A Review on Short-Term Load Forecasting Using Different Techniques

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Nomenclature

STLF	Short-Term Load Forecasting
LR	Linear Regression
TS	Time Series
GES	General Exponential Smoothing
SS	State Space
KBES	Knowledge-Based Expert System
ALF	Adaptive Load Forecasting
IRLS	Iterative Reweighted Least Squares
SD	Similar Day
DM	Data Mining
FL	Fuzzy Logic
NN	Neural Network
WT	Wavelet Transform
SVM	Support Vector Machine
EA	Evolutionary Algorithm
ANN	Artificial Neural Network
HRESDR	Hybrid Renewable Energy Sources and Demand Response
AR	Autoregressive
MA	Moving average
ARMA	Autoregressive Moving average

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ARIMA	Autoregressive Integrated Moving average
SARIMA	Seasonal Autoregressive Integrated Moving average
MAPE	Mean Absolute Percentage Error
PV	Photovoltaic
FC	Fuel Cell
NVC	Novel Voltage Controller
BESS	Battery Energy Storage System
STATCOM	Static Synchronous Compensator

1 Introduction

Power system plays a significant role with short-term load forecasting (STLF) for electricity distribution. The load prediction for 24 h ahead (STLF) is required in different areas of the energy system such as generation, transmission, and distribution sites. The energy system takes different decisions with STLF such as unit commitment, spinning reserve capacity, device maintenance plan, etc. When STLF calculates the load 24 h ahead in power system operation, unsuitable load determination will make high cost [1]. So, that different statistical and artificial intelligence (AI) methods have been applied in STLF to calculate the load simply with consideration of important factors. Generally, these factors are weather, dates, etc. Today also, these factors are important for the construction of load structures with new techniques [2]. With the implementation of programs and artificial intelligence (AI) techniques, various excellent parts of the investigation are attracted to statistical [3] and AI [4] methods for the prediction of demand. This review manuscript includes some important statistical and AI methods. Statistical methods are linear regression (LR), time series (TS), general exponential smoothing (GES), state-space (SS), knowledge-based expert system (KBES), adaptive load forecasting (ALF), iterative reweighted least-squares (IRLS), similar day (SD), data mining (DM), and AI techniques are fuzzy logic (FL), neural network (NN), wavelet transform (WT), support vector machine (SVM), and evolutionary algorithm (EA) are powerful methods for STLF.

The AI techniques without computational algorithms can be divided into several different methods. Similarly, it should be known that the various intelligence techniques will not be considered as various methods for STLF. The methods are used to find out the output of forecasting, while techniques are used for computational calculation like LR or NN computational calculation. Such as in [5, 6], both manuscripts have used artificial neural networks (ANN) for STLF with different approaches. The paper in [5] presents less error using a stepwise approach, while in [6], it explains the calculation of daily demand 24 h ahead using the SD method. The calculation of error is not significant but utilization of method is important. Normally, at the time of exact prediction of load in STLF, both techniques, as well as methods, are significant. But reviews on methods are less as compare to techniques because maximum surveys find STLF techniques [7, 8]. In [8], the STLF method is divided by statistical methods as well as AI techniques. In [7], a survey is presented on STLF using ANN. This survey uses important methods; still, also new investigators are unable to understand the advantages regarding the construction of a particular load structure. All types of difficulties will be cleared by this review manuscript where different methods are applied for STLF using AI techniques. A significant survey on methods and techniques is given by different investigators to clear the difficulties for new investigators in this manuscript. These methods and approaches are divided into 14 classes depending on their work. Each method and technique are cleared by effective work on the construction of load structure.

The other parts of this manuscript are categorized into the following ways. Section 2 gives a review of statistical methods as well as AI for subsection which presents details of each method and technique. Section 3 represents the merits and demerits of statistical methods as well as AI. Besides this, in Sect. 3, a hybrid method is proposed with merits. At last, the conclusion parts are discussed in Sect. 4.

2 STLF Techniques

The methods, as well as techniques, are helping to control the STLF. The selection of STLF techniques depends on various factors such as past data, prediction method, climate, exact prediction, etc. Similarly, the choice of the exact load estimation method is initially based on the time calculation of forecasting. The time calculation for load forecasting depends on effective work in designed energy areas. Such as from 1 hour to 1 week, STLF will be applicable for distribution as well as transmission areas, but for more than 1 year, the load prediction will apply for financial decisions as well as designed energy areas. Similarly, for the exact prediction of load, the periods are not the same because decision-making is primary in long term as well as large changes are required to construct the model because of variation of input information. But in STLF, the prediction stage is high because it gives the data 24 h ahead. Besides it, the various factors are required for each forecast such as long term load forecasting is considered with the demand of people, improvement of price, the building of plant as well as improvement of techniques, while STLF is normally considered with dates, climate as well as consumer's class. Normally, depending on the period, both the forecasts are very significant in running of the energy system as well as its improvement because of connection of distributed exciters to the power station which further connects with steady as well as the load for energy transmission. The survey of this manuscript is representing the importance of STLF techniques by utilizing a review of the research work in these areas. The techniques used for STLF can be implemented for long-term load forecasting. Based on time, the forecasters are not the same.

The 14 techniques discussed for STLF help to find out the solution to STLF difficulties. These 14 techniques are LR, TS, GES, SS, KBES, ALF, IRLS, SD, DM, FL, NN, WT, SVM, and EA which are classified according to their work on STLF. Such that LR is used to make the connection between load structure and various factors such as climate, date and consumer's class, etc. TS depends on information like autocorrelation and change of seasons to build a load structure. The GES technique is used to record the data for forecasting. SS method is used to design the structure. KBES is used to analyze the conclusion taken for the energy system corresponding to the prediction of load in the future. ALF functions in the control unit. IRLS method recognizes structure size and constraints. A SD approach calculates the past data with equal characteristics. DM gives the large information to construct the rule, learning, etc. FL helps to calculate the exact load by the connection between inputs and output with logic conditions. NN predicts the load with very fast speed and depends on the hidden layer. WT designs the transient properties of load structure and develops the work of traditional ANN. SVM divides the input information for accurate prediction of load as well as EA like genetic algorithm (GA), particle swarm optimization (PSO), artificial immune system (AIS), and ant colony optimization (ACO) to run the NN for good accuracy in STLF.

From above, it is found that the approaches are representing their effectiveness by examining the work but STLF does not work like that. So more surveys have been done on STLF with the above approaches. Such that the LR method minimizes the forecast error by selecting external factors like climate. Extra new methods also review for the above approaches like LR, weather-sensitive method, parametric regression technique, quantile regression method. Especially, the researchers are interested to do the work on STLF using metaheuristic techniques. The metaheuristic techniques consist of more than one technique applied to STLF. These investigations divide the approaches into 14 techniques for STLF. These techniques are significant to STLF because of their minimum error estimation and exactness of prediction.

The other techniques applied to STLF are hybrid renewable energy sources and demand response (HRESDR). The details of HRESDR are presented in Sect. 3. The HRESDR works for the balance between generation and load areas in STLF which automatically increases the efficiency of the plant as well as reduces the price of functioning. Thus, some techniques are also discussed for HRESDR where every technique has effective work in STLF. Some techniques calculate the exact load and other techniques control the power system. Till now, the novel approaches for HRESDR are demand forecasting, price forecasting as well as controlling the energy system. Due to the advantages of HRESDR, it is frequently applied in the energy system. Thus, HRESDR is considered as a new technique in STLF and novel techniques applicable for HRESDR are also discussed in this paper which supports the new researcher to work out on STLF.

With a discussion of HRESDR, one point should come to mind that how it is working with real information. The techniques applicable for HRESDR are highlighted in this manuscript to solve this question. The approaches which will be discussed for STLF are represented by a tree diagram as shown in Fig. 1. As the number of approaches can discuss for STLF like individual, group or hybrid wise. All 14 approaches are discussed to the equation, subsection, and construction of the model.

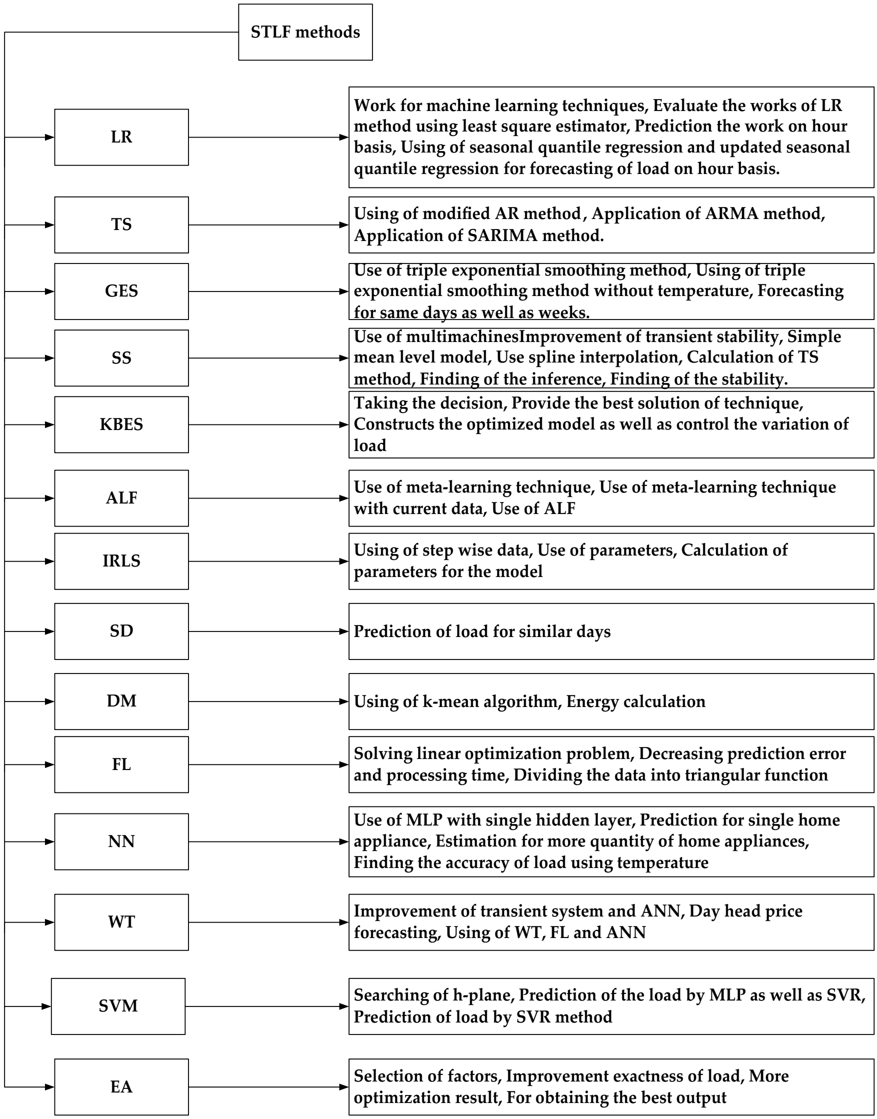

Fig. 1 Tree diagram of STLF methods

2.1 *Linear Regression (LR)*

It is a good forecasting method and is reported in [9]. STLF can use different approaches using the LR method. This method is suitable for its easiness and working. It creates a link among forecaster or various constraints and loads which will be forecasted. This method minimizes the forecast error due to its selection of exact factors.

Table 1 Error estimator technique for LR method

Paper	Method	Formula	Parameters
Hong and Fan [10]	Least square estimator	$\hat{\beta} = (\sum_{t=1}^{n} x_t y_t^T)^{-1} \sum_{t=1}^{n} x_t y_t (1)$	$\beta^{\hat{}}$ = least square estimator x_t = information of constraints controlling the load y_t = dependent variable

Table 2 Published articles of LR method

Publication	Proposed
Alfares and Nazeeruddin [9]	Finding the work of machine learning techniques
Hong and Fan [10]	Evaluate the works of the LR method using the least square estimator
Charlton and Singleton [11]	Prediction of the work on hour basis
Haben and Giasemidis [12]	Using seasonal quantile regression
Haben et al. [13]	Updated seasonal quantile regression for forecasting of load on an hour basis

By this method, we are familiar with various factors such as dates, historical demand, climate as well as a customer class.

Normally, regression coefficients are calculated by the least-square formula [10] in Eq. (1) as given in Table 1. This method also helps to predict the load on an hourly basis [11]. In [12, 13], the main function of this method is to estimate the dependent and independent factors. For the dependent factor, it calculates the average value and for the independent factor, it gives harmonics. In [12], the use of the seasonal quantile regression method was modified in [13] which is used for the prediction of load on an hourly basis. Table 2 gives an idea of the LR method with different suitable papers for STLF. The papers are classified based on their proposes like work on machine learning techniques, least-square estimator, prediction of load on hour basis, use of seasonal quantile regression, and update of seasonal quantile regression methods.

2.2 Time Series (TS)

This method is good for autocorrelation and alteration of seasons, etc. It is also applicable in other fields like price, digital wave transformation, and load prediction. It is suitable for time series methods like auto-regression (AR), moving average (MA) as well as autoregressive moving-average (ARMA) because these require past data dependent on time for prediction of load. So in this section, AR, MA as well as

Table 3 Published articles of TS method

Publication	Proposed
References [9, 13–15]	Using of modified AR method
Box et al. [16]	Application of ARMA method
Singh et al. [17]	Application of SARIMA method

Table 4 Published articles of the GES method

Publication	Proposed
Taylor [18]	Use of triple exponential smoothing method
Taylor [19]	Using of triple exponential smoothing method without temperature
References [13, 20]	Forecasting for same days as well as weeks

ARMA are reviewed. AR depends on past load as well as disturbance signal, whereas LR depends on outside factors like weather. It is also used for the prediction of load in consumer areas by using the Burg method for the calculation of constraints [13]. The updated AR is also applicable for load design. It is discussed with examples in [9, 14, 15] for the prediction of the total load. MA predicts the load by presentation as well as past unauthorized disturbance signals. This disturbance signal is created from the wrong prediction of previous values. The use of MA is large in prediction areas [16]. It also gives importance to seasonal ARMA [17]. The combination of AR and MA is known as ARMA. It predicts the load to be of subtracting type. It is also known as autoregressive integrated moving-average (ARIMA) whose work helps to predict the exact load [16, 17]. It can also use for seasonal methods like an hour, 24 h, week, month, annual, or other time series method which is called seasonal autoregressive integrated moving-average (SARIMA) [17]. In Table 3, the TS method is classified by different researcher's which is explained by various important papers.

2.3 General Exponential Smoothing (GES)

It constructs the load structure from calculated data. In [18], it is called as Holt-Winter exponential smoothing method which is first used by [19]. In [13, 20], the same model is used for STLF with the addition of same day and same week. The GES method explains the work for STLF with different manuscripts in Table 4.

2.4 State Space (SS)

This method approaches the control of linear and nonlinear in energy areas [21, 22]. It is used for the determination of unrecorded parameters. The working of this method

Table 5 Published articles of SS method

Publication	Proposed
Chen et al. [21]	Use of multi-machines
Wang and Qiu [22]	Improvement of transient stability
Durbin and Koopman [23]	Simple mean level model
Valderramam et al. [24]	Use spline interpolation
Samé and El-Assaad [25]	Calculation of TS method
Helske [26]	Finding of the inference
Koopman and Durbin [27]	Finding of the stability

is to first convert the unrecorded data into recorded parameters and then apply the Kalman filter for the calculation. This method can construct more structure for STLF with logic as well as accuracy. It can transfer ARMA or vice versa. It contains many changes but very concise to build the model. This method is very sensitive to STLF [23–25]. Inference and stability of SS models are explained in [26, 27]. The work of the SS method is explained in Table 5 with important manuscripts.

2.5 Knowledge-Based Expert System (KBES)

It means some rules are implemented for the prediction of load in STLF. Here, we are considering the rule made by experts in required areas which are called decision methods. The algorithms are written by the decision taken for STLF which is further converted to software knowledge for prediction of load without experts. So, this approach depends on rules as well as constraints affecting the load which will be calculated from rule-based areas. These rule-based areas help in STLF and efficiency will increase by consulting corresponding experts. This model is approached in STLF with different factors for exact load estimation in [28] as well as it is considered for the representation of various techniques [29]. So, this method is discussed in the construction of the model with GA, as well as Cooperative ACO in [30]. Table 6 helps the new researcher in finding the work of the KBES method from the citations.

Table 6 Published articles of the KBES method

Publication	Proposed
Kyriakides and Polycarpou [28]	Taking the decision
Tripathi [29]	Provide the best solution of technique
Ghanbari [30]	Constructs the optimized model as well as control the variation of load

Table 7 Published articles of ALF method

Publication	Proposed
Vilalta and Drissi [31]	Use of the meta-learning technique
Vilalta et al. [32]	Use of meta-learning technique with current data
Matijaš et al. [33]	Use of ALF

2.6 Adaptive Load Forecasting (ALF)

Normally, the methods are predicted by the load with knowing past information during the test period and errors are coming in forecasting results due to unnecessary data and some other methods predict the load with unnecessary past information. These types of demerits are removed by ALF. The working capacity of STLF is also increased by this approach.

In this method, the load is predicted automatically with minimization of error and a meta-learning technique is discussed for the prediction of load [31]. This technique is the best algorithm for the present information [32] and this technique is compared with ALF in [33]. When techniques are more in ALF, the time taken for calculation will increase. The result in ALF is considered for particular conditions. The model of ALF is cheap which provides the updating model for novel techniques and this is the merit of ALF. It helps in the selection of the best constraints for the construction of the model. Table 7 explains the important purposes of the ALF method in STLF with new citations.

2.7 Iterative Reweighted Least Square (IRLS)

It helps to find the structure size as well as constraints [34]. The parameters are controlled at any time by the controller [35]. This method calculates the value of the weight, tuning capacity as well as total weighted value in the number of ideas for constructing the good structure as well as confirms the constraints of prediction [36]. The IRLS method helps to predict the load in STLF by handling of data as well as parameters in Table 8.

Table 8 Published articles of IRLS method

Publication	Proposed
Almeshaiei and Soltan [34]	Using stepwise data
Srivastava et al. [35]	Use of parameters
Singh et al. [36]	Calculation of parameters for the model

Table 9 Published articles of SD method

Publication	Proposed
References [37–41]	Prediction of load for similar days

Table 10 Published articles of DM method

Publication	Proposed
Kim et al. [42]	Using of k-mean algorithm
Devi and Manonmani [43]	Energy calculation

2.8 *Similar Day (SD)*

In this method, the past load should have the same properties for the prediction of load and it is searched by this method [37–41]. The past load carries the information for one, two, or three years like that. The prediction of load from past information of the same characteristics like climate, day of the week as well as the calendar is considered as predicted load. The prediction load consists of the same characteristics of various dates regardless of a single date. The constraints of past times are utilized for this method. This approach is also applicable for the prediction of load at low as well as high frequency. Nowadays, the prediction of load with similar days is very important which has been given in Table 9 with important manuscripts.

2.9 *Data Mining (DM)*

It is the best approach in STLF where information is discussed and makes it suitable information because it helps to make conditions, learning, etc. It correctly forecasts the cost of electricity as well as separates them for design [42] which uses the technique of k-mean for the separation of information. It is also surveyed for the prediction of load using STLF [43]. It is formed of a hybrid method for STLF using the LR method as well as ANN. This method divides the load information into different groups as well as calculates the suitable groups for the prediction of load according to dividing methods. After that, the load information runs with MLP for every group. Table 10 explains the work of the DM method in STLF with different citations.

2.10 *Fuzzy Logic (FL)*

This method is applied in STLF for the accurate prediction of load. It uses Boolean logic for the construction of the model and makes the connection between inputs and outputs. This advantage constructs the strong structure for STLF. In [44], explains

Table 11 Published articles of FL method

Publication	Proposed
Al-Kandari et al. [44]	Solving the linear optimization problem
Mamlook et al. [45]	Decreasing prediction error and processing time
Aggarwal et al. [46]	Dividing the data into the triangular function

the prediction of load in summer as well as winter season. The forecasted value with the fuzzy method is good as compare to the conventional method [45]. In [46], the information is performed with the fuzzy condition and the defuzzification is applied to the output of the system. The error is calculated by adaptive fuzzy interference system in load forecasting which is less. It is best in terms of exactness, strongness, and simplicity as compared to ANN. The work of the FL method is very sensitive to STLF which predicts the load accurately knowing its proposes from Table 11.

2.11 Neural Network (NN)

A NN is also known as an ANN. The work of ANN is similar to the human brain. Such as it takes and processes the information through nodes (neurons). From input to output, it consists of a hidden layer (invisible layer). The learning of ANN depends on the hidden layer. It means if calculation is faster then it consists of one or two hidden layers or if the calculation is very deep, then it consists of more hidden layers. So that it predicts the exact load for the value of time which is complicated. ANN runs with active function (hyperbolic tangent or sigmoid function) is known as backpropagation (BP). In [47–49], ANN is used as a multi-layer perceptron (MLP) when there is the necessity of prediction of consumers personally, calculation as well as the value of time. In [48, 49], MLP is described in personal information of intelligent meter with two samples which consist of the single hidden layer. In [48], MLP consist of 49, 38 as well as 24 perceptrons in input, hidden as well as output layers, respectively, which are used for the prediction of load on an hourly basis. In [49], MLP consists of 200 perceptrons for the calculation of load (a large number of home appliances) among exact as well as correct period. In [13], temperature affects the exactness of load. NN is a simple and easy method for a new researcher by knowing the purpose from Table 12 with important citations.

Table 12 Published articles of NN method

Publication	Proposed
Wijaya et al. [47]	Use of MLP with the single hidden layer
Gajowniczek and Zabkowski[48]	Prediction for single home appliance
Zufferey et al. [49]	Estimation for more quantity of home appliances
Haben et al. [13]	Finding the accuracy of load using temperature

Table 13 Published articles of WT method

Publication	Proposed
Li and Fang [50]	Improvement of the transient system and ANN
Tan et al. [51]	Day head price forecasting
Chauhan and Hanmandlu [52]	Using WT, FL, and ANN

2.12 *Wavelet Transform (WT)*

It is used to design the nonlinear transient as well as develop the working of conventional ANN [50]. It builds three layers using an evolutionary algorithm (EA) such as wavelet node which is the first layer used to break the input signal to form the different range of signal and the second layer of WT is the weighting node whose function is to assign this signal with a value of weight. Now, this weighted value binds with output by the third layer summing node. After this, the WT runs by EA to form the best solution for STLF. The information for STLF is considered from the Taiwan grid. Now the result of wavelet transform is compared with NN-BP. The result of WT-ANN is good, exact as well as faster in response. It brings a good result for price forecasting compared to other methods in STLF [51]. Wavelet fuzzy neural network is apply's for the prediction of load in STLF [52]. It is a new technique for STLF where the prediction of load depends on the works of WT which are given in Table 13 with new citations.

2.13 *Support Vector Machine (SVM)*

It is an AI technique that works with division. In [53], it divides the input information by searching the affective plane. This plane divides the groups (similar characteristics) utilizing properties that may be considered valuable. This effective plane is known as the hyperplane (h-plane). Therefore, the work of SVM in searching the h-plane which represents the separation of nearest value is high. In [54, 55], SVM is used in the regression method (SVR) for the prediction of load. Here, SVR divides

Table 14 Published articles of the SVM method

Publication	Proposed
Dunant and Zufferey[53]	Searching of h-plane
Humeau et al. [54]	Prediction of the load by MLP as well as SVR
Vrablecova et al. [55]	Prediction of load by SVR method

Table 15 Published articles of EA method

Publication	Proposed
References [56–59]	Selection of factors
References [60–64]	Improvement exactness of load
References [65–69]	More optimization in result
References [70–72]	For obtaining the best output

the information without h-plane. The work of SVR is to search the exact method which is closed to the exact calculation of load with minimum error. In [54], the prediction of load for hour basis as well as 24 h ahead is done by MLP as well as SVR by taking the information of Irish intelligent meter. In [55], the prediction of the load is done by the SVR method as well as kernel method by taking the information from the Irish intelligent meter. Thus, in the above studies, we decide that SVR is the best method for the prediction of total load, and its effectiveness decreases for a single load. Table 14 gives the important purposes of SVM which is not only helpful to predict the load bus but also used in STLF.

2.14 Evolutionary Algorithm (EA)

It consists of machine learning techniques such as GA [56–59], PSO [60–64], AIS [65–69] as well as ACO [70–72], etc. In STLF, this method is used to run the ANN. The predicted load obtained by this technique is more accurate for BP. Table 15 helps to know the proposed work of EA in STLF.

3 Method Evaluation

STLF is completely discussed in the previous section with different approaches. Normally, every approach has some effective work on STLF. So, researcher can choose any method depending upon the research work. As LR method bring the relation between load which will predict and external factors like climate, dates as well as consumer class. But TS depends on information like autocorrelation, changes of season, etc. So the researcher can analyze the research work whether the research work is constructing of the model with an external factor or completely depends on information to predict the demand because the load is nonlinear. The merits and demerits of every approach have been written in Table 16. Such as in the LR method, designing the model of load structure with external factors will not get in the TS method which will depend on information like autocorrelation, variation in the season like summer, winter, or rain. In the approaches, some characteristics may be the same but their application to the STLF is different. So, one demerit column is also added in Table 16. The LR method helps to construct the structure with external factors which forecast the load 24 h ahead in STLF, while the AI is working with little information. Finding the exactness of various factors in the LR approach is the same in TS. Such as in [12], the TS method is applied to the design of ARMA with various factors.

Like other technique is HRESDR, where the LR or TS method may be considered for the prediction of load in STLF. For the GES method, a researcher can work with external factor like white noise. The use of HRESDR is reducing the price of the generation of electricity [73, 74] as well as meeting the demand [75, 76]. So that, it can meet the demand of the whole country [77, 78], and sometimes the HRESDR is not able to meet with the demand due to some unfavorable conditions such as weather [79, 80]. The photovoltaic (PV) cell is a good example of HRESDR in [81].

It can meet all conditions of generation as well as demand areas [74, 76, 82–89]. Such as solar-wind [86], wind-PV-hydrogen [90], hybrid solar structure with diesel exciter [19] as well as PV-diesel-battery [20] are used for the prediction of load. It is also using in large power system areas with more optimization techniques [91] and helps to reduce the price of operation in power systems [89]. It runs the small as well as large grids [73, 74, 76, 83, 88, 92]. The HRESDR helps researchers with the design of the structure, transfer of electricity and accurate forecasting, etc. It will be used for a power system where the load is fixed [93, 94] and make more profit to electricity areas [95, 96]. It also provides electricity using a battery [97]. The HRESDR can work for more generating as well as more storage areas [92]. From the above discussion, a new researcher can know the advantages of HRESDR and its stability in fault, demand prediction, and control of voltages, etc., which are also reviewed by some other effective manuscripts which have been discussed as follows.

The use of MLP/garch model, WT as well as forecasting components predict the accurate demand [98]. But a large amount of power acquired from hybrid wind-PV-FC (fuel cell) using radial basis function network sliding model (RBFSM) with the best speed of turbine [99]. The energy system is improving by good prediction of load [100]. With the use of vanadium redox battery and solar energy, the novel voltage controller (NVC) model is increased by the emission of carbon dioxide (CO_2) [101]. The result of the hybrid approach is increased for ARIMA as well as ANN on nonlinear structure [102]. The operation of the power system becomes smooth with good control of demand on the flexible system [103] and the energy is properly utilized using the price forecasting method in the energy system [104]. The SS, and enKF (enable Kalman filter) methods are used for the design of electricity demand in [105]. The unsymmetrical fault is also improved using a hybrid compensator for the microgrid (MG) distribution system [106]. The ground fault of the microgrid

Table 16 Merits and Demerits of STLF techniques

Method	Merits	Demerits
Linear regression (LR)	• Dependent variables are important • The cost of electricity is the dependent variable	• The consideration of the first variable is the independent variable • The weather-related such as temperature, humidity, or wind speeds are independent variables
Time series (TS)	• Datasets are checked sequentially • The cost of operation is less	• Its work is not effective • The searching for an energy source is critical
General exponential smoothing (GES)	• The prediction of the load is exact • It gives exact observation	• The predicted load is lagging behind the actual trend • The changes are not controlled well
State-space (SS)	• It helps to find the unrecorded data	• The static information is only working with this method
Knowledge-based expert system (KBES)	• It is a software method • The construction of the structure has been done by experts	• It depends on the expert • The off-line rules are implementing
Adaptive load forecasting (ALF)	• It is a meta-learning-based technique	• It is difficult to find the local optima as well as convergence
Iterative reweighted least square (IRLS)	• It helps in the construction of model size as well as constraints	• Its accuracy depends on choosing of parameters
Similar day (SD)	• A load of a similar day is considered as predict	• It is very difficult to consider the similar conditions of load

(continued)

Table 16 (continued)

Method	Merits	Demerits
Data mining (DM)	• It gives the exact load information • MAPE (Mean absolute percentage error) is less	• The input information is dividing
Fuzzy logy (FL)	• It makes the connection between input and output without the mathematical model • It does not depend on input without noise	• The design of the digital circuit depends on FL • It uses the rule for input data in the form of 0 or 1
Neural network (NN)	• The work of NN is similar to the human brain • It designs the nonlinear structure	• Implementation of the NN structure is critical • Over-fitting problems are occurring
Wavelet transforms (WT)	• The calculation time is very fast • It minimizes the error	• The decay of serial past information is allowing in subsequence
Support vector machine (SVM)	• The input information is divided by the decision boundary • The classification, as well as regression problems, are solved by this method	• The selection of kernel function creates a problem in STLF • The process of training is slow
Evolutionary algorithm (EA)	• It runs the ANN • The predicted load is more accurate	• Choosing the parameters is difficult

is improved by the direct building method and the details of the ground fault are discussed for the battery energy storage system (BESS) [107]. The use of energy systems is increased with a static synchronous compensator (STATCOM) by the reduction of fault, voltage support, and harmonics using the technique of a novel intelligent damping controller (NID) [108]. The details of the development of the power system as well as long-term load forecasting are given by [109].

4 Conclusions

This survey manuscript gives an idea of 14 approaches which are statistical methods like linear regression (LR), time series (TS), general exponential smoothing (GES), state-space (SS), knowledge-based expert system (KBES), adaptive load forecasting (ALF), iterative reweighted least-squares (IRLS), similar day (SD), data mining (DM) and artificial intelligence techniques are fuzzy logic (FL), neural network (NN), wavelet transform (WT), support vector machine (SVM), and evolutionary algorithm (EA) are used for prediction of load in STLF. The LR method is used for the prediction of the load with the estimation of load and various factors affecting the load like weather, date, historical load as well as customer's behavior. But the TS method helps to calculate the load 24 h ahead depending on past load. While the GES methods predict the load depending on the calculated data. Similarly, the SS method calculates the load based on the construction of the structure of the load. Another method of STLF is KBES which evaluates the future load by deciding on the trainer who controls the energy area. While the ALF helps to know the constraint situation which affects the load. Due to this, the accuracy of STLF is increasing. Another method of STLF is IRLS which calculates the size of the model as well as constraints because it is affecting the predicted load. These constraints are controlled by the trainer. Like, the SD method is used to find out the past data with the same characteristics which is good in STLF because the demand on the same day is considered as predicted load. While the DM gives more information to build the STLF such as new conditions, learning etc. and it is considering as a hybrid method over NN and LR. In STLF, the FL method helps to connect between the input as well as output of the system. So, that the system accuracy is increasing and the NN approach predicts the load with the help of hidden layer as well as MLP. But the WT method is used to design the transient nature of the load and helps to increase the performance of traditional ANN. The ANN has immunity to design the nonlinear curve fitting which consists of useful active function and trained learning process. The useful method in STLF is SVM which increases the accuracy of predicted load by considering the performance of parameters. It can also apply to nonlinear regression as well as time series problems. While the EA approach is good for the prediction of load by running, the NN as compared to BP and has immunity for finding. At last, by knowing the merits and demerits of every approach, STLF will strongly be applied to the individual method in a hybrid system. More works of the hybrid system on STLF are considered for future work.

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References

1. Shahidehpour M, Yamin H, Li Z (2003) Market operations in electric power systems: forecasting, scheduling, and risk management. John Wiley & Sons, Hoboken, NJ, USA
2. Hong T, Fan S (2016) Probabilistic electric load forecasting: a tutorial review. Int J Forecast 32:914–938
3. Amjady N (2001) Short-term hourly load forecasting using time-series modeling with peak load estimation capability. IEEE Trans Power Syst 16:498–505
4. Panda SK, Ray P, Mishra DP (2020) An efficient short term electric power load forecasting using hybrid techniques. Int J Comput Inf Syst Industr Manage Appl 12:387–397
5. Fan S, Hyndman RJ (2012) Short-term load forecasting based on a semi-parametric additive model. IEEE Trans Power Syst 27:134–141
6. Panda SK, Ray P, Mishra DP (2021) Short term load forecasting using metaheuristic techniques. IOP conference Series: Material Science and Engineering 1033:1–10
7. Moghram I, Rahman S (1989) Analysis and evaluation of five short-term load forecasting techniques. IEEE Trans Power Syst 4:1484–1491
8. Raza MQ, Khosravi A (2015) A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings. Renew Sustain Energy Rev 50:1352–1372
9. Alfares HK, Nazeeruddin M (2002) Electric load forecasting: literature survey and classification of methods. Int J Syst Sci 33(1):23–34
10. Hong T, Fan S (2016) Probabilistic electric load forecasting: a tutorial review. Int J Forecast 32(3):914–938
11. Charlton N, Singleton C (2014) A refined parametric model for short term load forecasting. Int J Forecast 30(2):364–368
12. Haben S, Giasemidis G (2016) A hybrid model of kernel density estimation and quantile regression for gefcom2014 probabilistic load forecasting. Int J Forecast 32(3):1017–1022
13. Haben S, Giasemidis G, Ziel F, Arora S (2019) Short term load forecasting and the effect of temperature at the low voltage level. Int J Forecast 35(4):1469–1484
14. Weron R (2007) Modeling and forecasting electricity loads and prices: a statistical approach. Wiley 403
15. Taylor JW, McSharry PE (2007) Short-term load forecasting methods: an evaluation based on european data. IEEE Trans Power Syst 22(4):2213–2219
16. Box G, Jenkins G, Reinsel G (2008) Time series analysis: forecasting and control. Wiley Series in Probability and Statistics. Wiley
17. Singh RP, Gao PX, Lizotte DJ (2012) On hourly home peak load prediction. In: 2012 IEEE Third International Conference on Smart Grid Communications (Smart Grid Comm), 163–168
18. Taylor JW (2003) Short-term electricity demand forecasting using double seasonal exponential smoothing. J Oper Res Soc 54(8):799–805
19. Taylor JW (2010) Triple seasonal methods for short-term electricity demand forecasting. Eur J Oper Res 204(1):139–152
20. Arora S, Taylor JW (2013) Short-term forecasting of anomalous load using rule-based triple seasonal methods. IEEE Trans Power Syst 28(3):3235–3242
21. Chen M, Chen J, Judging MD (2007) Self-excitation in multi-machine system by state-space method. Power System Technol 15(28):53–56
22. Wang X, Qiu X (2007) An decentralized nonlinear optimal excitation control strategy based on observation decoupled state space model for multi-machine power systems. Relay 1(33):38–41

23. Durbin J, Koopman SJ (2012) Time series analysis by state space methods. Oxford University Press (OUP), Oxford, UK, 38
24. Valderrama MJ, Moreno MO, González P, Aguilera AM (2003) Derivation of a state-space model by functional data analysis. Comput Stat 18:533–546
25. Samé A, El-Assaad H (2014) A state-space approach to modeling functional time series application to rail supervision. IEEE Conference Publication. In Proceedings of the 22nd European Signal Processing Conference, Lisbon, Portugal
26. Helske J (2017) KFAS: exponential family state space models in R. J Stat Softw Art 78:1–39
27. Koopman SJ, Durbin J (2003) Filtering and smoothing of state vector for diffuse state-space model. J Time Ser Anal 24:85–98
28. Kyriakides E, Polycarpou M (2007) Short term electric load forecasting: a tutorial. Stud Comput Intell (SCI) 35:391–418
29. Tripathi KP (2011) A review on knowledge-based expert system: concept and architecture, IJCA Special Issue on "Artificial Intelligence Techniques - Novel Approaches & Practical Applications" AIT, 19–23
30. Ghanbari A, Kazemi SMR, Mehmanpazir F, Nakhostin MMA (2013) A cooperative ant colony optimization-genetic algorithm approach for construction of energy demand forecasting knowledge-based expert systems knowledge based expert systems 39: 194-206
31. Vilalta R, Drissi Y (2002) A perspective view and survey of meta-learning. Artif Intell Rev 18:77–95
32. Vilalta R, Giraud-Carrier C, Brazdil P (2010) Meta-learning—concepts and techniques. In Data mining and knowledge discovery handbook, Maimon O, Rokach L (Eds.) Boston, MA, USA, Springer, pp 717–731
33. Matijaš M, Suykens JA, Krajcar S (2013) Load forecasting using a multivariate meta-learning system. Expert Syst Appl 40:4427–4437
34. Almeshaiei E, Soltan H (2010) A methodology for electric power load forecasting. Alex Eng J 50:137–144
35. Srivastava AK, Pandey AS, Singh D (2016) Short-term load forecasting methods: a review. International Conference on Emerging Trends in Electrical, Electronics and Sustainable Energy Systems, 130–138
36. Singh AK, Ibraheem KS, Muazzam M, Chaturvedi DK (2012) Load forecasting techniques and methodologies: a review. 2nd International Conference on Power, Control and Embedded Systems, Allahabad, India, 1–10
37. He Y (2005) Similar day selecting based neural network model and its application in short-term load forecasting, Machine Learning and Cybernetics Proceedings of 2005 International Conference, 4760–4763
38. Mandal P, Senjyu T, Urasaki N, Funabashi T (2006) A neural network based several-hour-ahead electric load forecasting using similar days approach. Int J Electr Power Energy Syst 28:367–373
39. Mu, Q., Wu, Y., Pan, X., Huang, L, Li, X.: Short-term load forecasting using improved similar days method. Asia-Pacific Power and Energy Engineering Conference, Chengdu, China, 1–4 (2010).
40. Dudek G (2015) Pattern similarity-based methods for short-term load forecasting-Part 1: principles. Appl Soft Comput 37:277–287
41. Chen Y, Luh PB, Guan C, Zhao Y, Michel LD, Coolbeth MA, Friedland PB, Rourke SJ (2010) Short-term load forecasting: similar day-based wavelet neural networks. IEEE Trans Power Syst 25:322–330
42. Kim CH, Koo BG, Park JH (2012) Short.term electric load forecasting using data mining technique. J Electr Eng Technol 7(6): 807–813
43. Devi MR, Manonmani R (2012) Electricity forecasting using data mining techniques in Tamil Nadu and other countries-A survey. Int J Emerg Trends Eng Dev 6(2)
44. Al-Kandari A, Soliman S, El-Hawary M (2004) Fuzzy short-term electric load forecasting. Int J Electr Power Energy Syst 26(2):111–122

45. Mamlook R, Badran O, Abdulhadi E (2009) A fuzzy inference model for short-term load forecasting. Energy Policy 37(4):1239–1248
46. Aggarwal S, Kumar M, Saini LM, Kumar A (2011) Short-term load forecasting in deregulated electricity markets using fuzzy approach. J Eng Technol 1(1):24–31
47. Wijaya TK, Vasirani M, Humeau S, Aberer K (2015) Cluster-based aggregate forecasting for residential electricity demand using smart meter data. IEEE International Conference on Big Data, 879–887
48. Gajowniczek K, Ząbkowski T (2014) Short term electricity forecasting using individual smart meter data. Proced Comput Sci 35: 589–597
49. Zufferey T, Ulbig A, Koch S, Hug G (2016) Forecasting of smart meter time series based on neural networks. International workshop on data analytics for renewable energy integration, Springer, pp 10–21
50. Li Y, Fang T (2003) Wavelet and support vector machines for short - term electrical load forecasting. Proceed Int Conf Wavelet Anal Appl 1:399–404
51. Tan Z, Zhang J, Wang J, Xu J (2010) Day-ahead electricity price forecasting using wavelet transform combined with ARIMA and GARCH models. Appl Energy 87(11):3606–3610
52. Chauhan BK, Hanmandlu M (2010) Load forecasting using wavelet fuzzy neural network. Int J Knowl Based Intell Eng Syst 14(2):57–71
53. Dunant J, Zufferey T (2018) Investigation of forecasting techniques in distribution grids. Semester project of power system laboratory, ETHZ
54. Humeau S, Wijaya TK, Vasirani M, Aberer K (2013) Electricity load forecsting for residential customers: exploiting aggregation and correlation between households. IEEE Sustainable Internet and ICT for Sustainability, 1–6
55. Vrablecova P, Ezzeddine AB, Rozinajova V, Sarik S, Sangaiah AK (2018) Smart grid load forecasting using online support vector regression. Comput Electr Eng 65:102–117
56. Carbonell SM (2019) Github - source code for rethinking weather station selection for electric load forecasting using genetic algorithms
57. Xie J, Hong T (2016) GEFCom2014 probabilistic electric load forecasting: An integrated solution with forecast combination and residual simulation. Int J Forecast 32(3):1012–1016
58. Panda SK, Ray P, Mishra D (2019) Effectiveness of GA on short term load forecasting. In: 18th IEEE International Conference on Information Technology (ICIT), Dec., pp 27–32
59. Ray P, Panda SK, Mishra D (2017) Short-term load forecasting using genetic algorithm. In: 4th Springer International Conference on Computational Intelligence in Data Mining, pp 863–872
60. Song WQ, Cheng XX, Cattani C (2020) Multi-fractional brownian motion and quantum-behaved partial swarm optimization for bearing degradation forecasting. Complexity
61. Boubaker S (2017) Identification of nonlinear hammerstein system using mixed integer-real coded particle swarm optimization: application to the electric daily peak-load forecasting. Nonlinear Dyn 90:797–814
62. Soufi Y, Kahla S, Bechouat M (2016) Feedback linearization control based particle swarm optimization for maximum power point tracking of wind turbine equipped by pmsg connected to the grid. Int J Hydrogen Energy 41:20950–20955
63. Xue T, Li R, Tokgo M, Ri J, Han G (2017) Trajectory planning for autonomous mobile robot using a hybrid improved qpso algorithm. Soft Comput 21:2421–2437
64. Panda SK, Ray P, Mishra D (2019) Effectiveness of PSO on short-term load forecasting. In: 1st Springer international conference on application of robotics in industry using advanced mechanisms, pp 122–129
65. Dasgupta D, Yu S, Nino F (2011) Recent advances in artificial immune systems: models and applications. Appl Soft Comput 11(2):1574–1587
66. Hart E, Timmis J (2008) Application areas of AIS: the past, the present and the future. Appl Soft Comput 8(1):191–201
67. Dudek G (2008) Artificial immune system for short-term electric load forecasting. Proceedings of 9th ICAISC, LNAI 5097, pp 1007–1017

68. Dudek G (2011) Artificial immune clustering algorithm to forecasting seasonal time series. In: Proceedings of 3rd ICCCI, LNAI 6922, pp 468–477
69. Yue H, Li D, Liqun G (2012) Power system short-term load forecasting based on neural network with artificial immune algorithm. In: Proceedings of control and decision, pp 844–848
70. Yin C, Kang L, Sun W (2007) Hybrid neural network model for short term load forecasting. In: third international conference on natural computation
71. Maniezzo V, Gamberdella LM, Lungi FB (2004) Ant colony optimization. In: New optimization techniques in engineering, Springer, Heidelberg, pp 101–117
72. Han Y, Shi P (2007) An improved ant colony algorithm for fuzzy clustering in image segmentation. J Neuro Comput 70:665–671
73. Potli, M., Mallikarjuna, A., Balachandra, J.C., Venugopal, N.: Optimal Sizing of Wind/Solar/Hydro in an Isolated Power System using SMFFT based Cuckoo Search Algorithm. IEEE 6th International Conference on Power Systems (ICPS), New Delhi, India (2016).
74. Upadhyay S, Sharma MP (2015) Development of hybrid energy system with cycle charging strategy using particle swarm optimization for a remote area in India. Renew Energy 77:586–598
75. Nojavan S, Majidi M, Zare K (2017) Performance improvement of a battery/PV/fuel cell/grid hybrid energy system considering load uncertainty modeling using IGDT. Energy Convers Manage 147:29–39
76. Arsalis A, Georghiou GE (2018) A decentralized, hybrid photovoltaic-solid oxide fuel cell system for application to a commercial building. Energies 11
77. Scientist N (2017) Record amounts of renewable energy added to the mix in 2016. https://www.newscientist.com/article/2127056-record-amounts-of-renewable-energy-added-tothe-mix-in-2016/. Last Accessed March 27, 2021
78. IRENA (2018) Renewable Capacity Statistics2018, International Renewable Energy Agency (IRENA): Abu Dhabi, Arab
79. Upadhyay S, Sharma MP (2014) A review on configurations, control and sizing methodologies of hybrid energy systems. Renew Sustain Energy Rev 38:47–63
80. Krishna KS, Kumar KS (2015) A review on hybrid renewable energy systems. Renew Sustain Energy Rev 52:907–916
81. Schopfer S, Tiefenbeck V, Staake T (2018) Economic assessment of photovoltaic battery systems based on household load profiles. Appl Energy 223:229–248
82. Bento P, Nunes H, Pombo J, Mariano S, Calado MD (2018) Daily operation optimization for grid-connected hybrid system considering short-term electricity price forecast scheme. In: IEEE International Conference on Environment and Electrical Engineering and IEEE Industrial and Commercial Power Systems Europe, Palermo, Italy, pp 1–6
83. Ma T, Yang H, Lu L, Peng J (2014) Technical feasibility study on a standalone hybrid solar-wind system with pumped hydro storage for a remote island in Hong Kong. Renew Energy 69:7–15
84. Xu L, Ruan X, Mao C, Zhang B, Luo Y (2013) An improved optimal sizing method for wind-solar-battery hybrid power system. IEEE Trans Sustain Energy 4:774–785
85. Malheiro A, Castro PM, Lima RM, Estanqueiro A (2015) Integrated sizing and scheduling of wind/PV/ diesel/battery isolated systems. Renew Energy 83:646–657
86. Reddy SS (2017) Optimal scheduling of thermal-wind-solar power system with storage. Renew Energy 101:1357–1368
87. Kong W, Dong ZY, Hill DJ, Luo F, Xu Y (2017) Short-term residential load forecasting based on resident behaviour learning. IEEE Trans Power Syst 33:1087–1088
88. Lu J, Wang W, Zhang Y, Cheng S (2017) Multi-objective optimal design of stand-alone hybrid energy system using entropy weight method based on HOMER. Energies 10
89. An L, Tuan TD (2018) Dynamic programming for optimal energy management of hybrid wind–PV–Diesel–Battery. Energies 11
90. Sanchez VM, Chavez-Ramirez AU, Duron-Torres SM, Hernandez J, Arriaga LG, Ramirez JM (2014) Techno-economical optimization based on swarm intelligence algorithm forest

and-alonewind-photovoltaic hydrogen power system at south-east region of Mexico. Int J Hydrogen Energy 39:16646–16655
91. Zheng JH, Chen JJ, Wu QH, Jing ZX (2015) Multi-objective optimization and decision making for power dispatch of a large-scale integrated energy system with distributed DHCs embedded. Appl Energy 154:369–379
92. Dong W, Li Y, Xiang J (2016) Optimal sizing of a stand-alone hybrid power system based on battery/hydrogen with an improved ant colony optimization. Energies 9:785
93. Yamamoto S, Park JS, Takata M, Sasaki K, Hashimoto T (2003) Basic study on the prediction of solar irradiation and its application to photovoltaic-diesel hybrid generation system. Sol Energy Mater Sol Cells 75:577–584
94. Lujano-Rojas JM, Monteiro C, Dufo-López R, Bernal-Agustín JL (2012) Optimum load management strategy for wind/diesel/battery hybrid power systems. Renew Energy 44:288–295
95. Šajn N (2016) Electricity "Prosumers", European Parliamentary Research Service (EPRS): Brussels, Belgium
96. Kästel P, Gilroy-Scott B (2015) Economics of pooling small local electricity prosumers - LCOE & self-consumption. Renew Sustain Energy Rev 51:718–729
97. Khare V, Nema S, Baredar P (2016) Solar-wind hybrid renewable energy system: A review. Renew Sustain Energy Rev 58:23–33
98. Nguyen HT, Nabney IT (2010) Short-term electricity demand and gas price forecasts using wavelet transforms and adaptive models. Energy 35:3674–3685
99. Ou TC, Hong CM (2014) Dynamic operation and control of microgrid hybrid power systems. Energy 66:314–323
100. Palensky P, Dietrich D (2011) Demand side management. Demand response, intelligent energy systems, and smart loads. IEEE Trans Ind Inf 7(3): 381–388
101. Ou TC (2018) Design of a novel voltage controller for conversion of carbon dioxide into clean fuels using the integration of a vanadium redox battery with solar energy. Energies 11:1–10
102. Unsihuay-Vila C, Zambroni de Souza AC, Marangon-Lima JW, Balestrassi PP (2010) Electricity demand and spot price forecasting using evolutionary computation combined with chaotic nonlinear dynamic model. Int J Electr Power Energy Syst 32(2): 108–116
103. Amini MH, Nabi B, Haghifam MR (2013) Load management using multi-agent systems in smart distribution network. In: IEEE Power Energy Society General Meeting, pp 1–5
104. Haider HT, See OH, Elmenreich W (2016) Residential demand response scheme based on adaptive consumption level pricing. Energy 113:301–308
105. Takeda H, Tamura Y, Sato S (2016) Using the ensemble Kalman filter for electricity load forecasting and analysis. Energy 104:184–198
106. Ou TC (2012) A novel unsymmetrical faults analysis for microgrid distribution systems. Electr Power Energy Syst 43:1017–1024
107. Ou TC (2013) Ground fault current analysis with a direct building algorithm for microgrid distribution. Int J Electr Power Energy Syst 53:867–875 December
108. Ou TC, Lu KH, Huang CJ (2017) Improvement of transient stability in a hybrid power multi-system using a designed NIDC (Novel Intelligent Damping Controller). Energies 10:1–16
109. He Y, Jiao J, Chen Q, Ge S, Chang Y, Xu Y (2017) Urban long term electricity demand forecast method based on system dynamics of the new economic normal: the case of Tianjin. Energies, 9–22