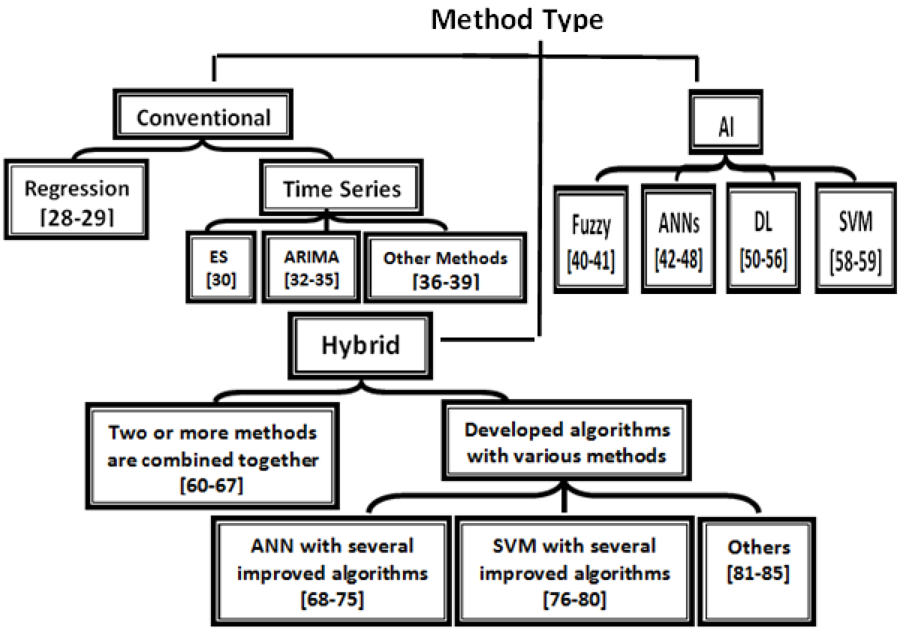

Figure 3: Classifications of load forecasting according to modeling techniques.

multi-block forecast engine. The forecast engine is composed of multi Elman neural network (ENN). An improved environmental adaptation model with real parameters (IEAM-R) and controlled Gaussian mutation (CGM) method are introduced by Singh et al. in [75] for STLF to find optimal ANN weights. Dual extended Kalamn filter (DEKF) is employed by Ko and Lee [61] to optimize RBFNN parameters, whereas SVR is used to determine the structures and parameters of RBFNN.

- *Combining SVM with several improved algorithms*

In recent years, several improved algorithms are utilized to find optimal parameters of SVM in order to enhance the accuracy of prediction. Ceperic et al. [76] introduced a generic strategy for STLF based on seasonality-adjusted, SVR method (SSA-SVR). The hyper-parameters of SVR are optimized using the particle swarm pattern search method (PSwarm) to minimize the operator interaction.
A combination of firefly algorithm (FA), SVM and season specific similarity concept (SSSC) is presented by Barman and Choudhury [80]. SSSC is exploited to perceive the seasonality effect in the prediction process, whereas FA is utilized to optimize SVM parameters. Another hybrid model, namely SVR-MFA, is proposed by Kavousi-Fard et al. in [77] for STLF based on SVR with modified firefly algorithm (MFA). Selakov et al. [78] introduced a hybrid model, namely PSO–SVM, for STLF based on PSO algorithm and SVM. PSO–SVM consists of preprocessing module, SVM module and PSO module whereas PSO module is used to get optimal parameters of SVM.
A hybrid method, namely AS-GCLSSVM, is proposed by Yang et al. in [79] for STLF based on optimal feature selection. This method combines auto correlation function (ACF) and LSSVM optimized by grey wolf optimization (GWO) and cross validation (CV) algorithms. The ACF is exploited to select the best input features of LSSVM Whereas LSSVM is used for prediction.

- *Other Hybrid Techniques*

Some of published papers introduced other hybrid techniques to improve the predication accuracy for load forecast. Bahrami et al. [81] introduced a hybrid method, namely WGMIPSO, for STLF based on WT and grey method improved by PSO algorithm (GMIPSO). WT is exploited to remove the high frequency components from the lagged load data, whereas PSO algorithm is employed to estimate the grey model parameters.
Two hybrid methods are presented by Ray et al. in [82] for STLF. The two methods comprise DWT to perform load decomposition in conjunction with ANN or SVM. Also, a forward feature selection (FFS) technique is used during the training phase of ANN or SVM to get the optimal set of features thereby minimizing the computational burden and improving the accuracy.
A hybrid model is introduced by Li et al. in [83] for STLF based on ELM, WT and modified artificial bee colony (MABC) algorithm. The load series can be decomposed into a set of essential components by using WT. Each one of these components is then predicted separately by an integrated model of ELM and MABC (ELM-MABC). MABC is employed to get the optimal parameters of input weights and hidden biases for ELM.
Ziel in [84] introduced a multivariate time series method based on lasso algorithm for the parameter estimation. This method applies an autoregressive moving average (ARMA) approach with generalized autoregressive conditional heteroskedasticity (GARCH) approach, namely a threshold ARMA-GARCH method, to model and predict hourly German electricity load. Zeng et al. [85] presented a hybrid model, namely SDPSO-ELM, for STLF based on the integration between switching delayed particle swarm optimization (SDPSO) algorithm and ELM. SDPSO is used to get optimal parameters of ELM.
Figure 3 summarizes the classifications of load prediction according to the modeling techniques. Reference numbers of the papers that are studied in this section have been included.

7. Comparison of the previous studies

The purpose of this section is to investigate the previous studies according to the forecasting horizon, the metrics, the forecasting methods (ANN, DL, LR, SVM, etc), the method type (conventional, AI or hybrid) and the features (input variables). All of them have been ranked

according to their usage in the previous works. The next investigations are summarized and highlighted from Table 2. This table shows forecasting horizon, modeling techniques and metrics for the papers which are investigated in this survey.
Regarding the forecasting horizons, STLF is the most important forecasting horizon with 74.36% of the total works as appeared in Figure 4a, whereas VSTLF is the lowest one with 5.13%. The remaining forecasting horizons are MTLF and LTLF with 10.26% and 10.25%, respectively.
With respect to the metrics, the most popular used measures in load prediction from superior to the inferior are MAPE, RMSE, MAE, MSE and ME with 51.72%, 18.97%, 17.24%, 6.03% and 6.03% of the total works respectively as shown in Figure 4b.
According to the forecasting methods, each method whether used in the individual or hybrid level (i.e., SVM which is used in the individual level as in references [58-59] or hybrid level as in references [20-21], [25-26], [60], [76-80], [82]) is taken into account. All the methods are evaluated by the same way. More than 42% of the papers use the ANN as shown in Figure 4c. The second popular used modeling technique is SVM with 20.55%. The remaining papers are distributed across the other methods such as DL, ARIMA, Fuzzy, ES and LR. Due to the rapidly increasing improvement in computers capabilities and the enhanced learning algorithms which are used to construct ANN architecture and find optimal parameters automatically, ANN is considered one of the most important forecasting methods.
Regarding the method type, Figure 4d shows the percentage of usage for each one. They are ranked from superior to the inferior as hybrid, AI and conventional with 54.29%, 28.57% and 17.14%, respectively. Thus, the research direction has shifted towards hybrid methods which are used between two or more models to overcome the drawbacks of individual models and take the advantages of each one.
Table 3 shows the forecast period and the performance from which the efficiency of each model is specified as well as the advantage and drawback of each one.
For the features, the investigation is extracted and summarized from Table 3. The input features are categorized to two groups (single variable and multi variables) as shown in Figure 5. Single variable group comprises load only, whereas multi variables can be classified into three categories which are (i) load and weather, (ii) load and other variables (calendar, price of electricity, population, etc), and (iii) load and weather as well as other variables. The most widely used feature is load values only with 37.14% of the total works as appeared in Figure 4e. The secondly used feature is load and weather conditions with 27.14%. The remaining papers are distributed to the other groups (ii) and (iii) with 17.14% and 18.57%, respectively. Thus, the exogenous variables may influence the load forecasting accuracy. Particularly, temperature is one of the most important exogenous variables that can influence the load forecasting accuracy. Temperature is fed as input to 32 works, which represents 45.71% of the total works presented here (70 works).

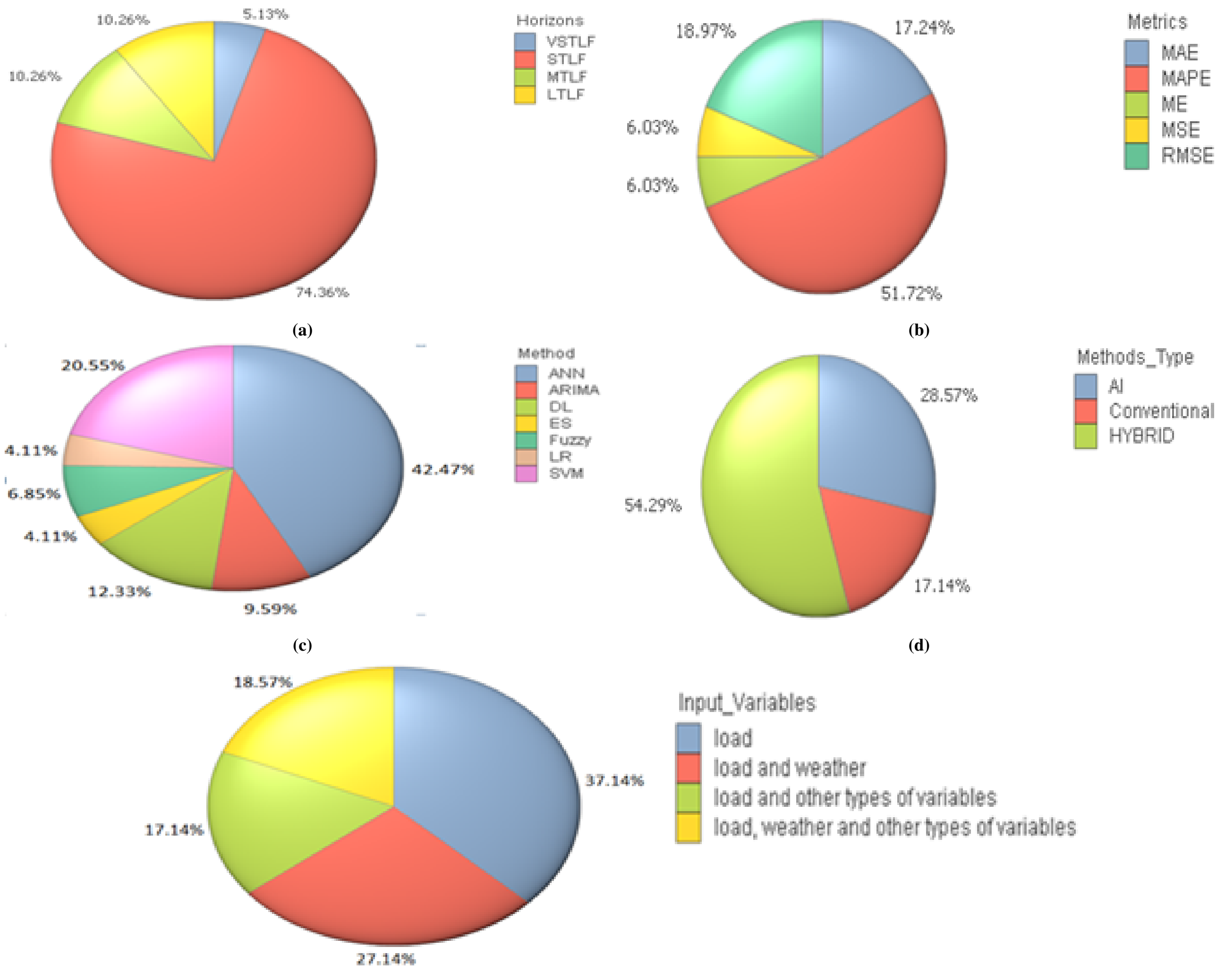

Figure 4: (a) Forecast Horizon. (b) Metrics. (c) Forecasting Methods. (d) Methods Type. (e) Features (Input Variables).

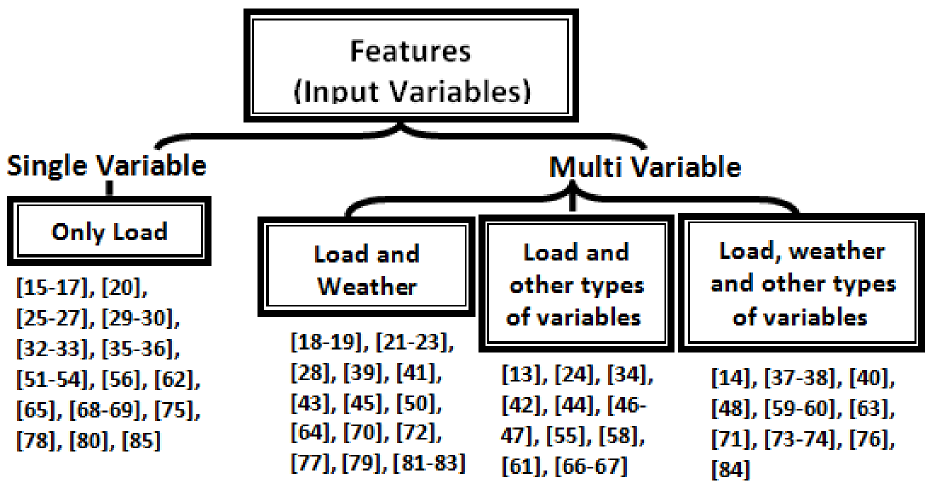

Figure 5: Classifications of the input features according to single and multi variables.

Table 2: Description of load forecasting horizon and modeling techniques

Ref.	Ref. Type.	Horizon	Forecasting Methods	Method Type	Metrics
[13]	Journal	VSTLF	WNN + spike filtering technique	Hybrid	MAPE, MAE and mean absolute scaled error (MASE)
[14]	Journal	VSTLF	Moving average, inter-cluster classification and intra-cluster prediction	Hybrid	MAPE and MASE
[15]	Journal	VSTLF	HFCM	Hybrid	Absolute Percentage Error (APE) and MAPE
[16]	Conference	STLF	Polynomial, Exponential, Mixed, AR, NN, SVM and BNN	Conventional and AI	MAPE
[17]	Conference	STLF	HWT, GMDH and ANN using DWT	AI	MAPE
[18]	Journal	STLF	BaNNs	Hybrid	MAPE
[19]	Journal	STLF	BOONN	Hybrid	MAPE
[20]	Journal	MTLF	SVR + CABC	Hybrid	MAPE
[21]	Journal	MTLF	SVR + CIA	Hybrid	MAPE
[22]	Conference	MTLF	NN	AI	MAE and MSE
[23]	Journal	MTLF	Dynamic model+ fuzzy time series	Hybrid	MAPE
[24]	Conference	LTLF	Fuzzy linear regression	Hybrid	MAPE
[25]	Journal	LTLF	LSSSVM+ FFO	Hybrid	MAPE and MSE
[26]	Journal	LTLF	SVR + DE algorithm	Hybrid	MAPE
[27]	Journal	LTLF	GRNN + FOA algorithm	Hybrid	MAPE and MSE
[28]	Conference	STLF	Regression based moving window model	Conventional	MAPE
[29]	Journal	STLF	LR, PCR, PLSR, stepwise and lasso regressions	Conventional	MAPE
[30]	Journal	STLF	Exponentially weighted methods	Conventional	MAPE
[32]	Journal	STLF	lifting scheme + ARIMA	Conventional	MAPE and maximum APE (MAXPE)
[33]	Conference	STLF	SARIMA	Conventional	MAPE
[34]	Conference	STLF	SARIMA	Conventional	MSE, RMSE, MAE and MAPE
[35]	Journal	STLF	Sliding window based ARIMA	Conventional	MAPE
[36]	Journal	STLF, MTLF and LTL	Moving Average and probability plots of load noise	Conventional	MAPE
[37]	Journal	STLF	Semi-Parametric additive model	Conventional	MAE and MAPE
[38]	Journal	STLF and MTLF	Semi-parametric additive models: middle term (MT) and short term (ST) models	Conventional	MAPE
[39]	Journal	STLF	Additive time series method	Conventional	MAE and MAPE
[40]	Journal	STLF	IT2 TSK FLS	AI	RMSE
[41]	Conference	STLF	Fuzzy logic	AI	RMSE
[42]	Journal	STLF	MLP	AI	MAPE
[43]	Conference	STLF	ANNs	AI	MAPE
[44]	Conference	STLF	ANN	AI	MAPE
[45]	Journal	STLF	D-PNN	AI	MAPE and RMSE
[46]	Conference	STLF	NNs, DT and CRBMs	AI	MAE and MAPE
[47]	Journal	STLF, MTLF and LTLF	RELM	AI	RMSE
[48]	Journal	STLF	ANN	AI	MSE, MAE, MAPE, MPE and RMSE
[50]	Conference	STLF	DNN with RBM and DNN with ReLU	AI	MAPE and Relative RMSE (RRMSE)
[51]	Conference	STLF	LSTM-RNN	AI	MAPE and RMSE
[52]	Conference	STLF	LSTM-RNN	AI	Normalized RMSE (NRMSE)
[53]	Conference	STLF	LSTM-RNN	AI	MAPE
[54]	Journal	STLF	LSTM-RNN	AI	MAPE
[55]	Journal	STLF	LSTM	AI	MAPE
[56]	Journal	STLF	PDRNN	AI	MAE, RMSE and NRMSE

[58]	Conference	LTLF	SVR	AI	—
[59]	Conference	STLF and MTLF	NARX-NN and SVR	AI	MAPE and NRMSE
[60]	Conference	STLF	ARIMA+SVM	Hybrid	MAPE and RMSE
[61]	Journal	STLF	Fuzzy expert system + MSDM and the overall model namely FISDM	Hybrid	MAE, MAPE and Percentage RMSE (PRMSE)
[62]	Conference	STLF	C-F model	Hybrid	MAPE
[63]	Journal	STLF	WT+ELM+PLSR	Hybrid	MAE, MAPE and RMSE
[64]	Conference	STLF and LTLF	HWT and ANN	hybrid	MAE, MAPE and RMSE
[65]	Journal	VSTLF and STLF	EMD+DBN	Hybrid	MAPE and RMSE
[66]	Conference	STLF	ANFIS	hybrid	RMSE, NRMSE and ME
[67]	Conference	STLF	CGA+RBFNN	Hybrid	average error rate
[68]	Journal	STLF	CS algorithm, BPNN+ RBFNN+ GRNN+ GABPNN	Hybrid	MAPE, ME, MAE and MSE
[69]	Conference	STLF	PSO+BPNN+ GA-BPNN	Hybrid	ME, MAE, MAPE and MSE
[70]	Journal	STLF	BNN+DWT+GA	Hybrid	MAPE and RMSE
[71]	Journal	STLF	EMD+mRMR+ GRNN+FOA	Hybrid	MAE, MAPE, relative error (RE) and RMSE
[72]	Journal	STLF	MI+ANN+mEDE	Hybrid	MAPE
[73]	Journal	STLF and STPF	ENN and enhanced shark smell optimization(ESSO) algorithm	Hybrid	MAPE, Normalized MAPE (NMAPE), RMSE and NRMSE
[74]	Journal	STLF	ANN + IEAMCGM-R algorithm	Hybrid	MAE and MAPE
[75]	Journal	STLF	SVR+DEKF+ RBFNN	Hybrid	MAPE and RMSE
[76]	Journal	STLF	SVR+PSwarm algorithm	Hybrid	MAPE
[77]	Journal	STLF	FA+SVM and SSSC	Hybrid	MAPE
[78]	Journal	STLF	SVR+MFA algorithm	Hybrid	APE, MAE, MAPE and RMSE
[79]	Journal	STLF	SVM+PSO algorithm	Hybrid	MAPE
[80]	Journal	STLF	ACF+GWO+CV+ LSSVM	Hybrid	MAE and MAPE
[81]	Journal	STLF	WT+GMIPSO	Hybrid	APE, MAE, MAPE and MPE
[82]	Conference	STLF	FFS, DWT+ANN and DWT+SVM	Hybrid	MAPE
[83]	Journal	STLF	WT+ELM+MABC	Hybrid	MAPE and MAE
[84]	Conference	STLF	ARMA+GARCH and lasso algorithm	Hybrid	-
[85]	Journal	STLF	ELM+SDPSO	Hybrid	MAE and MAPE

Table 3: Analysis of the previous studies of electrical load forecast techniques

Ref.	Forecast	Features	performance	disadvantage	advantage
[13]	1 hour ahead every 5 minutes	Electric load, time and date indices.	**Using WNN method** *Classroom-type problem* - MAE: 0.85 *WNN with spike filtering* - MAPE(%): 0.09 - 0.45 - MAE(MW): 12.5 - 71.0 - MASE: 0.23 - 1.35	Small data set for validation of abnormal days.	WNN method exhibits superior performance over ISO-NE's method. It can capture components of the load at various frequencies.
[14]	30 minutes, 2 hours and 1 day ahead	Electric load, calendar, weather condition and economic.	**Using context information and daily schedule pattern analysis** For 30 minutes, 2 hours and 1 day ahead forecast, respectively *Individual Household* MAPE(%): 3.23, 3.52 and 4.34 MASE: 0.22, 0.15 and 0.16 *Aggregated Load* MAPE(%): 2.44, 3.1 and 4.12	Context features are not sufficient. The size of data was small and the data period was short.	The proposed model exhibits superior performance over LR, BPNN, SVR, SVR based on similar historical days (SVR2), RW and ARIMA models.
[15]	an hour-ahead	Electric load.	**Using HFCM method** *French load data* - MAPE in normal days: 0.478% - MAPE in public holidays: 0.863% *Australian load data* - MAPE for all the days of 2007: 0.860% - MAPE in public holidays: 1.048%	Exogenous variables such as weather data are not used.	HFCM has better performance in both normal and special daily load conditions than the others (SARIMA, HWT, BPNN, ANFIS, adaptive Holt's exponential smoothing (AHES), and WNN) methods.
[16]	1 to 6 days ahead	Electric load, negligible the influence of weather.	*For one day-ahead forecasting* MAPE(%) values for Workdays, Saturdays and Sundays, respectively - **AR**: 5.3, 8.72 and 6.6 - **NN**: 11.87, 12.55 and 7.89 - **Polynomial**: 11.22, 13.86 and 7.43 - **SVM**: 5.79, 9.28 and 6.96 *MAPE(%) values for 2nd, 3rd, 4th, 5th and 6th days ahead, respectively* - **AR**: 8.4, 9.1, 9.6, 10.3 and 11.01 - **Polynomial**: 12.7, 13.3, 13.8, 14.6 and 15.5 - **SVM** : 8.9, 9.7, 10.1, 10.8 and 11.5 - **NN**: 12.8, 13.6, 14.3, 14.9 and 15.49	This methodology is used only to STLF in non-residential buildings but cannot be used in normal STLF.	In non-residential buildings, a forecasting models should be simple, avoid complicated trial and error customisation, able to work with any or scarce historical data and accurate. Time series model (Autoregressive AR) outperforms Polynomial, Exponential, NN, SVM and BNN.
[17]	24 hours ahead	Electric load.	**HWT, GMDH and ANN methods** For Monday, Weekdays, Saturday and Sunday, respectively *using GMDH with DWT* - MAPE(%): 1.016, 1.014, 0.6, and 0.8 *using GMDH without DWT* - MAPE(%): 2.57, 1.99, 1.96 and 2.74 *using ANN with DWT* - MAPE(%): 1.29, 1.3, 0.99, and 1.1 *using ANN without DWT* - MAPE(%): 1.36, 1.3, 2.29, and 2.03 *using HWT* - MAPE(%): 1.94, 1.92, 2.6 and 2.3	Complicated trial and error for selecting ANNs architecture and Holt-Winters parameters.	GMDH using DWT has satisfactory performance and gives the lowest forecasting error. Load pattern can be classified and predicted without concerning non-stationary.
[18]	24 hourly consumption values	Electric load and temperature.	**Using BaNN method** **-** MAPE(%): 1.75 *Years 2004-2006* - monthly MAPE(%): 1.5	Complicated trial and error for choosing a proper sample size and number of iterations.	BaNNs can minimize the errors of load prediction. It can be utilized to enhance the forecasting accuracy and minimize variations in predicted values.

[19]	24 hours ahead	Electric load and temperature.	**Using BooNN method** *Years 2004-2006* - Average MAPE(%): 1.43 *Year 2008* - monthly MAPE(%): 1.42	Complicated trial and error for choosing a proper sample size and number of iterations. BooNN requires more computation time than single ANN.	BooNN can minimize the error of load prediction. It requires less computational time than BaNN.
[20]	7 months ahead	Monthly electric load.	**Using SRSVRCABC method** Average MAPE(%): 2.387	Flow of the load prediction process is very long.	SRSVRCABC exhibits superior performance over ARIMA and TF-ε -SVR-SA methods.
[21]	Monthly load	Load and climate variables.	**Using SSVRCIA method** MAPE (%): 1.766	CIA flowchart is very long.	SSVRCIA is a promising tool for load prediction.
[22]	Monthly peak loads ahead	Monthly load, wind speed, humidity and temperature.	**Using NN method** *Testing performance* - MAE: 11.96 - MSE: 204.74	Complicated trial and error for selecting ANNs architecture. NN model needs more computational time than MLR model.	NN model outperforms the MLR model and found more reasonable and satisfactory.
[23]	4 months ahead	Electric load and air temperature.	**Using Dynamic model with fuzzy time series** MAPE for Household : 2.6% MAPE for Public: 2.6% MAPE for Service: 3.1% MAPE for Industrial: 5.1%	Several terms must be defined before building the fuzzy time series.	The hybrid model exhibits superior performance over Koyck and ARIMA models.
[24]	Several years ahead	Population, Load and annual growth factors.	**Using Fuzzy Linear Regression method** MAPE: 3.68%	The model is not compared with any other model.	Fuzzy linear regression has satisfactory performance of load forecasting.
[25]	Annual load	Electric load.	**Using LSSVM-FOA method** MAPE(%): 1.305 MSE: 2476	LSSVM-FFO flowchart is very long.	LSSVM-FOA outperforms the other ANN-based methods.
[26]	Annual load	Electric load.	**Using DESVR method** *Training set* - average MAPE: 1.8% *Testing set* - average MAPE: 1.1% *Total* - average MAPE:1.6%	The flowchart of DESVR method is long.	DESVR outperforms the other (regression, BPNN and SVR with default parameters) methods. This method can capture the increasing trends of annual load more easily.
[27]	Annual load	Electric load.	**Using FOAGRNN method** *Annual load data of Beijing city* - average MAPE(%): 1.149 - average MSE: 1.421 *Annual load data of China* - average MAPE(%): 1.252 - average MSE: 2839.47	FOAGRNN method needs large amount of data in the training set. Flow of the load prediction process is very long.	FOAGRNN outperforms LSSVM with simulated annealing algorithm (SALSSVM), GRNN model with PSO (PSOGRNN), GRNN and ordinary least squares-LR (OLS_LR). It requires shorter training time than PSOGRNN and SALSSVM.
[28]	30 minutes up to 24 hours ahead	historical load and weather conditions.	**Using Regression based Moving Window method** For typical Winter week, typical Summer week and Whole year 2000 *Half an hour ahead forecasting* - MAPE(%): 0.5, 0.79 and 0.59 *24 hours ahead forecasting* - MAPE(%): 1.88, 4.26 and 2.3	For the longer time scale, this model has imperfect performance where the MAPE values can increase quickly and reach to more than 2% for 24 hours ahead.	Moving Window model outperforms the ANN model. With the ability to adjust the window size, this model can predict for more than one step ahead.

[29]	24 hours ahead	Electric load.	**Using LR method** Polish power system from 2012 to 2014 *using Partial least-squares regression* - MAPE: 1.34% *using Principal component regression* - MAPE: 1.44%	N–WE gives better results than LR for three datasets (Polish, British and Victoria power system).	LR has superior performance over ARIMA, ES, MLP and Nadaraya–Watson estimator (N-WE) methods.
[30]	24 hours ahead	Electric load.	**Using Exponentially weighted methods** -	These methods cannot deal with unusual days, large errors happened on the day following a public holiday.	The simplicity of the HWT method. The ability to yield prediction intervals from a model. The exponential smoothing method was the best performing method.
[32]	one-day-ahead	Electric load.	**Using lifting scheme with ARIMA** *Case 1: Winter load (Weekdays)* - MAPE(%): 0.87 and MAXPE(%): 1.44 *Case 2: Spring load (Weekdays)* - MAPE(%): 0.48 and MAXPE(%): 1.39 *Case3: Summer Load(Weekdays)* - MAPE(%): 0.94 and MAXPE(%): 2.02 *Case 4: Autumn load (Weekdays)* - MAPE(%): 0.66 and MAXPE(%): 1.35 *Case 5: Annual load (Weekends)* - MAPE(%): 2.99 and MAXPE(%): 0.86	The framework of the lifting scheme with ARIMA methods is long.	The lifting scheme can minimize computational complexity and memory requirement in a classical wavelet transforms. The proposed method outperforms BPNN and traditional ARIMA methods in the five cases.
[33]	Few days ahead	Electric load	**Using SARIMA method** MAPE (%): 1.5	The model is not compared with any other model.	SARIMA can be exploited to predict future load more accurately.
[34]	Fourteen days ahead	Load in kW and days.	**Using SARIMA method** MAPE (%): 3.91	The model is not compared with any other model.	SARIMA has satisfactory performance for load prediction.
[35]	Hourly and daily ahead	Electric load	**Using sliding window-based ARIMA** MAPE(%) values for validation window size (24, 48, 72 and 96) are 9.53, 10.32, 10.78 and 9.04**.**	Sliding window flowchart is long.	This methods has satisfactory performance for load prediction.
[36]	Daily load forecast	Electric load.	**Using moving average method** *For 7-day moving average* - MAPE(%): 3.84 - Mean Error: 30.55 MW *For 30-day moving average* - Mean Error: 174.47 MW	The flowchart for EPLF methodology is long. The model is not compared with any other model.	This methodology is used as a guide for building EPLF models. It has superior performance of load forecasting.
[37]	Half-hour ahead up to seven days ahead	Lagged load, calendar and temperature.	**Using semi-parametric additive method** *OUT-OF-SAMPLE TEST FOR JANUARY 2009* - average MAE(MW): 110.21 - average MAPE(%): 1.88 *OUT-OF-SAMPLE TEST FROM OCTOBER 2008 TO MARCH 2009* - average MAE(MW): 92.82 - average MAPE(%): 1.68	Several hundreds of sub-functions have been estimated based on the selected variables.	The additive method has satisfactory performance in both on-site implementation and out-of-sample test.
[38]	Day and month ahead	Electric load, calendar, temperature and price of electricity (tariffs).	**Using MT and ST methods** *Forecasting set on the 1900 substations* - MAPE for MT method: 8% By detrending the data, - MAPE for MTD method: 6% - MAPE for ST method: 5% *Forecasting set on one substation* - MAPE for ST method: 1.5%	For each substation, some work has to be done to choose automatically the feature and the way to include it in the model. The dependency between two or more substations are not exploited.	Mt and ST models have satisfactory performance of load forecasting. Semi-parametric additive models are utilized to deal with different features of electricity consumption. The evaluation of these models over big datasets is feasible on a personal computer.

[39]	One day and two days ahead	Electric load and temperature.	**Using Additive time series method** The error has been minimized from 50% to about 20%.	Steps of the designed time series prediction method are long.	Time series model with or without temperature exhibits superior performance over Naive model especially for a longer period load forecast.
[40]	Two-days-ahead	Lagged load, day of the week and temperature.	**Using IT2 TSK FLS method** RMSE: 0.163	The classes of the model are complex.	IT2 TSK FLS exhibit superior performance over the traditional T1 TSK FLS and NN methods in terms of accuracy and generalization power.
[41]	Daily ahead	Load, temperature and humidity	**Using Fuzzy logic** RMSE for 27th July 2017: 27.8 MW	The production rules is long.	Fuzzy logic is robust in combining the weather parameter in the load prediction model.
[42]	24 hours ahead	Electric load and calendar	**Using MLP method** MAPE: 2.47%.	-	MLP is a promising tool in predicting short-term load demand.
[43]	8 days ahead	Electric load and temperature.	**Using ANN method** For 10, 20 and 30 neurons *using Levenberg-Marquardt* - MAPE(%): 7.39, 6.16 and 8.5 *using Bayesian Regularization* - MAPE(%): 5.74, 9.28 and 7.62	Complicated trial and error for selecting ANNs architecture. ANN method is not compared with any other method.	ANN method has satisfactory performance of load forecasting.
[44]	3 days ahead	Electrical appliance consumption, numbers of occupants and hourly meter system.	**Using ANN method** *Average daily energy consumption* - MAPE(%): 4.20 *Hourly Energy Demand* For 1^{st}, 2^{nd} and 3^{th} days - MAPE(%) for household (H64): 16, 10 and 12.9 - MAPE(%) for household (H65): 21.5, 19 and 23.5	Complicated trial and error for selecting a proper ANNs parameters.	ANN is able to accurately predict the household energy consumption. It is able to forecast hourly and daily energy consumption, as well as a reliable load profile.
[45]	24 hours ahead	Electric load and temperature.	**Using D-PNN method** MAPE for national grid, U.K. electricity transmission: 1.56% MAPE for Canadian houses: 37.9%	D-PNN takes more computational time than SVM and GMDH models	D-PNN exhibits superior performance over ANN, SVM and GMDH.
[46]	Hour and day ahead	Year, month, day of week, day of month and power consumption.	**Using NN, DT and CRBM methods** *Institutional Block Data* MAPE(%) for day-ahead forecasting (22nd March 2016) - using NN: 6.429 and DT: 7.254 MAPE(%) for hour-ahead forecasting (24th March 2016) - using NN: 5.54, DT: 5.59 and CRBM: 3.9 *Test Site Data* MAPE(%) for day-ahead forecasting (2nd February 2016) - using NN: 9.34 and DT: 9.7 MAPE(%) for hour-ahead forecasting (9th February 2016) - using NN: 9, DT: 9.96 and CRBM: 4.87	CRBM needs a large amount of training data. Due to missing some days, CRBM produces large errors. Test site exhibits higher variation in the load which causes larger prediction error in comparison with institutional block.	For day-ahead forecasting, NN outperforms DT whereas for hour-ahead forecasting CRBM exhibits superior performance over NN and DT methods. NN and DT methods are more robust and execute with reasonable precision even in absence of consistent data.
[47]	Daily, weekly, monthly, quarterly, yearly and two yearly load	Electric load and the day of week.	**Using RELM method** Average RMSE by RELM is approximately twice less than the other existing (ELM, GRNN, LR, RNN, k-smooth regression, Gaussian process regression and k nearest neighborhood regression) methods.	Exogenous variables such as population, price of electricity or weather data are not used.	RELM outperforms the other existing methods in terms of accuracy and the training speed.

[48]	Half-hourly load	Lagged load, temperature and the type of day, week, month and year.	**Using MLP Lm method** MAPE: 1.1% - 3.4%	ANN method has some insufficiencies. This method is not compared with any other method.	LM algorithm outperforms conjugate gradient and resilient back algorithms. Lm quickly converges with high precision. The optimal structure of ANN depends on the pattern search optimization algorithm and not on a trial-and-errors process.
[50]	24 hours ahead	Electric load, weather variables and date.	*Single load type* **Using DNN(RBM) method** - MAPE(%): 3.2 - RRMSE(%): 4.1 **Using DNN(ReLU) method** - MAPE(%): 3.45 - RRMSE(%): 4.36 *Various load type (40 CUSTOMERS)* **Using DNN(RBM) method** -MAPE(%): 8.84 - RRMSE(%): 10.62 **Using DNN(ReLU) method** - MAPE(%): 8.85 - RRMSE(%): 10.69	DNN requires more computational time and power.	DNN(RBM) and DNN(ReLU) models exhibit superior performance over ARIMA, shallow neural network (SNN) and double seasonal Holt-Winters. Particularly, DNN(ReLU) requires less computational power and time than DNN(RBM). DNN predicts accurately without being affected by seasonal variation.
[51]	Prediction horizon H = 12 and 96 steps.	Electric load.	**Using LSTM- RNN method** *Airline passengers data set* - MAPE: 0.0345 - RMSE : 0.0435 *Electric load data set* - MAPE: 0.0535 - RMSE : 0.0702	Exogenous variables such as weather data are not used.	LSTM-RNN outperforms the traditional methods.
[52]	24 hours ahead	Electric load.	**Using LSTM-RNN method** NRMSE for January: 4.4% NRMSE for May: 5.9% NRMSE for September: 3.8%	The algorithms of forward pass and the back-propagation through time are complicated.	LSTM-RNN outperforms the ANN and ARIMA.
[53]	24 hours ahead.	Electric load.	**Using LSTM-RNN method** MAPE for special day: 2.57% MAPE for common day: 2.13%	The model cannot deal with load with irregular jitters.	LSTM-RNN outperforms the ENN method.
[54]	Prediction horizon H =2, 6 and 12 steps.	Electric load.	**Using LSTM-RNN method** *Individual households* - MAPE: 44.06% - 44.39% *Aggregated loads* - MAPE: 8.18% - 8.64% *Forecasting the aggregate* - MAPE: 8.58% - 9.14%	When the inconsistency in the residential load is small, the enhancement of LSTM is marginal. When data patterns are not so prominent in the load on aggregation level, the advantage of using LSTM is not as large as applying it on individual loads.	Overall, the predictions for individual household are not as precise as the predictions for substation loads. However, LSTM-RNN outperforms the other existing methods for both individual and aggregated load forecasting.
[55]	Day ahead	Electric load and appliance measurements.	**Using LSTM method** *LSTM-WA/2 time intervals* MAPE: 21.99%	The model requires more time consuming.	LSTM outperforms all other methods. The appliance measurements are exploited to improve load forecasting.

[56]	Day ahead	Electric load.	**Using PDRNN method** RMSE (KWh): 0.4505 NRMSE (KWh): 0.0912 MAE (KWh): 0.2510	Flow of the load prediction process is very long. Pooling customers with various features, such as similar social status or similar geographic locations are not introduced to exploit optimal pooling strategy.	The pooling strategy is developed to tackle the over fitting problem and the inherent high uncertainties in household load profiles. PDRNN exhibits superior performance over ARIMA, RNN, SVR and DRNN methods.
[58]	Five years ahead	Electric load and GDP.	**Using SVR method** -	SVR needs large amount of data in the training set.	SVR outperforms LR and BPNN.
[59]	Day, week and month ahead.	Load, temperature, features and contextual information.	**Using NARX-NN and SVR methods** *Day ahead forecasting* - the mean prediction accuracy: 93% *Week ahead forecasting* - the mean prediction accuracy: 88%-90% *Month ahead forecasting* - the mean prediction accuracy: 85%-87%	The block-diagram for the energy management system is long.	NARX-NN and SVR outperform the ARIMA and LR. Particularly, SVR has better performance and exhibits superior performance over all other methods.
[60]	24 hours ahead	load, weather and days of the week.	**Using ARIMA-SVM method** MAPE(%): 3.85	Complicated trial and error for selecting a proper SVMs parameters.	ARIMA-SVM exhibits superior performance over the individual (ARIMA and SVMs) methods.
[61]	24 hours ahead	Hourly load, and Coincidence.	**Using FISDM method** MAPE(%): 4.08 PRMSE(%): 4.73 MAE(MW): 53.84	The preprocessing stage requires more computational time.	The simplicity of FISDM. It exhibits superior performance over MSDM and NN-based methods.
[62]	1 day ahead	Electric load.	**Using C-F method** MAPE (%): 0.85	Exogenous variables such as weather data or price of electricity are not used.	C-F model outperforms the individual neural methods. One-neuron model is used to form the relationship between predictors and output variables locally.
[63]	1 hour and 24 hours ahead	Lagged load, temperature and calendar variables.	**Using hybrid WT, ELM and PLSR methods** **-** Case1: MAPE(%) for 1-hour and 24 hours ahead in winter are 0.27 and 1.42. - Case2: the hybrid method is 12.9 and 26.6 better in MAPE(%) than SIWNN and SNN - Case3: MAPE(%) is 0.41 and MAE is 70.2 - Case4: MAPE(%) values for year 2010 and 2011 are 1.5 and 1.8, respectively. - Case5: with weekends and holidays MAPE(%) for 1-hour and 24 hours ahead using actual temperature are 0.59 and 1.86. - Case6: MAPE(%) for 1-hour and 24 hours ahead are 0.54 and 2.02, respectively.	The model structure is long.	The ensemble model outperforms the other state-of-the-art methods. Thus, this model can significantly enhance the performance of prediction. It can mitigate numerous problems, such as wavelet parameter determination and overtraining.
[64]	Hour, week and three years ahead	Electric load and weather data.	**Using HWT and ANN methods** HWT has satisfactory performance on both LTLF and STLF with MAPE of almost 3% and 9%, respectively.	Complicated trial and error for selecting ANNs parameters. ANN has poor performance due to the limited weather data.	HWT outperforms ANN. The integration between HWT and ANN improve the accuracy of STLF.

[65]	Half an hour and 24 hours ahead	Electric load.	**Using EMD-DBN method** *Monthly load in Northeastern China* - MAPE(%): 1.99 *New South Wales in 2007* For small sample size: - MAPE(%): 0.66 - RMSE: 83.57 For large sample size: - MAPE(%): 0.91 - RMSE: 118.49	The ensemble deep learning model requires more time consumption than the single structure model.	EMD based hybrid models outperform the single structure models. EMD-DBN exhibits superior performance over nine benchmark methods.
[66]	Hour ahead.	Load data	**Using ANFIS method** RMSE(kWh): 1.79 nRMSE(%): 28.4 ME(kWh): 0.538	The model is not compared with any other model.	ANFIS has satisfactory performance of load forecasting for small grid systems.
[67]	24 hours ahead	Electric load and holiday index.	**Using RBFNN method** *Micro-grid* - Average error rate: 3.09% *UK national grid* - Average error rate: 1.86%	The model is not compared with any other model.	RBFNN can achieve satisfactory results without requiring a lot of data preprocessing. Parallel computing is used to reduce the computation time.
[68]	Half-hourly load	Electric load.	**Using the combined method** MAPE on Monday: 1.2952% MAPE on Friday: 1.3263%	The process of CS algorithm is long.	The hybrid method exhibits superior performance over ARIMA and RW methods.
[69]	48 half-hours ahead	Electric load.	**Using hybrid PSO, BPNN and GA-BPNN methods** The combined method improves the accuracy of load prediction, according to MAPE(%), by 1.5 and 1.84 over BPNN and GA-BPNN, respectively.	Exogenous variables such as weather data are not used.	The combined method exhibits superior performance over the individual (BPNN and GA-BPNN) methods.
[70]	24 hours ahead	Electric load and temperature.	**Using hybrid wavelet- BNN methods** *For year 2006* - Average MAPE: 0.4383%	The hybrid method requires more computational time than the individual models	The hybrid method has satisfactory performance in comparison with the other techniques.
[71]	24 hours ahead	Load, temperature, meteorology conditions and day types.	**Using EMD-mRMR-FOA-GRNN method** minimum RE: 0.0023% maximum RE: -2.86%	The flow chart of EMD-mRMR-FOA-GRNN is long.	EMD-mRMR-FOA-GRNN outperforms the other (FOA-GRNN, mRMR-FOA-GRNN, SVM and GRNN) methods. This method is efficient, effective and practicable in STLF.
[72]	Daily load	Load, temperature and day types (working day or holiday).	**Using MI+ ANN+ mEDE method** prediction accuracy: 98.76%	The flow chart of MI+ ANN+ mEDE is long.	MI+ANN+mEDE outperforms the bi-level and MI+ANN methods in terms of precision, scalability and execution time. The trade-off between prediction and convergence rate is not created.
[73]	One-hour and one-day ahead	Load, price and temperature.	**Using HP method** *North American* - MAPE(%): 1.14 - MAE: 62.44	A complex forecasting approach.	HP method outperforms the other existing methods.

[74]	Day ahead	Load, temperature, hour of day, day of week, weekend and holiday.	**Using ANN-IEAMCGM-R method** *ISO electricity market* - Enhancement in the prediction accuracy by 3.69% and 11.76% MAPE over ANN-IEAMGM-R and ANN-IEAM-R. *NSW electricity market* - Enhancement in MAPE(%) of 2.6, 3.64, 6.13 and 7.7 for spring, winter, autumn and summer seasons over ANN-IEAM-R.	The flowchart of ANN-IEAMCGM-R method is very long.	ANN-IEAMCGM-R method generates the least error and outperforms the other state-of-the-art methods in terms of accuracy and generalization ability.
[75]	24, 72 and 168 hours ahead.	Electric load.	**Using SVR-DEKF-RBFNN** *Weekdays* - MAPE(%) values for 24, 72 and 168 hours ahead are 0.6, 1.03 and 0.99. *weekends* - MAPE(%) values for 24, 72 and 168 hours ahead are 0.72, 0.89 and 1.04. *holidays* - MAPE(%) values for 24 and72 hours ahead are 0.56 and 0.66.	Exogenous variables such as weather data or price of electricity are not used.	SVR-DEKF-RBFNN has better performance and accuracy than DEKF-RBFNN and gradient decent RBFNN methods.
[76]	24 hours ahead	Load, temperature, humidity and binary variables.	**Using SSA-SVR method** *North-American test cases* - prediction accuracy has been enhanced from 2.5% up to 34.2%. *ISO-NE load forecasting test cases* - prediction accuracy has been enhanced from 20% up to 23.4%.	Steps of the designed method are long.	SSA-SVR has satisfactory performance for STLF in both data sets. The training time of SSA-SVR is shorter than the prediction horizon of one hour.
[77]	1 day up to seven days ahead	Electric load, temperature, wind speed and cloud cover.	**Using Season specific method** *Spring* - MAPE(%): 1.56 *Summer* - MAPE(%): 1.66 *Autumn* - MAPE(%): 1.58 *Winter* - MAPE(%): 1.79	The flowchart of season specific FA-SVM approach is long.	Season specific approach outperforms the other two traditional approaches in the four cases. Thus, season specific approach is a promising alternative for electric load prediction.
[78]	Daily load	Electric load.	**Using SVR-MFA method** *Results of First Case* - MAPE(%): 1.69, MAXPE: 4.05, RMSE: 2.06 and MAE: 22.5	The flowchart of the MFA is long.	SVR-MFA exhibits superior performance over ANN, ARMA, SVR-FA, SVR-GA and SVR-PSO.
[79]	Hourly load	Electric load and temperature.	**Using PSO–SVM method** MAPE for case No.1: 6.15% MAPE for case No.2: 6.13% MAPE for case No.3: 1.85%	Few data for training model.	PSO–SVM exhibits superior performance over the classical methods.
[80]	Half-hour ahead	Electric load.	**Using AS-GCLSSVM method** *Forecasting Results in VIC* - MAPE(%): 0.77 and MAE: 37.22 *Forecasting Results in NSW* - MAPE(%): 0.52 and MAE: 45.98 *Forecasting Results in QLD* - MAPE(%): 0.55 and MAE: 32.2	AS-GCLSSVM model requires more time consumption than other models. This model is more complicated.	AS-GCLSSVM method outperforms the other benchmark methods.
[81]	Daily, weekly and monthly load.	Lagged load, humidity, temperature and wind speed.	**Using WGMIPSO method** *New York load prediction for July 2004* - MAPE(%): 1.82 and MAE(MW): 122.4 *Iran load prediction* On 14th March 2010 - MAPE(%): 0.72, MPE(%): 0.54 and MAE(MW): 171.7 On 10th August 2010 - MAPE(%): 0.45, MPE(%): -0.34 and MAE(MW): 161.27	Few data for training model.	WGMIPSO exhibits superior performance over the other existing methods in both cases, Iran and New York network data sets.

[82]	1 day ahead	Load, dew point, humidity and temperature.	**Using DWT-ANN and DWT-SVM methods** *using DWT-ANN method* - MAPE(%): 0.6 *using DWT-SVM method* - MAPE(%): 0.1	Complicated trial and error for choosing proper parameters. Both methods are not compared with any other method.	DWT-ANN and DWT-SVM methods have satisfactory performance. Particularly, DWT-SVM exhibits superior performance over DWT-ANN.
[83]	1 and 24 hours ahead	Electric load and temperature.	**Using WT-ELM-MABC** *ISO New England data* - MAPE(%) values for 1 and 24 hours ahead are 0.55 and 1.59, respectively. *North American electric utility data* - MAPE(%) values for 1 and 24 hours ahead with actual temperature are 0.67 and 1.87.	The performance is not satisfactory if MABC algorithm is not used in the model. The training phase of the proposed method requires large amount of time about 38 min.	WT-ELM-MABC can overcome the difficulty induced by the nonstationarity. It is very robust to temperature forecasting errors. The testing time only needs several seconds. It exhibits superior performance over the other standard and state-of-the-art methods.
[84]	Two weeks ahead.	Load, temperature, the clock change and public holidays.	**Using ARMA with GARCH methods** -	The method is not compared with any other method. There is not explicit formula for this method available. the uncertainty at public holidays is quite large.	A huge amount of information can be included into the ARMA-GARCH model. Also, the estimated non-linear effects can be visualized in this model.
[85]	24 hours ahead	Electric load.	**Using SDPSO-ELM method** MAPE(%) : 2.182 MAE(MW): 22.93	This method requires more time to select the parameters of input weights and basis.	SDPSO-ELM can avoid overtraining problems and adding unnecessary hidden nodes. It exhibits superior performance over the RBFNN method.

8. CONCLUSION

According to our survey, several pervious researches are applied different techniques to improve the accuracy of the electric load predictions for power system security and reliability. In the opposite, inaccurate electric load predictions may increase operating costs. For a good load forecasting process one needs to collect historical data about the electricity such as previous load, calendar, economic and weather data. As a result of this investigation, the following main conclusions could be drawn:

1. MAPE and RMSE are the most important metrics, which are used to measure the accuracy of prediction for each fitted model.
2. STLF period is the most important forecasting horizon, where it can be used to forecast peak load, unit start-up, scheduling of generation capacity, scheduling of fuel and coal purchases.
3. The most popular used methods in load prediction is AI then conventional, but nowadays the hybrid methods are used between two or more methods to overcome the drawbacks of the individual methods.
4. In recent years, rarely ARIMA models are used alone but they are combined with other methods.
5. Over the years, ANN method is considered one of the most important individual models of load forecasting.
6. In past few years, DL methods such as RNN and LSTM are suggested as a future alternative to feed forward ANNs.
7. Accuracy of load forecasting process may be improved based on really good parameter estimates. So, several algorithms can be used to find optimal parameters automatically.
8. Temperature is one of the most important exogenous variables that can influence the load forecasting accuracy.

Acknowledgement

First and foremost, all thanks and praise are due to ALLAH Almighty, the absolute source of knowledge and wisdom, without His guidance and help nothing of this work would have been achieved.

References

[1] Hobbs, Benjamin F and Jitprapaikulsarn, Suradet and Konda, Sreenivas and Chankong, Vira and Loparo, Kenneth A and Maratukulam, Dominic J, “Analysis of the value for unit commitment of improved load forecasts”, *IEEE Transactions on Power Systems*, Vol.14, No.4, (1999), pp.1342-1348.
[2] Bunn, Derek W, “Forecasting loads and prices in competitive power markets”, *Proceedings of the IEEE*, Vol.88, No.8, (2000), pp.163-169.
[3] Hippert, Henrique Steinherz and Pedreira, Carlos Eduardo and Souza, Reinaldo Castro, “Neural networks for short-term load forecasting: A review and evaluation”, *IEEE Transactions on power systems*, Vol.16, No.1, (2001), pp.44-55.
[4] Alfares, Hesham K and Nazeeruddin, Mohammad, “Electric load forecasting: literature survey and classification of methods”, *International journal of systems science*, Vol.33, No.1, (2002), pp.23-34.
[5] Singh, D and Singh, SP, “Self organization and learning methods in short term electric load forecasting: a review”, *Electric Power Components and Systems*, Vol.30, No.10, (2002), pp.1075-1089.
[6] Metaxiotis, K and Kagiannas, A and Askounis, D and Psarras, J, “Artificial intelligence in short term electric load forecasting: a state-of-the-art survey for the researcher”, *Energy conversion and Management*, Vol.44, No.9, (2003), pp.1525-1534.
[7] Taylor, James W and De Menezes, Lilian M and McSharry, Patrick E, “A comparison of univariate methods for forecasting electricity demand up to a day ahead”, *International Journal of Forecasting*, Vol.22, No.2, (2006), pp.1-16.
[8] Hahn, Heiko and Meyer-Nieberg, Silja and Pickl, Stefan, “Electric load forecasting methods: Tools for decision making”, *European journal of operational research*, Vol.199, No.3, (2009), pp.902-907.
[9] Hernandez, Luis and Baladron, Carlos and Aguiar, Javier M and Carro, Belén and Sanchez-Esguevillas, Antonio J and Lloret, Jaime and Massana, Joaquim, “A survey on electric power demand forecasting: future trends in smart grids, microgrids and smart buildings”, *IEEE Communications Surveys & Tutorials*, Vol.16, No.3, (2014), pp.1460-1495.
[10] Campo, R and Ruiz, P, “Adaptive weather-sensitive short term load forecast”, *IEEE Transactions on Power Systems*, Vol.2, No.3, (1987), pp.592-598.
[11] Zhang, Guoqiang and Patuwo, B Eddy and Hu, Michael Y, “Forecasting with artificial neural networks:: The state of the art”, *International journal of forecasting*, Vol.14, No.1, (1998), pp.35-62.
[12] Hyndman, Rob J and Koehler, Anne B, “Another look at measures of forecast accuracy”, *International journal of forecasting*, Vol.22, No.4, (2006), pp.679-688.
[13] Guan, Che and Luh, Peter B and Michel, Laurent D and Wang, Yuting and Friedland, Peter B, “Very short-term load forecasting: wavelet neural networks with data pre-filtering”, *IEEE Transactions on Power Systems*, Vol.28, No.1, (2012), pp.30-41.
[14] Hsiao, Yu-Hsiang, “Household electricity demand forecast based on context information and user daily schedule analysis from meter data”, *IEEE Transactions on Industrial Informatics*, Vol.11, No.1, (2014), pp.33-43.
[15] Laouafi, Abderrezak and Mordjaoui, Mourad and Haddad, Salim and Boukelia, Taqiy Eddine and Ganouche, Abderahmane, “Online electricity demand forecasting based on an effective forecast combination methodology”, *Electric Power Systems Research*, Vol.148, No.1, (2017), pp.35-47.
[16] Penya, Yoseba K and Borges, Cruz E and Fernández, Iván, “Short-term load forecasting in non-residential buildings”, *IEEE Africon'11*, Vol.148, (2011), pp.1-6.
[17] Koo, Bon-gil and Lee, Heung-seok and Park, Juneho, “A study on short-term electric load forecasting using wavelet transform”, *IEEE PES Innovative Smart Grid Technologies, Europe*, (2014), pp.1-6.
[18] Khwaja, AS and Naeem, M and Anpalagan, A and Venetsanopoulos, A and Venkatesh, B, “Improved short-term load forecasting using bagged neural networks”, *Electric Power Systems Research*, Vol.125, (2015), pp.109-115.
[19] Khwaja, AS and Zhang, X and Anpalagan, A and Venkatesh, B, “Boosted neural networks for improved short-term electric load forecasting”, *Electric Power Systems Research*, Vol.143, (2017), pp.431-437.
[20] Hong, Wei-Chiang, “Electric load forecasting by seasonal recurrent SVR (support vector regression) with chaotic artificial bee colony algorithm”, *Energy*, Vol.36, No.9, (2011), pp.5568-5578.
[21] Hong, Wei-Chiang and Dong, Yucheng and Lai, Chien-Yuan and Chen, Li-Yueh and Wei, Shih-Yung, “SVR with hybrid chaotic immune algorithm for seasonal load demand forecasting”, *Energies*, Vol.4, No.6, (2011), pp.960-977.
[22] Feilat, EA and Bouzguenda, M, “Medium-term load forecasting using neural network approach”, *2011 IEEE PES Conference on Innovative Smart Grid Technologies-Middle East*, (2011), pp.1-5.
[23] Lee, Woo-Joo and Hong, Jinkyu, “A hybrid dynamic and fuzzy time series model for mid-term power load forecasting”, *International Journal of Electrical Power & Energy Systems*, Vol.64, (2015), pp.1057-1062.
[24] Al-Hamadi, HM, “Long-term electric power load forecasting using fuzzy linear regression technique”, *IEEE Power Engineering and Automation Conference*, Vol.3, (2011), pp.96-99.
[25] Li, Hongze and Guo, Sen and Zhao, Huiru and Su, Chenbo and Wang, Bao, “Annual electric load forecasting by a least squares support vector machine with a fruit fly optimization algorithm”, *Energies*, Vol.5, No.11, (2012), pp.4430-4445.
[26] Wang, Jianjun and Li, Li and Niu, Dongxiao and Tan, Zhongfu, “An annual load forecasting model based on support vector regression with differential evolution algorithm”, *Applied Energy*, Vol.94, (2012), pp.65-70.
[27] Li, Hong-Ze and Guo, Sen and Li, Chun-Jie and Sun, Jing-Qi, “A hybrid annual power load forecasting model based on generalized regression neural network with fruit fly optimization algorithm”, *Knowledge-Based Systems*, Vol.37, (2013), pp.378-387.

[28] Vu, Dao H and Muttaqi, Kashem M and Agalgaonkar, Ashish P, "Short-term load forecasting using regression based moving windows with adjustable window-sizes", *IEEE Industry Application Society Annual Meeting*, (2014), pp.1-8.
[29] Dudek, Grzegorz, "Pattern-based local linear regression models for short-term load forecasting", *Electric Power Systems Research*, Vol.130, (2016), pp.139-147.
[30] Taylor, James W, "Short-term load forecasting with exponentially weighted methods", *IEEE Transactions on Power Systems*, Vol.27, No.1, (2011), pp.458-464.
[31] Box, George EP and Jenkins, Gwilym M, "Time series analysis: Forecasting and control San Francisco", *Calif: Holden-Day*, (1976).
[32] Lee, Cheng-Ming and Ko, Chia-Nan, "Short-term load forecasting using lifting scheme and ARIMA models", *Expert Systems with Applications*, Vol.38, No.5, (2011), pp.5902-5911.
[33] He, Hongming and Liu, Tao and Chen, Ruimin and Xiao, Yong and Yang, Jinfeng, "High frequency short-term demand forecasting model for distribution power grid based on ARIMA", *2012 IEEE International Conference on Computer Science and Automation Engineering (CSAE)*, Vol.3, No.5, (2012), pp.293-297.
[34] Matsila, Hulisani and Bokoro, Pitshou, "Load forecasting using statistical time series model in a medium voltage distribution network", *IECON 2018-44th Annual Conference of the IEEE Industrial Electronics Society*, (2018), pp.4974-4979.
[35] Alberg, Dima and Last, Mark, "Short-term load forecasting in smart meters with sliding window-based ARIMA algorithms", *Vietnam Journal of Computer Science*, Vol.5, No.3-4, (2018), pp.241-249.
[36] Almeshaiei, Eisa and Soltan, Hassan, "A methodology for electric power load forecasting", *Alexandria Engineering Journal*, Vol.50, No.2, (2011), pp.137-144.
[37] Fan, Shu and Hyndman, Rob J, "Short-term load forecasting based on a semi-parametric additive model", *IEEE Transactions on Power Systems*, Vol.27, No.1, (2011), pp.134-141.
[38] Goude, Yannig and Nedellec, Raphael and Kong, Nicolas, "Local short and middle term electricity load forecasting with semi-parametric additive models", *IEEE transactions on smart grid*, Vol.5, No.1, (2013), pp.440-446.
[39] Ding, Ni and Bésanger, Yvon and Wurtz, Frédéric, "Next-day MV/LV substation load forecaster using time series method", *Electric Power Systems Research*, Vol.119, (2015), pp.345-354.
[40] Khosravi, Abbas and Nahavandi, Saeid and Creighton, Doug and Srinivasan, Dipti, "Interval type-2 fuzzy logic systems for load forecasting: A comparative study", *IEEE Transactions on Power Systems*, Vol.27, No.3, (2012), pp.1274-1282.
[41] Mukhopadhyay, P and Mitra, G and Banerjee, S and Mukherjee, G, "Electricity load forecasting using fuzzy logic: Short term load forecasting factoring weather parameter", *2017 7th International Conference on Power Systems (ICPS)*, (2017), pp.812-819.
[42] Hernandez, Luis and Baladrón, Carlos and Aguiar, Javier and Carro, Belén and Sanchez-Esguevillas, Antonio and Lloret, Jaime, "Short-term load forecasting for microgrids based on artificial neural networks", *Energies*, Vol.6, No.3, (2013), pp.1385-1408.
[43] Webberley, Ashton and Gao, David Wenzhong, "Study of artificial neural network based short term load forecasting", *2013 IEEE Power & Energy Society General Meeting*, (2013), pp.1-4.
[44] Rodrigues, Filipe and Cardeira, Carlos and Calado, João Manuel Ferreira, "The daily and hourly energy consumption and load forecasting using artificial neural network method: a case study using a set of 93 households in Portugal", *Energy Procedia*, Vol.62, (2014), pp.220-229.
[45] Zjavka, Ladislav and Snášel, Václav, "Short-term power load forecasting with ordinary differential equation substitutions of polynomial networks", *Electric Power Systems Research*, Vol.137, (2016), pp.113-123.
[46] Warrior, Karun P and Shrenik, M and Soni, Nimish, "Short-term electrical load forecasting using predictive machine learning models", *2016 IEEE Annual India Conference (INDICON)*, (2016), pp.1-6.
[47] Ertugrul, Ömer Faruk, "Forecasting electricity load by a novel recurrent extreme learning machines approach", *International Journal of Electrical Power & Energy Systems*, Vol.78, (2016), pp.429-435.
[48] Houimli, Rim and Zmami, Mourad and Ben-Salha, Ousama, "Short-term electric load forecasting in Tunisia using artificial neural networks", *Energy Systems*, Vol.78, pp.1-19.
[49] Almalaq, Abdulaziz and Edwards, George, "A review of deep learning methods applied on load forecasting", *2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA)*, (2017), pp.511-516.
[50] Ryu, Seunghyoung and Noh, Jaekoo and Kim, Hongseok, "Deep neural network based demand side short term load forecasting", *Energies*, Vol.10, No.1, (2016), pp.3.
[51] Zheng, Jian and Xu, Cencen and Zhang, Ziang and Li, Xiaohua, "Electric load forecasting in smart grids using long-short-term-memory based recurrent neural network", *2017 51st Annual Conference on Information Sciences and Systems (CISS)*, (2017), pp.1-6.
[52] Narayan, Apurva and Hipel, Keith W, "Long short term memory networks for short-term electric load forecasting", *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, (2017), pp.2573-2578.
[53] Liu, Chang and Jin, Zhijian and Gu, Jie and Qiu, Caiming, "Short-term load forecasting using a long short-term memory network", *2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, (2017), pp.1-6.
[54] Kong, Weicong and Dong, Zhao Yang and Jia, Youwei and Hill, David J and Xu, Yan and Zhang, Yuan, "Short-term residential load forecasting based on LSTM recurrent neural network", *IEEE Transactions on Smart Grid*, Vol.10, No.1, (2017), pp.841-851.
[55] Kong, Weicong and Dong, Zhao Yang and Hill, David J and Luo, Fengji and Xu, Yan, "Short-term residential load forecasting based on resident behaviour learning", *IEEE Transactions on Power Systems*, Vol.33, No.1, (2017), pp.1087-1088.
[56] Shi, Heng and Xu, Minghao and Li, Ran, "Deep learning for household load forecasting—A novel pooling deep RNN", *IEEE Transactions on Smart Grid*, Vol.9, No.5, (2017), pp.5271-5280.
[57] Vapnik, Vladimir N, "The nature of statistical learning", *Theory*, (1995).
[58] Zhang, Zhiheng and Ye, Shijie, "Long term load forecasting and recommendations for china based on support vector regression", *2011 International conference on information management, innovation management and industrial engineering*, Vol.3, (2011), pp.597-602.
[59] Thokala, Naveen Kumar and Bapna, Aakanksha and Chandra, M Girish, "A deployable electrical load forecasting solution for commercial buildings", *2018 IEEE International Conference on Industrial Technology (ICIT)*, (2018).
[60] Nie, Hongzhan and Liu, Guohui and Liu, Xiaoman and Wang, Yong, "Hybrid of ARIMA and SVMs for short-term load forecasting", *Energy Procedia*, Vol.16, (2012), pp.1455-1460.
[61] Ko, Chia-Nan and Lee, Cheng-Ming, "hort-term load forecasting using SVR (support vector regression)-based radial basis function neural network with dual extended Kalman filter", *Energy*, Vol.49, (2013), pp.413-422.
[62] Ebrahimi, Akbar and Moshari, Amir, "Holidays short-term load forecasting using fuzzy improved similar day method", *International transactions on electrical energy systems*, Vol.23, No.8, (2013), pp.1254-1271.
[63] Dudek, Grzegorz, "Short-term load cross-forecasting using pattern-based neural models", *2015 16th International Scientific Conference on Electric Power Engineering (EPE)*, (2015), pp.179-183.
[64] Li, Song and Goel, Lalit and Wang, Peng, "An ensemble approach for short-term load forecasting by extreme learning machine", *Applied Energy*, Vol.170, (2016), pp.22-29.
[65] Bantugon, Mary Joyce T and Gallano, Russel John C, "Short-and long-term electricity load forecasting using classical and neural network based approach: A case study for the Philippines", *2016 IEEE Region 10 Conference (TENCON)*, (2016), pp.3822-3825.
[66] Qiu, Xueheng and Ren, Ye and Suganthan, Ponnuthurai Nagaratnam and Amaratunga, Gehan AJ, "Empirical mode decomposition based ensemble deep learning for load demand time series forecasting", *Applied Soft Computing*, Vo.54, (2017), pp.246-255.
[67] Akarslan, Emre and Hocaoglu, Fatih Onur, "A novel short-term load forecasting approach using Adaptive Neuro-Fuzzy Inference System", *2018 6th International Istanbul Smart Grids and Cities Congress and Fair (ICSG)*, (2018), pp.160-164.
[68] Liu, Feng and Wang, Zhifang, "Electric load forecasting using parallel RBF neural network", *2013 IEEE Global Conference on Signal and Information Processing*, (2013), pp.531-534.
[69] Xiao, Liye and Xiao, Liyang, "Combined modeling for electrical load forecasting with particle swarm optimization", *2014 IEEE Workshop on Electronics, Computer and Applications*, (2014), pp.395-400.
[70] Ghayekhloo, M and Menhaj, MB and Ghofrani, M, "A hybrid short-term load forecasting with a new data preprocessing framework", *Electric Power Systems Research*, Vo.119, (2015), pp.138-148.
[71] Xiao, Liye and Wang, Jianzhou and Hou, Ru and Wu, Jie, "A combined model based on data pre-analysis and weight coefficients optimization for electrical load forecasting", *Energy*, Vo.82, (2015), pp.524-549.

[72] Liang, Yi and Niu, Dongxiao and Hong, Wei-Chiang, "Short term load forecasting based on feature extraction and improved general regression neural network model", *Energy*, Vo.166, (2019), pp.653-663.

[73] Ahmad, Ashfaq and Javaid, Nadeem and Mateen, Abdul and Awais, Muhammad and Khan, Zahoor, "Short-term load forecasting in smart grids: an intelligent modular approach", *Energies*, Vo.12, No.1, (2019), pp.164.

[74] Gao, Wei and Darvishan, Ayda and Toghani, Mohammad and Mohammadi, Mohsen and Abedinia, Oveis and Ghadimi, Noradin, "Different states of multi-block based forecast engine for price and load prediction", *International Journal of Electrical Power & Energy Systems*, Vo.104, (2019), pp.423-435.

[75] Singh, Priyanka and Dwivedi, Pragya and Kant, Vibhor, "A hybrid method based on neural network and improved environmental adaptation method using Controlled Gaussian Mutation with real parameter for short-term load forecasting", *Energy*.

[76] Ceperic, Ervin and Ceperic, Vladimir and Baric, Adrijan, "A strategy for short-term load forecasting by support vector regression machines", *IEEE Transactions on Power Systems*, Vo.28, No.4, (2013), pp.4356-4364.

[77] Kavousi-Fard, Abdollah and Samet, Haidar and Marzbani, Fatemeh, "A new hybrid modified firefly algorithm and support vector regression model for accurate short term load forecasting", *Expert systems with applications*, Vo.41, No.13, (2014), pp.6047-6056.

[78] Selakov, A and Cvijetinović, D and Milović, L and Mellon, S and Bekut, D, "Hybrid PSO–SVM method for short-term load forecasting during periods with significant temperature variations in city of Burbank", *Applied Soft Computing*, Vo.16, (2014), pp.80-88.

[79] Yang, Ailing and Li, Weide and Yang, Xuan, "Short-term electricity load forecasting based on feature selection and Least Squares Support Vector Machines", *Knowledge-Based Systems*, Vo.163, (2019), pp.159–173.

[80] Barman, Mayur and Choudhury, Nalin Behari Dev, "Season specific approach for short-term load forecasting based on hybrid FA-SVM and similarity concept", *Energy*, Vo.174, (2019), pp.886-896.

[81] Bahrami, Saadat and Hooshmand, Rahmat-Allah and Parastegari, Moein, "Short term electric load forecasting by wavelet transform and grey model improved by PSO (particle swarm optimization) algorithm", *Energy*, Vo.72, (2014), pp.434-442.

[82] Ray, Papia and Sen, Santanu and Barisal, AK, "Hybrid methodology for short-term load forecasting", *2014 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES)*, (2014), pp.1-6.

[83] Li, Song and Wang, Peng and Goel, Lalit, "Short-term load forecasting by wavelet transform and evolutionary extreme learning machine", *Electric Power Systems Research*, Vo.122, (2015), pp.96-103.

[84] Ziel, Florian, "Modelling and forecasting electricity load using Lasso methods", *2015 Modern Electric Power Systems (MEPS)*, (2015), pp.1-6.

[85] Zeng, Nianyin and Zhang, Hong and Liu, Weibo and Liang, Jinling and Alsaadi, Fuad E, "A switching delayed PSO optimized extreme learning machine for short-term load forecasting", *Neurocomputing*, Vo.240, (2017), pp.175-182.