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Review

Load Forecasting Techniques and Their Applications in Smart Grids

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Abstract: The growing success of smart grids (SGs) is driving increased interest in load forecasting (LF) as accurate predictions of energy demand are crucial for ensuring the reliability, stability, and efficiency of SGs. LF techniques aid SGs in making decisions related to power operation and planning upgrades, and can help provide efficient and reliable power services at fair prices. Advances in artificial intelligence (AI), specifically in machine learning (ML) and deep learning (DL), have also played a significant role in improving the precision of demand forecasting. It is important to evaluate different LF techniques to identify the most accurate and appropriate one for use in SGs. This paper conducts a systematic review of state-of-the-art forecasting techniques, including traditional techniques, clustering-based techniques, AI-based techniques, and time series-based techniques, and provides an analysis of their performance and results. The aim of this paper is to determine which LF technique is most suitable for specific applications in SGs. The findings indicate that AI-based LF techniques, using ML and neural network (NN) models, have shown the best forecast performance compared to other methods, achieving higher overall root mean squared (RMS) and mean absolute percentage error (MAPE) values.

Keywords: load forecasting; smart grids; machine learning; deep learning; artificial intelligence

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1. Introduction

The considerable increase in the global number of people and economy, besides the rush raise in civilization, has great chances to accelerate the demand for the consumed power in the near future [1]. Additionally, the progress and extensive increase in the population raises the demand for electricity, which automatically affects the demand for higher electricity generation. Power production, transmission, and distribution are the most vital problems included in energy management [2,3]. The ordinary electrical grid is defined as an interconnected network that links the users to the power producers and transfers the electricity from the source to the users.

Recently, smart grid (SGs) has attracted extreme concern in several technological fields such as academia and industry. It is considered the smart alternative for aging power grids [4,5]. It has great capability to provide smart services since it combines diversified technologies for instance cloud computing (CC), big data (BD), internet of things (IoT), etc. [6]. SGs is defined as a novel digital electric power grid that provides bidirectional communication to provide better security, efficiency, resiliency, and reliability of the electric power systems for higher electrical power production through the most recent communication technologies [7,8]. It is a bidirectional energy delivery and transportation system, which authorizes the users to take actions relevant to energy consumption to reduce the electricity cost [9–11]. SGs improves the security measures taken during the consequences of natural disasters and other human attacks [12]. On the other hand, it decreases risks resulting in damage to human lives and other physical infrastructure relevant to ordinary grid-related activities. Regarding the set-up aspects, SGs integrates electric vehicles (EVs) and renews the transport section. In the area of global warming issues and the need for optimal energy utilization, SGs minimizes wasted energy and environmental contamination caused by the emission from the greenhouses.

SGs offers several smart solutions to the whole activities related to electricity. It offers real-time surveillance of power consumption, dynamic pricing, faster and more effective restoration of electricity after a power outage, in-house electrical displays, altering the electricity usage during daytime based on the pricing signals and consumption rates, making the consumer work as a power producer, online monitoring of the power consumption through the use of smart apps such as mobile apps and web pages [13–16]. Various components in SGs are integrated with sensor nodes and communication links to provide interoperability in business, manufacturing, and residential applications. The goal is to limit power disturbance that can occur due to element failures, natural catastrophes, and capacity limits by introducing real-time smart power surveillance and control systems. SGs provides state-of-the-art smart services with automated monitoring, and self-regenerative capabilities. SGs supports demand management by predicting energy usage.

Load forecasting (LF) has attracted considerable interest which is commonly needed for different applications to consolidate the performance of SGs. These applications include electricity theft detection, smart meters (SMs) false reading detection, energy cost optimization, power management, micro-grids, etc. [17,18]. Additionally, LF is a remarkable research topic in SGs, particularly the grid-interactive and efficient building energy process. LF is an essential element in sophisticated management and operation planning to provide efficient building energy. It is a fundamental element in the cost control operation of model predictive control (MPC) for building energy management [19]. LF is substantial in constructing grid combinations such as demand response and load management [20]. It is the prime actor to improve the connection between the demand part and SGs, which is important to coordinate the charging of energy systems, reliability of the power systems, and economical energy deployment and distribution [21]. Finally, LF contributes significantly in the primary phase to build the energy parameters and evaluate the performance in SGs. Meanwhile, it is a regression-based problem, so several machine learning (ML) models have been excessively used in this area [22].

LF is defined as the technique used by SGs to predict the energy needed to meet the consumers' requirements [23]. Precise electric LF is significant in terms of economic, stability, and reliable operation of the power systems. It helps the SGs to make important decisions including decisions on purchasing and generating electric power, load switching, infrastructure management and on how to plan energy upgrades since they can understand the future consumption and load demand, it also helps to avoid under or over-power generation [24]. As illustrated in Figure 1 LF, the methods can be divided into four types based on the forecasting horizon [25]:

- Very short-term load forecasting (VSTLF): The forecasting process is performed a few minutes before, and the forecasted values are sent to the operator to be used in almost real time. It is eligible to be utilized in high-speed applications to interact with the very fast variation in electricity demands [26]
- Short-term load forecasting (STLF): It aims to predict the load for the following thirty minutes till the next fifteen days. The reliability and operation costing of the energy system are affected by the precision of this method. The improper method could cause a deficiency of reserved capacity which will be distributed costly or waste resources by reservation of not needed capacity [27,28].

- Medium-term load forecasting (MTLF): It aims to estimate the load that covers a time span of a month up to a year and depends on growth factors. This forecasting method suits outage and maintenance planning in addition to load-switching operations [29].
- Long-term load forecasting (LTLF): It aims to estimate the load that covers forecasting of a year up to ten years and sometimes up to several decades. This method is important for energy utilities and planners in terms of smart grid expansion planning, future investments, and distribution planning [30,31].

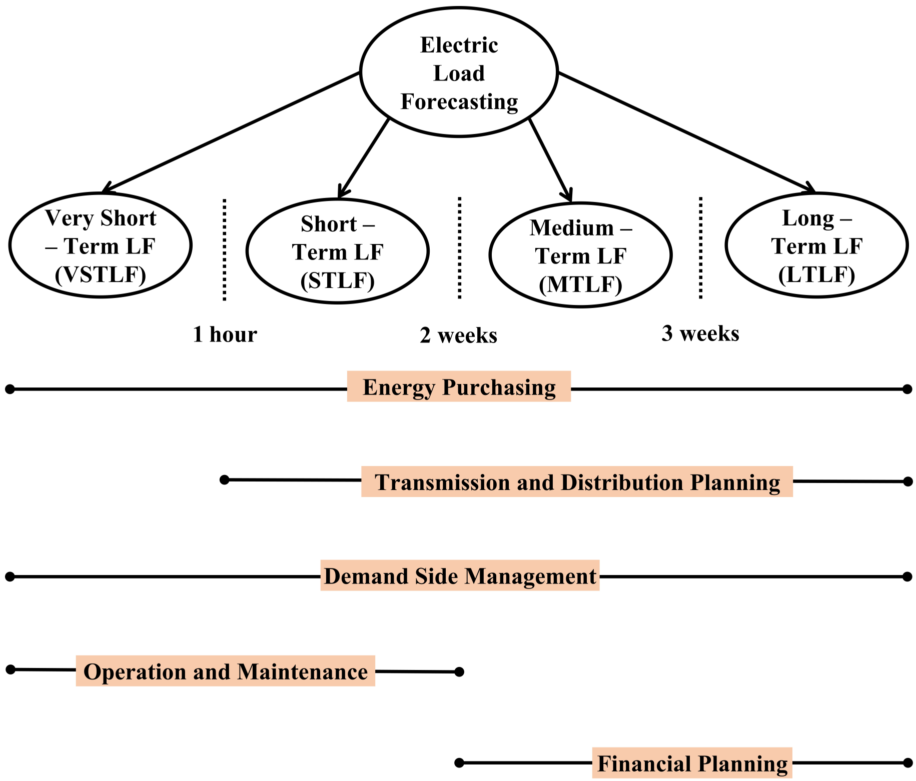

Figure 1. Types of load forecasting based on forecasting horizon.

The LF based on different time horizons is very important for various operations within energy utility [32]. These models provide proper planning of the power systems, financing, and electric sales. In addition to these four types depending on the horizon, LF can further be categorized into demand forecasting and energy forecasting. Demand forecasting is utilized to define the number of resources including the production, transmission, and distribution system [33]. It is the process of making future estimations related to the customers' demands over a given time period and it gives the estimated rate of increase in load. Energy forecasting is utilized to define the type of needed facilities, such as future fuel requirements [23].

LF plays an essential role in the charging coordination schemes [34] and the management of the energy system, as it can help SGs to manage their capacity and operations to supply reliably all consumers with the required energy. Although this can be very beneficial for SGs, there are several factors to be considered for providing precise data and predictions and for quantifying uncertainties in the future as shown in Figure 2. These factors that can affect the LF model are listed as follows:

- Weather: It includes the most significant parameters that affect the STLF such as temperature degree, wind speed, humidity condition, and cloudiness status [35].
- Calendar: The prediction process could vary extremely throughout the week. Typically, electricity usage is high during weekdays as most users are at working buildings or educational buildings, and usage is usually low during the weekend as users are at home and some businesses are closed [36].

- Rooftop Solar: The solar panels and other types of electricity generators installed can reduce the amount of electricity a user draws from the grid. Rooftop installations can be hard to gauge as the addition and removal of these panels are hard to pinpoint at a given time [37].
- Economic Conditions: The amount of electricity required by commercial and industrial consumers is an important factor in the total demand. In a strong economy, manufacturers with power-intensive machines are likely to use more energy than in a weak economy [38].
- Consumer Behavior: It includes the quantity and quality of electrical instruments that customers utilize in their units or intend to install including heating, ventilation, and air conditioning (HVAC) systems [39].
- Plug-In EVs: Charging EVs requires a significant amount of electricity. With increasing numbers of EVs, the impact they have on the grid increases proportionally [40].

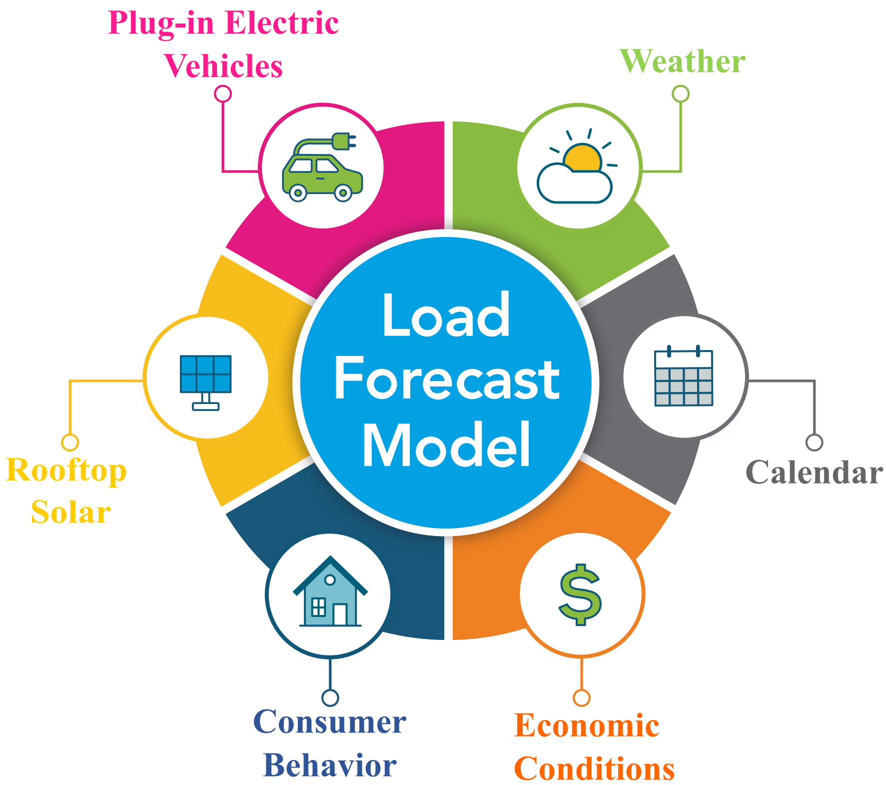

Figure 2. The factors that can affect the LF model.

There are several other factors that can be taken into consideration, but these are among the crucial ones that require immediate attention [41]. Acknowledging their impact on LF can significantly help SGs to take accurate decisions such as decisions of purchasing or generating power, load switching, and infrastructure development. In this paper, we offer a comprehensive survey on the LF techniques in SGs including the existing literature review and the most recent proposed LF techniques.

The remainder of this paper is organized as follows. The preliminaries and necessary background information are provided in Section 2. Section 3, presents the related works. Section 4, highlights the most recently existing LF techniques in SGs. Section 5 introduces the recommendations. Finally, the conclusions are given in Section 6.

2. Preliminaries

In this section, we introduce the necessary background that shall be used in this paper, including temperature scenario generation methods, multiple linear regression models, K-means clustering, and neural network.

2.1. Temperature Scenario Generation Methods

An overview of three commonly used methods for generating weather scenarios in order to create a probabilistic load forecast (PLF). One popular approach is to use a point LF model with simulated weather scenarios, which is known for its simplicity and ease of understanding. These methods are widely used in the industry [42]. These methods can be divided into three groups organized from easy to difficult in terms of implementation as follows:

- Fixed-date: It selects the climate history of a previous period (maybe year) and determines the range of temperatures chronically to the next years to obtain the complete prediction scenario [43]. The probabilistic forecast (PF) comes from n scenarios with balanced probability, where n is the accumulation of a specific period of the climate profile (range of temperatures) [44].
- Shifted date: It selects the temperature profile exactly like the previous method, then moves it forward and backward with a specific window (could be one day or more), then determines each shifted profile chronically to the next years to get the complete prediction scenario. PF is calculated by $(2d + 1)n$ scenarios with balanced probability, where d is the number of days and the basic temperature profile is being shifted around [45,46]. Figure 3 explains the shifting process of a temperature series by moving one day forward and backward to make two extra temperature scenarios. The first row represents the basic temperature series. The following rows represent the shifted series by one day forward and backward. This method keeps the correlation of the temperature series while making extra scenarios to improve the efficiency of the PLF.
- Bootstrap: the climate profile of every original year is segmented into blocks with similar lengths, then the blocks are at random picked with surrogates from any of the original years to create a novel temperature profile [47]. Figure 4 explains the method as follows: in the first scenario, the first block could be obtained from the first block of the year 2001, the second block could be obtained from the second block of the year 1973, and so on [48].

Day of year	**365**	**1**	**2**	**…**	**364**	**365**	**1**
Original	$T_{D365,Y(i-1)}$	$T_{D1,Yi}$	$T_{D2,Yi}$	…	$T_{D364,Yi}$	$T_{D365,Yi}$	$T_{D1,Yi}$
1-day forward	$T_{D364,Y(i-1)}$	$T_{D365,Y(i-1)}$	$T_{D1,Yi}$	…	$T_{D363,Yi}$	$T_{D364,Yi}$	$T_{D365,Yi}$
1-day backward	$T_{D1,Yi}$	$T_{D2,Yi}$	$T_{D3,Yi}$	…	$T_{D365,Yi}$	$T_{D1,Y(i+1)}$	$T_{D2,Y(i+1)}$

Figure 3. Shifted dates method to generate extra temperature scenarios.

Scenario 1	**Block 1: 2001**	**Block 2: 1973**	**Block 3: 1998**	**…**	**Block 41: 2004**
Scenario 2	**Block 1: 1993**	**Block 2: 1997**	**Block 3: 2001**	**…**	**Block 41: 1975**
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.					
.					
Scenario n	**Block 1: 1986**	**Block 2: 2004**	**Block 3: 1981**	**…**	**Block 41: 1995**

Figure 4. Bootstrapping method to generate extra temperature scenarios.

These three methods can be used either individually or together to address weather-related research challenges. Studies show that the quantile score of each method offers a small enhancement as the length of the available original temperature increases. The shifted-date method enhances the quantile score with a small value as the number of shifted days increases. The bootstrap method provides the ability to produce more global scenarios without enhancing the quantile score of the fixed-date method. Among the three, the easiest implementation is the fixed-date method, the lowest quantile score can be obtained using the shifted-date method, and the generation of a very large number of scenarios can be achieved using the bootstrap method [49].

2.2. Multiple Linear Regression Models

In addition to methods used in temperature scenario generation, multiple linear regression (MLR) models have been utilized in a large scale for LF. MLR models are used to seek statistical insight into the correlation between dependent and independent parameters. These models are highly valuable in LF as there are transparent, interpretable, and popular [50]. These models are listed as follows:

- T-Cube Model: includes gross state product (GSP) and third-order polynomials of the current hour temperatures.
- Vanilla Model: includes schedule parameters, such as a month, day, and hour, and their interaction with the polynomials of current hour temperatures [51].
- Hong-2014 Model: includes several effects such as recency, weekend, and the holiday effect. The recency effect denotes the reality that the required amount of energy is influenced by the temperatures of the previous hours [52]. The weekend effect denotes the fact that weekend load characteristics have a low level of load and are sensitive to meteorological conditions. The holiday effect denotes the fact that holidays affect electricity load widely, causing inaccurate forecasts.

The models described above are combined to create a probabilistic forecast which will be evaluated using quantile scores to determine which temperature scenario method is the most effective.

2.3. K-Means Clustering

K-means is a tool that can help to organize a dataset into groups with similar characteristics. The main purpose of using K-means is to simplify the large dataset to be easier for analysis. This is because instead of analyzing each SM as a single data point which could lead to thousands of data points, it uses only a handful of groups as the data points. The calculations involved with neural networks will be faster and easier [2].

To group a dataset using K-means, first, the number of groups needs to be determined, this will be the "K" value in K-means. Then, K random data points need to be generated, these will be the K values. Next, every single data point in the dataset needs to be assigned to one of the groups based on the nearest K value [53]. After all the data points are assigned, the K values need to be updated to become the average value of all the data points which are in the group. Finally, some of the data points will move from one group to another if a different K value is closer than the currently assigned K value. This will happen on a loop until no more data points change groups, which means that an equilibrium has been found [54]. Figure 5 explains the working of the K-means clustering algorithm.

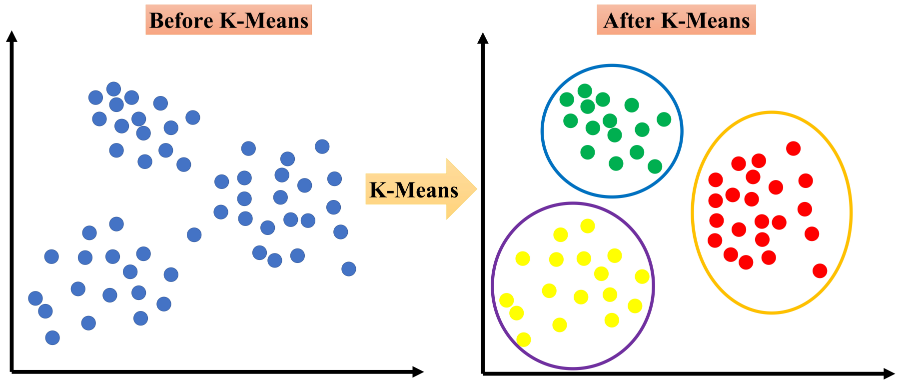

Figure 5. K-means clustering.

2.4. Neural Network

Neural networks (NN) are just trying to figure out what function was used to get from an input number to the output number. The inputs do not necessarily have to be just one number, but they can also be a matrix of numbers. In NN with multilayer perceptrons, there are multiple layers between the input and output layers, known as hidden layers, with a different function between each layer [55]. Figure 6 provides an example of a neural network with three hidden layers. Additionally, between each layer, there are weights, which are what the input is multiplied by, and biases, which are what is added to inputs multiplied by weights to get the output. The goal of training a NN is to find out what are the weights and biases to get an accurate model of some real-life system. This is achieved by randomly generating starting weights. Then, the error generated due to the produced output by the NN and the expected output is calculated. The error is used to slightly adjust the weights and this repeats until the error does not decrease anymore or the accuracy of the system is satisfactory [56].

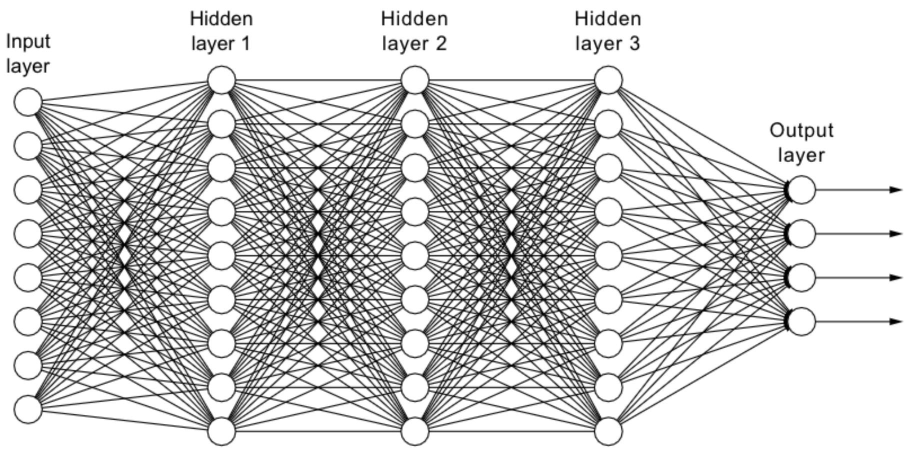

Figure 6. An example of a neural network with three hidden layers.

The shape of the NN is very important for balancing the speed and accuracy of the model being developed. Choosing the right shape can help to reach a better convergence point faster. The convergence point is when the system no longer produces a better output after changing the weights and the error no longer decreases [57]. A small network can be trained quickly, but with a less accurate convergence point, whereas a large network takes a long time to train, but with a much more accurate convergence point.

During the training of the NN, it is not ideal to use the entire dataset just for finding the weights. The dataset is usually broken up into two groups with no overlap, the training data, and the testing data. The training data are used to generate the weights during the training process. The testing data are used to evaluate the effectiveness of the NN [58]. If the same data are used for the training and testing of the NN, there is a chance that overfitting may occur. This is when the network does not learn the model but rather memorizes the training data. This can lead to very high results in simulated environments, but very low results with actual data. This makes the generalization process very difficult for the NN. To prevent overfitting, the regularization technique is applied which changes the way the NN reads the data and makes it very difficult to just memorize the data, and instead forces the NN to learn the patterns of the mode [59].

3. Related Work

In this section, we will demonstrate the different ways in which survey papers have approached the subject of LF models. We have classified these survey papers into two main categories. The first category covers papers that examine LF models from artificial intelligence (AI) perspective, particularly those that focus on ML and deep learning (DL) models. The second category includes a variety of papers that offer a broader view of the LF problem, approaching it from a variety of different angles. Table 1 summarizes the review paper.

The AI, especially ML and DL models, have successfully achieved great results in SGs applications to achieve improved accuracy, reliability, stability, and efficiency, particularly in the LF field. There exists an extreme need to analyze and evaluate the various ML and DL models, thereby identifying the most appropriate one to be applied to LF techniques in SGs. In this category, we demonstrate several survey papers that reviewed ML- and DL-based LF techniques.

In [15], a comparative study including the most recent ML algorithms that work in LF techniques of SGs was introduced. This study concluded that the decision tree model surpassed other ML techniques, including the support vector machine (SVM), K-nearest neighbors algorithm (KNN), neural network (NN), logistic regression and Naive Bayes, are some examples of the algorithms used in the field. The decision tree achieved a perfect precision rate, recall rate of almost 100%, a F1 score of 100%, and an accuracy rate of 99.96%.

Yildiz et al. [60] reviewed different regression models based LF techniques. They discussed their usage, commonly employed regression variables, and methods for enhancing the performance and accuracy of various algorithms. They compared LF techniques for predicting hourly electricity usage for the next day using real applications. They found that the artificial neural network (ANN) with Bayesian regularization back-propagation yielded the best results in terms of root mean squared (RMS) and mean absolute percentage error (MAPE) performance.

In [61], the current LF techniques were reviewed to identify which technique is best proper for a specific case or scenario. The applied criteria to compare these various techniques were time frame, inputs, outputs, scale, data sample size, error type, and value. The regression and multiple regression were the most common techniques used in LTLF. For STLF and VSTLF applications, ML-based techniques, in particular, ANN, SVM, and time series analysis involving auto-regressive integrated moving average (ARIMA) and the auto-regressive moving average (ARMA) were used.

Furthermore, Deb et al. [62] introduced a survey on the current ML techniques for predicting time series energy consumption. They investigated the most common nine ML based prediction techniques. They discussed hybrid models that merge two or more prediction techniques, and they summarized that hybrid models are the most efficient prediction models in time series energy for the building.

A different literature survey was introduced by Zhang et al. [20]. They reviewed the application of ML algorithms in building LF that carry out task T using P to evaluate and analyze the performance and depend on learning from the accepted expertise E. Task T showed the application of ML algorithms, performance measure P determined how well the task was executed, and experience E was obtained from different sources, pre-processing, and feature extraction.

Runge et al. [63] reviewed the proposed works which have used ANN for predicting building energy demand. Furthermore, Amasyali et al. [64] reviewed the developed data-driven building energy LF techniques. Both surveys discussed their applications, dataset, predicting models, and performance evaluating metrics.

In [65], another survey on the building electrical energy consumption prediction techniques that include both the conventional and AI models. This survey aimed to study each model individually and discussed the possibility of integrating the two models. The integration of SVM and swarm intelligence (SI) provided excellent results.

Gerwig et al. [66] introduced an overview of the methods used for STLF for residential buildings, and identifies which methods are most effective for different purposes. A structured literature review was conducted, analyzing 375 papers and categorizing them using a concept matrix. The study revealed that using ANN, autoregressive techniques, and their combination (hybrid methods) are effective in LF demands in small scale households (1–1000) and individual users. Furthermore, linear regression appears to be effective in LF for single users, while SVR is suitable for LF demands in groups of more than 32 households. Combining clustering techniques with ANN or autoregressive methods may further improve the accuracy of the predictions. The paper suggests that further research is needed in this area and suggests the use of publicly available datasets for benchmarking and comparison of methods.

In the second category, we demonstrate several survey papers that reviewed LF models from various points of view. Khan et al. [67] provided a survey on LF techniques based on dynamic pricing schemes in SGs. They investigated some pricing schemes such as real-time pricing (RTP), time of use (ToU), and critical peak pricing (CPP). They assorted LF techniques into mathematical and AI based computational models.

Furthermore, Nowotarski et al. [68] introduced a comprehensive survey of electricity price forecasting (EPF) as well as the necessary guidelines for the precise use of methods, measures, and tests. It is considered as an extension and update of [69]. All the reviewed topics can be used for probabilistic energy forecasting, as VSTLF for SM applications or wind and solar power forecasting.

Lazos et al. [70] discussed the various aspects and significance of prediction and energy optimization models for energy systems in commercial buildings, particularly in regard to weather-related input parameters, as well as their usage in energy management. They concluded that weather factors play an important role in the assessment of building energy systems and can reduce uncertainty in forecasting by 15–30% compared to a deterministic and non-weather-based scheme. For energy management in small buildings, a simple statistical model with stored data can be used. However, in larger and more dynamic buildings, the existence of accurate weather forecasts is very essential.

A comparative study of prediction techniques of power consumption and their relevant applications was presented in [71]. This study concluded that power consumption prediction architecture for metering, communication, supervisory control, and data acquisition (SCADA) monitoring, and a database storing that is used for different smart applications such as the mining industry, smart grid, smart cities, and industry 4.0.

A tutorial survey of probabilistic electric LF, involving the most prominent methods and assessment techniques, was introduced in [72]. This study provided some insights and new knowledge for researchers and practitioners to develop and improve the field of LF.

Moreover, a survey of the most significant energy forecasting techniques was introduced in [73]. It included short summary of hot topics research, an investigation of the significant open data sources, giving recommendations about publishing effective articles, and finally, a discussion of the future of energy forecasting.

Nespoli et al. [74] introduced a comparison of various PLF strategies for projecting the load demand of secondary substations and cabinets in a distributed low-voltage grid. Standard KPIs for deterministic and probabilistic predictions were used to analyze the techniques. They also evaluated the effectiveness of several hierarchical approaches to improve the performance of bottom-level predictors.

Table 1. Survey papers of load forecasting techniques.

Ref.	Summarized Highlights
[15]	• A comparative study covered the most recent ML algorithms applied in LF techniques of SGs; • It was found that the decision tree model surpassed other ML algorithms; • The decision tree achieved 100% precision, 99.9% recall, 100% F1 score, and 99.96% accuracy.
[60]	• This paper reviewed various regression models for LF techniques; • The authors discussed the usage, commonly used regression variables and methods for enhancing the performance and accuracy of different algorithms; • They compared LF techniques for predicting next-day hourly electricity consumption using real applications; • They found that ANN with Bayesian regulation back-propagation indicated the best results in terms of RMS and MAPE performance.
[61]	• The applied criteria to compare these various techniques were time frame, inputs, outputs, scale, data sample size, error type, and value; • The regression and multiple regression were the most common techniques used in LTLF; • Regarding to VSTLF and STLF applications, ML based techniques in particular ANN, SVM, and time series analysis involving ARIMA and ARMA were used.
[62]	• This paper introduced a survey on the current ML techniques for predicting time series energy consumption; • The authors discussed hybrid models that merge two or more prediction techniques, and they summarized that hybrid models are the most efficient prediction models in time series energy for the building.
[20]	• This work reviewed the application of ML algorithms in building LF that carry out task T using P to evaluate and analyze the performance and depend on learning from the accepted expertise E; • Task T showed the application of ML algorithms, P evaluate the performance, and experience E was obtained from different sources, pre-processing, and feature extraction.
[63]	• They reviewed the proposed works which have used ANN for predicting building energy demand; • They discussed the applications, dataset, predicting models, and performance evaluating metrics.
[64]	• This paper reviewed the developed data-driven building energy LF techniques; • It discussed the applications, dataset, predicting models, and performance evaluating metrics.
[65]	• This paper studied each model individually and discussed the possibility of integrating the two models. • The integration of SVM and swarm intelligence (SI) provided excellent results.
[66]	• This paper introduced a survey on the applied LF techniques and denoted identical results. • An overview was executed with an analysis of more than three hundred research papers that were classified via a concept matrix. • They indicated the best purpose of each technique based on its results and which available and suitable datasets can be utilized for the assessment process.

Table 1. *Cont.*

Ref.	Summarized Highlights
[67]	• This paper reviewed LF techniques based on dynamic pricing schemes in SGs. • They investigated some pricing schemes such as (RTP), (ToU), and (CPP). • They assorted LF techniques into mathematical and AI-based computational models.
[68]	• This paper introduced a comprehensive survey of EPF, as well as the necessary guidelines for the precise use of methods, measures, and tests; • All the reviewed topics can be used for PLF, as VSTLF for SM applications or wind and solar power forecasting.
[70]	• This paper discussed the various aspects and significance of prediction and energy optimization models for energy systems in commercial buildings, specifically in regard to weather-related input parameters and their usage in energy management; • They concluded that weather factors have a significant impact on evaluating building energy systems; • For energy management in small buildings, a simple statistical model with stored data can be used, while larger and more dynamic buildings require accurate weather forecasts to be effectively managed.
[71]	• This paper discussed power consumption prediction architecture for metering, communication, SCADA monitoring, and a database storing that is used for different smart applications such as the mining industry, smart grid, smart cities, and industry 4.0.
[72]	• This paper introduced a tutorial survey of probabilistic electric LF, involving the most prominent methods and assessment techniques; • It provided some insights and new knowledge for researchers and practitioners to develop and improve the field of LF.
[73]	• This paper provided a survey of the most significant energy forecasting techniques; • It included short summary of hot topics research, an investigation of the significant open data sources, giving recommendations about publishing effective articles and a discussion of the future of energy forecasting.
[74]	• This paper introduced a comparison of various PLF strategies for projecting the load demand of secondary substations and cabinets in a distributed low-voltage grid; • They used standard KPIs for deterministic and probabilistic predictions to analyze the techniques; • They evaluated the effectiveness of several hierarchical approaches to improve the performance of bottom-level predictors.

4. Existing Applied Load Forecasting Techniques

In this section, we provide a comprehensive overview of the existing LF techniques and their usage in SGs context. This section is broken down into five main parts. In the first part, Section 4.1, we provide a brief summary of traditional LF techniques. The second part, Section 4.2, discusses clustering-based LF techniques. The third part, Section 4.3, focuses on AI-based LF techniques including ML and DL algorithms, as well as related approaches to enhance performance and accuracy. The fourth part, Section 4.4, delves into time series LF techniques specifically. Finally, the fifth part, Section 4.5, presents an overview of meta-heuristic-based LF techniques.

4.1. Traditional Load Forecasting Techniques

Traditional LF techniques refer to a set of methods and algorithms used to predict future electricity demand. These techniques have been used for decades by electric utilities and power system operators to plan and manage their power generation and distribution systems. In this part, we demonstrate several traditional LF techniques that have been applied in SGs.

Alberg et al. [75] presented five sliding window-based forecasting algorithms for predicting electricity load in SMs, which use a combination of non-seasonal and seasonal time series models and an incremental learning methodology called online information network (OLIN). These algorithms differed in how they take seasonality into account and how they construct their models. The researchers used SMs technology to collect data, which was preprocessed before use. The study found that the SWDP2A algorithm performed better than the other algorithms, and that accurate hourly predictions of electricity load could be made by using daily consumption data and aggregated hourly coefficients of daily profiles during the model induction phase.

Massana et al. [76] proposed a (STLF) technique for non-inhabitant buildings. The proposed model forecasts the hourly consumption for several months ahead and is dependent solely on occupancy. Other methods, in contrast, depend on auto-regression or additional parameters that are not readily available, and as a result, require weather forecasts or additional data to perform forecasting, making long-term hourly prediction very hard. The study also explores different methods of generating occupancy indexes. The authors compared different occupancy features, in order to determine the most effective techniques and data sources for forecasting purposes.

In [77] a new predictive control model for electricity forecasting using system identification schemes based on system features was proposed to enhance the efficiency and resiliency of the building's electricity. The results showed that the proposed model can predict with accuracy reaching up to 90% with only 60 s of calculation time.

Kaneriya et al. [78] utilized a weather-based LF model to determine the power demand using a time-based data-driven scheme. The results indicate that the applied LF model precisely predicted the power demand for residential and commercial applications.

Zhang et al. [43] proposed a novel hybrid model that combines three models: improved empirical mode decomposition (IEMD), (ARIMA), and wavelet neural network (WNN) that was optimized by fruit fly optimization algorithm (FOA). They exploited the advantages of each model to create a new robust and efficient hybrid model suitable for electricity LF. The experimental results proved its high accuracy and stability.

Xie et al. [79] investigated three techniques for generating temperature scenarios, namely, fixed-date, shift-date, and bootstrap, and focused on the PLF using the quantitative probabilistic forecast error that measures quantile score. Their research and data analysis found that the bootstrap technique provided the ability to generate more complete scenarios without enhancing the quantile score. Additionally, they found that the shifted-date technique dominates the fixed-date technique if the number of shifted date is within a range. Finally, they introduced an empirical formula that helps in selecting and appropriately using parameters when implementing the temperature scenario generation techniques. Table 2 offers a comprehensive summary of the traditional LF techniques previously mentioned.

Table 2. Traditional load forecasting techniques.

Ref.	Used Models	Summarized Highlights	Pros	Cons
[75]	SWDP2A (S)ARIMA OLIN	• This paper proposed five sliding window-based forecasting algorithms for predicting electricity load in SMs; • The researchers used SMs technology to collect data which were preprocessed before use; • The study found that the SWDP2A algorithm performed better than the other algorithms.	It provides accurate hourly predictions of electricity load.	It requires preprocessing of data collected using SMs technology

Table 2. *Cont.*

Ref.	Used Models	Summarized Highlights	Pros	Cons
[76]	It is dependent solely on occupancy	• This paper proposed an (STLF) technique for non-inhabitant buildings; • They authors also investigated the generation techniques of the occupancy indexes. Every occupancy feature was estimated to find out the technique and data source which achieve the best outcomes regarding forecasting.	It explores different methods of generating occupancy indexes, which can be useful for predicting hourly consumption in non-inhabitant buildings	It is limited to non-inhabitant buildings
[77]	system identification schemes based on system features	• This paper proposed a new predictive control model for electricity forecasting using system identification schemes based on system features to enhance the efficiency and resiliency of the building's electricity. • The results showed that the proposed model can predict with accuracy reached to 90% with only 60 s of calculation time.	The calculation time is relatively short (60 s)	The proposed model may not be able to predict extreme events or rare situations
[78]	Time-based data-driven scheme	• This paper utilized a weather-based LF model to determine the power demand using a time-based data-driven scheme. • The results indicate that the applied LF model precisely predicted the power demand for residential and commercial applications.	It improves the accuracy of the power demand prediction	The data-driven scheme used in the study may require large amounts of data to achieve high accuracy
[43]	IEMD ARIMA WNN FOA	• They Proposed a novel hybrid model consisting of three models: (IEMD), (ARIMA), and (WNN) optimized by (FOA); • They exploited the advantages of each model to create a new robust and efficient hybrid model suitable for electricity LF. The experimental results proved its high accuracy and stability.	It is highly accurate and stable	The proposed hybrid model is a complex model that may be difficult to implement in practice
[79]	PLF	• They investigated three techniques focusing on the PLF using the quantitative probabilistic forecast error that measures quantile score. • They found that the bootstrap technique provides the ability to generate more complete scenarios without enhancing the quantile score.	It uses a quantitative probabilistic forecast error that measures quantile score, which provides a more accurate measurement of performance	It is not applicable to other types of forecasting scenarios

4.2. Clustering Based Load Forecasting Techniques

Clustering-based LF techniques refer to a class of methods that utilize clustering techniques to group similar load patterns, and then use these patterns to forecast future demand. These techniques are built on the assumption that similar historical load patterns tend to repeat themselves in the future, making clustering a powerful approach to modeling and forecasting electricity demand. The clustering algorithm is applied to the historical load data to identify homogeneous groups of data points, which are then used to model and forecast future demand. Clustering-based methods have been found to be particularly useful in dealing with non-linear and complex patterns, and have been shown to improve the accuracy and robustness of LF. In this part, we offer clustering-based LF techniques that have been applied in SGs.

Quilumba et al. [80] explained the utilization of clustering as a means of grouping customers based on their load consumption similarities, which can be used to enhance the system level of LF. They clarified how data from SMs from individual households could be employed to enhance the LF of the whole system by aggregating predictions from each group. The effectiveness of the proposed model was demonstrated by using two different sets of real residential SM data. This was first achieved by classifying time periods with similar load patterns based on previous data, known as a longitudinal grouping. Secondly, by matching up SMs with similar usage patterns, which are known as a cross-sectional grouping. A majority of the article focused on cross-sectional grouping. They attempted to improve intraday LF by clustering groups of customers with similar load patterns from SM data before doing any LF calculations.

Jiao et al. [81] proposed a method for predicting short-term non-inhabitant clients' power consumption using a combination of K-means clustering, spearman correlation coefficient (SCC), and an LSTM-based framework. By analyzing the clients' power consumption patterns using k-means clustering, and measuring the correlation for sequence data with the SCC, the authors were able to identify relevant time series features to include in the framework. In some cases, if the correlation coefficient was high and the hypothesis H1 was accepted, these features were appended to the framework to enhance the prediction process. The results of this study demonstrated that the proposed technique achieved the best prediction outcomes when tested on a actual dataset.

Cugliari et al. [82] proposed clustering tools used for electricity LF. This tool divided the overall signal in which the sum of divided predictions enhances the prediction of the whole global signal. This technique started with defining super-consumers by curves clustering, then set up a hierarchy of partitions within which the best one is finally selected in terms of the standard of dividing prediction.

Chaouch et al. [83] proposed two LF techniques for households using SM data through functional time series. These two techniques were functional wavelet-kernel (FWK) and clustering-based FWK. They found that the load curve is most directly affected by consumer usage patterns, which are not consistent since the variability in household power usage can vary dramatically based on the day and specific circumstances. The clustering-based FWK technique proved to be much more accurate than standard FWK.

In [84], a novel approach called data-driven linear clustering (DLC) was introduced to address the problem of LTLF in some developed cities. The method involves using a large dataset of substation loads with annual intervals, preprocessing it using the DLC method, and creating optimal ARIMA models for each cluster to forecast future loads. The system LF results were obtained by summing up the forecasts from all the ARIMA models. The results of the analysis and application showed that the proposed DLC method effectively reduced random LF errors while preserving modeling precision, resulting in a more stable and accurate system LF.

Hamed [85] presented a new technique for STLF that combined various models and utilizes clustering methods to improve system performance and accuracy. The proposed models include a combination of Kalman filtering (KF), WNN, and ANN schemes. Six various methods were suggested based on clustering techniques. The simulation results showed improved performance for the addressed methods. The research was conducted using data which was scaled for the study. The proposed technique was verified using various datasets for various locations in Egypt and Canada.

Zhang et al. [86] introduced a new closed-loop clustering (CLC) algorithm that combined the hierarchical structure and the forecasting model. The algorithm connected the objectives of forecasting and clustering by using a feedback mechanism that returns the goodness-of-fit as the criterion for clustering. The suggested technique was compared to existing hierarchical LF methods and found to perform better. Table 3 summarizes the aforementioned clustering-based LF techniques.

Table 3. Clustering-based load forecasting techniques.

Ref.	Used Models	Summarized Highlights	Pros	Cons
[80]	Longitudinal grouping Cross-sectional grouping	• This paper explained the application of clustering to group clients through load consumption similarity as a tool to improve the system level of LF. • They attempted to improve intraday LF by clustering groups of customers with similar load patterns from SM data before doing any LF calculations.	Improve intraday LF by clustering groups of customers with similar load patterns from SM data before doing any LF calculations	It is not clear how well the method would perform in other types of datasets or in a large-scale real-world setting
[81]	SCC LSTM K-means	• They used the k-means clustering technique to analyze the clients' power consumption patterns, while the measurement of correlation for sequence data was given by SCC; • The results demonstrated that the proposed technique achieved the best prediction outcomes in a real dataset.	It achieved the best prediction outcomes when tested on actual dataset	It is not clear how well the method would perform in a large-scale real-world setting
[82]	defining super-consumers set up a hierarchy of partitions	• This paper proposed clustering tools used for electricity LF. • This tool divided the overall signal in which the sum of divided predictions enhances the prediction of the whole global signal.	Enhancing the prediction of the whole global signal	It does not specify the evaluation metric used to select the best partition
[83]	Clustering based FWK	• This paper proposed two LF techniques for households using SM data through functional time series. These two techniques were FWK and clustering-based FWK.	Clustering-based FWK technique much more accurate than standard FWK.	It does not specify the specific clustering algorithm used, which makes it difficult to replicate the results of the study
[84]	DLC ARIMA	• DLC method is proposed to address the LTLF problem caused by fluctuations in some developed cities. • An optimal ARIMA models were constructed for the sum of each cluster to forecast the future load.	It addresses the problem of LTLF in developed cities	The study does not specify any details about the preprocessing step
[85]	KF WNN ANN	• This paper proposed a novel technique for STLF based on hybrid models and clustering techniques. • Six different models are proposed based on clustering techniques.	The simulation results showed improved performance for the addressed methods	The method does not specify how the data were scaled for the study
[86]	CLC	• This paper proposed CLC algorithm that combined the hierarchical structure and the forecasting model. It connected the objectives of forecasting and clustering by using a feedback mechanism.	The proposed model outperformed the existing hierarchical LF methods	It does not provide any information about the dataset used to evaluate the algorithm

4.3. AI-Based Load Forecasting Techniques

AI-based methods, such as ANN and support vector regression SVR, are also increasingly being used for LF. These methods can be trained to model complex, non-linear relationships between input variables and the output variable, electricity demand, which may not be easily captured by traditional statistical or econometric methods. In this part, we offer several existent techniques that proposed the state-of-the-art of AI models, especially ML and DL models that have been deployed for LF applications.

In [87], a decision tree method for building an energy model was proposed. The experimental results have shown that using the C4.5 model can classify and forecast building energy demands with accurate levels of 93% for training data and 92% for testing data. The process of identifying and classifying the important parameters of building energy automatically uses intensity levels and provides the combination of important parameters as well as the threshold values that participate in the forecasting of high building energy performance.

In [88], different data mining techniques, including (SVR), ANN, classification and regression tree, chi-squared automatic interaction detector (CHAID), general linear regression, and merged inference model were proposed to estimate the energy performance of buildings. Comparing the results showed that the merged approach (SVR, ANN) and SVR were the best models for forecasting cooling load and heating load, respectively, with MAPE below 4%. Compared to previous works, the merged model and SVR model further obtained at least 39.0% to 65.9% lower RMSE, respectively, for forecasting cooling load and heating load, respectively.

Furthermore, Sha et al. [89] proposed a simplified LF technique for engineering applications based only on three features considered as model input. They converted the average daily dry-bulb temperature to degree-day and used it as a model input feature, and it provided better performance. They also proposed a method to obtain the balance point temperature based on the building usage characteristics represented by day-type and month-type. They used three ML models—multi-variable linear regression (MLR), (SVR), and ANN as forecasting models. The results presented that the SVR and ANN models outperformed the MLR model. The large contradiction between the cooling and heating forecasting performance referred to the importance of the training dataset size as a factor for forecasting model performance. All three techniques provided indigent performance in heating forecasting.

For the purpose of cooling control architecture for buildings, Peng et al. [90] proposed two types of ML techniques. These two models are supervised and unsupervised models which were utilized to figure out occupants' attitudes. The learned information is utilized by a set of rules to estimate the real-time building set points to manage the cooling system. This scheme minimized the need for human intervention to manage the cooling system in the buildings. This technique is not only restricted to managing cooling operations but also can be used to manage heat and ventilation using the same technique to infer humidity and CO2 concentration set-points. It aims to reduce useless electricity demands of HVAC systems related to occupants' attitudes.

Fan et al. [91] proposed an improved prediction model named (DEMD–SVR–AR) that surpasses the original SVR model to predict electricity consumption, particularly with unbalanced data and sophisticated systems. They used the training model not only to learn a precise representation of the training set itself, but also to define a statistical model that generalizes better prediction parameters for the new inputs. The proposed model performed better than the other algorithms in terms of its prediction capability, interpretability, prediction accuracy, and generalization ability.

Additionally, Fan et al. [92] discussed the possibility of utilizing DL in building cooling LF from two points of view, extracting meaningful features and developing prediction models. The results demonstrated that nonlinear prediction techniques outperform linear prediction techniques. The extreme gradient boosting (XGB) technique outperformed other techniques. The adaptation of XGB models using features extracted by unsupervised DL models such as deep auto-encoders provides the best forecasting results.

In [93], the stability of SGs was predicted using a new multi-directional long short-term memory MLSTM model. The proposed model outperformed the traditional ML models such as LSTM, gated recurrent unit GRU, RNN in terms of accuracy (3% higher), precision, loss, and ROC curve metrics.

Marinescu et al. [94] investigated the analyzed data from a small load, approximately equivalent to a single transformer. They used six different techniques to analyze the data from ANN, fuzzy logic, auto-regression, auto-regressive moving average, auto-regressive integrated moving average, and WNN. They found that the different techniques were approximately equivalent and provided similar results.

Badr et al. [23] proposed an encrypted energy forecasting technique to preserve the privacy of net-metering systems based on federated learning (FL). They designed a hybrid DL-based energy forecasting model; alongside it, they developed an efficient data aggregation scheme to preserve the consumers' privacy by ciphering their models' parameters during the FL training using functional encryption (FE). The results indicated that their technique achieved high accuracy, and the data aggregation scheme preserved privacy with high efficiency.

Ibrahem et al. [95] proposed an ML based scheme that allows the electricity utility to discover electricity stealing, compute bills, and observe the energy using FE to keep the privacy of the users. The encrypted readings were aggregated, and this aggregated value was released to the electricity utility for purpose of billing and load surveillance. The evaluations inferred that the scheme was efficient in terms of users' privacy preservation and the accuracy of electricity theft detection.

In [96], a method was proposed for predicting energy consumption/generation in net-metering systems while preserving customers' privacy. The proposed method is based on federated learning FL, and uses a multi-data-source hybrid deep learning approach, as well as an efficient inner-product functional encryption (IPFE) scheme to encrypt the models' parameters during training. To improve communication efficiency, the proposed method uses a change and transmit approach, only sending updates for parameters that have changed significantly. The results from experiments showed that this method provides accurate predictions while protecting the privacy and reducing communication costs. The above-mentioned AI Based LF techniques are summarized in Table 4.

Table 4. AI-based load forecasting techniques.

Ref.	Used Models	Summarized Highlights	Pros	Cons
[87]	Decision tree	• This paper proposed a decision tree method for building an energy model; • The experimental results showed that using the C4.5 model can classify and forecast building energy demands with accurate levels of 93% for training data and 92% for testing data.	High accuracy levels	The method is limited to only the C4.5 model
[88]	SVR ANN CHAID General linear regression Merged inference model	• This paper proposed different data mining techniques, including SVR, ANN, classification and regression tree, CHAID, general linear regression, and merged inference model to estimate the energy performance of buildings; • Comparing the results showed that the merged approach (SVR, ANN) and SVR were the best models for forecasting cooling load and heating load.	The use of a merged approach and SVR model resulted in the best forecasting for cooling and heating load	The study may not be generalizable to other datasets
[89]	MLR SVR ANN	• This paper proposed a simplified LF technique for engineering applications based only on three features considered as model input; • They also proposed a method to obtain the balance point temperature based on the building usage characteristics represented by day-type and month-type.	A simplified LF technique was proposed	The results revealed a large contradiction between the cooling and heating forecasting performance

Table 4. *Cont.*

Ref.	Used Models	Summarized Highlights	Pros	Cons
[90]	RNN	• This paper proposed two types of ML techniques for purpose of cooling control architecture for buildings; • These two models are supervised and unsupervised models were utilized to figure out occupants' attitudes.	Not limited to managing cooling operations	The technique may not take into account other factors that could affect building energy performance
[91]	LSTM-RNN-based univariate	• This paper proposed an improved prediction model named (DEMD–SVR–AR) that surpasses the original SVR model to predict electricity consumption, particularly with unbalanced data and sophisticated systems.	It surpasses the original SVR model	The study only focused on the unbalanced data and sophisticated systems
[92]	LSTM-RNN	• This paper discussed the possibility of utilizing DL in building cooling LF from two points of view, extracting meaningful features and developing prediction models; • The results demonstrated that nonlinear prediction techniques outperform linear prediction techniques.	Results showed that nonlinear prediction techniques outperform linear prediction techniques	It is not generalizable to other types of LF, such as heating or electricity consumption
[93]	new MLSTM	• This paper proposed a new MLSTM model to predict the stability of SGs; • The proposed model outperformed the traditional ML models such as LSTM, GRU, RNN in terms of accuracy (3% higher), precision, loss, and ROC curve metrics.	The proposed model outperformed traditional ML models	It is not suitable for all types of systems or stability prediction scenarios
[94]	ANN, fuzzy logic, auto-regression, auto-regressive moving average, auto-regressive integrated moving average, and WNN	• This paper investigated the analyzed data from a small load, approximately equivalent to a single transformer; • They used six different techniques to analyze the data from ANN, fuzzy logic, auto-regression, auto-regressive moving average, auto-regressive integrated moving average, and WNN; • They found that the different techniques were approximately equivalent and provided similar results.	Investigated data from a small load, equivalent to a single transformer, using six different techniques	It does not provide a clear advantage for one technique over the others for the analyzed data.
[23]	FL DL FE	• This paper proposed an encrypted energy forecasting technique to preserve the privacy of net-metering systems based on FL. • The results indicated that their technique achieved high accuracy, and the data aggregation scheme preserved privacy with high efficiency.	It provides privacy preservation with high efficiency	It is limited to energy forecasting for net-metering systems
[95]	ML FE	• This paper proposed an ML-based scheme that allows the electricity utility to discover electricity stealing, compute bills, and observe the energy using FE to maintain the privacy of the users; • The evaluations inferred that the scheme was efficient in terms of users' privacy preservation and accuracy of electricity theft detection.	High Accuracy	The study may not take into account other factors that could affect the system being analyzed.

Table 4. *Cont.*

Ref.	Used Models	Summarized Highlights	Pros	Cons
[96]	FL IPFE CAT	• This paper proposed predicting energy consumption/generation in net-metering systems; • An efficient IPFE scheme was used to preserve customers' privacy by encrypting their models' parameters during FL training; • Results from experiments show that the proposed approach accurately predicts future readings.	It provides accurate predictions while protecting privacy and reducing communication costs	Limited applications

4.4. Time Series Load Forecasting Techniques

Time series LF entails utilizing historical usage data over a defined period to anticipate future energy needs. The utilization of data, gathered at consistent intervals such as daily or hourly, allows for the identification of patterns and trends in energy consumption. These patterns and trends are subsequently employed to create predictions about future demand. The objective of time series LF is to offer precise predictions of energy demand for energy providers to plan adequately for generation and transmission capacity, and to reduce the likelihood of supply interruptions or power outages. In this section, we present various LF techniques that have been proposed using time series models.

Two recently developed time-series forecasting models for power consumption, the conditional restricted Boltzmann machine (CRBM) and the factored conditionally restricted Boltzmann machine (FCRBM), were discussed in [97]. The study found that the FCRBM surpassed (ANN), (SVM), recurrent neural networks (RNN), and CRBM.

Mocanu et al. [98] discussed two reinforcement learning algorithms to perform the building energy consumption. The deep belief network (DBN) and the automated feature extraction were combined to process a short-term building energy model. Experimental results showed that the energy forecasting accuracy in terms of RMSE was enhanced in 91.42% of the scenarios after using a DBN for automatically extracting high-level features from the unlabeled data, compared to the equivalent techniques without the DBN preprocessing.

Khan et al. [99] proposed a model that uses predictive analytics to forecast short-term power consumption in multi-family residential buildings, using a time-series dataset. They combined DL model with a statistical model to make the predictions. To evaluate the performance of the forecasting model, they employed four metrics: MAE, RMSE, MAPE, R-squared (R2) scores.

Sala et al. [100] proposed a new hybrid approach for forecasting the short-term thermal energy demand of HVAC systems in smart buildings, which is based on a data-driven method. The approach uses an RNN to learn the dynamics of an activity indicator, then an adaptive neuro-fuzzy inference system is employed to correlate the activity predictions obtained in this way with outdoor temperature and bus return temperature, in order to model the thermal energy demand of the building's HVAC system.

Bouktif et al. [101] proposed an optimized LSTM-RNN based univariate model for demand side LF, which worked over both STLF and MTLF. The proposed model was compared with seven ML based LF techniques, and it outperformed all of them, particularly in LF error rate.

Agrawal et al. [31] proposed a LSTM-RNN model for LTLF with the hourly resolution. The proposed model outperformed the other LTLF models by providing high accuracy with MAPE of 6.54 and a confidence interval of 2.25%. Although it has been implemented on a real dataset, the computation time was 30 min which is considered not appropriate for online applications.

Ahmad et al. [102] aim to figure out an efficient ML-based LF technique working for medium-term and long-term time horizons. They utilized ANN, multivariate linear regression model, and adaptive boosting model. The results of the study showed that the proposed models had superior performance when applied to LF in the SGs at different intervals, including monthly, seasonal, and annual.

Massaoudi et al. [103] proposed a new hybrid computing approach for STLF that accounts for the stochastic variations in load demand using a stacked generalization method. This approach involves combining three algorithms, namely, light gradient boosting machine (LGBM), XGB, and multi-layer perceptron (MLP), into a single model. The inner workings of the stacked XGB-LGBM-MLP technique involve creating meta-data from the XGB and LGBM models, which is then used to make final forecasts using the MLP network. The proposed technique was evaluated using several case studies to compare its performance to existing benchmark techniques and other hybrid models.

Wang et al. [104] proposed a technique for individual consumer PLF that deals with the variability and unpredictability of future load profiles. It uses both NN and LSTM to handle both LTLF and STLF. Rather than using MSE as the training loss, it employs a pinball loss function. The results showed that the proposed method outperforms traditional techniques.

In [105], a three-step method was proposed for forecasting electricity consumption at various household group levels. The method involves creating initial forecasts using generalized additive models, finding the optimal linear combination of these forecasts using the ML-Poly aggregation algorithm, and adjusting the forecasts to meet hierarchical constraints. This approach was found to improve the accuracy of the forecasts and was tested using household electricity consumption data.

Dan et al. [46] presented a method for forecasting hourly load time series that utilizes an improved temporal fusion transformer (ITFT) model in order to achieve more accurate and comprehensive results. The method involves reconstructing raw hourly load data into multiple day-to-day load time series at different hour points, which helps to balance the need for long-term temporal dependence with reducing model complexity. The ITFT model builds on the original temporal fusion transformer (TFT) model by using a GRU instead of an LSTM to more efficiently learn long-term dependencies and includes quantile constraints and prediction interval (PI) penalty terms in the quantile loss function to prevent quantile crossover and generate more compact prediction intervals. Results from two real examples showed that the proposed method is effective and significantly improves the reliability and compactness of the forecasting results compared to other commonly used methods.

Mancuso et al. [106] described a ML approach for forecasting time series with a hierarchical structure. It aimed to not only produce accurate forecasts, but also to select an appropriate method for reconciling these forecasts. The process of forecast reconciliation involved adjusting forecasts to make them consistent across different levels of the hierarchy. Traditional methods for enforcing coherence often involved post-processing techniques on base forecasts generated by other time series forecasting methods. This proposal suggested using a DNN to directly produce accurate and reconciled forecasts. The NN was able to extract information that captures the structure of the hierarchy and the reconciliation was enforced during the training process by minimizing a custom loss function. Additionally, many hierarchical time series data also included explanatory variables that can be used to improve forecasting accuracy. This approach incorporated these variables by linking them to the time series features at different levels of the hierarchy within an end-to-end NN. This approach was tested on three real datasets and outperformed other state-of-the-art methods for hierarchical forecasting.

In [107], a new forecasting model was presented for predicting the high-resolution plug-in EV load, taking into account various factors that affect the charging load. The proposed model utilized an enhanced attention-based LSTM approach and a feature upscaling and downscaling algorithm for processing hierarchical high-resolution data. The model was tested on real-world data from a charging station in Shenzhen, and results showed that the model structure and algorithm performed well in STLF and VSTLF hierarchical high-resolution plug-in EV charging load.

Additionally, in [108], a hierarchical time series approach was proposed to predict the load demand of a primary substation one hour ahead, using different forecasting models.

The performance of the forecasting models was evaluated using the MAPE indicator. The bottom-up approach was used to forecast at the top level. The results showed that the proposed hierarchical structure provides better performance with the employed forecasting models. The techniques for LF based on the time series discussed previously are outlined in Table 5.

Table 5. Summary of time series load forecasting techniques.

Ref.	Used Models	Summarized Highlights	Pros	Cons
[97]	CRBM FCRBM	• This paper proposed two newly short-term for time-series prediction models of power consumption, namely, CRBM and FCRBM.	FCRBM surpassed ANN, SVM, RNN, and CRBM	The proposed models may not be generalizable to other applications
[98]	DBN AFE	• This paper discussed two reinforcement learning algorithms to perform the building energy consumption; • It combined (DBN) and the automated feature extraction to process a building energy algorithm for STLF.	The results showed that the energy forecasting accuracy in terms of RMSE was enhanced	The proposed models may be complex and difficult to implement
[99]	DL statistical model	• This paper proposed a predictive and data analytic model to predict short-term power consumption based on a time-series dataset acquired from multifamily inhabitant buildings; • They combined DL model with a statistical model to predict short-term power consumption.	Using MAE, RMSE, MAPE, and R2 scores to evaluate the performance.	It needs to be compared to other models
[100]	RNN	• This paper proposed a new hybrid method for STLF of HVAC thermal energy demand in smart buildings that depends on a data-driven approach; • This proposed method used dedicated RNN to learn the dynamics present in the activity indicator developed for this approach.	High accuracy and performance level	It may not be suitable for all applications
[101]	LSTM-RNN-based univariate	• This paper proposed an optimized LSTM-RNN based univariate model for demand side LF which worked over both STLF and MTLF; • The proposed model was compared with seven ML based LF techniques, and it outperformed all of them particularly in LF error rate.	It outperforms seven ML-based LF techniques, and works over both STLF and MTLF	The results may be affected by the specific dataset used in the study
[31]	LSTM-RNN	• This paper proposed a LSTM-RNN model for LTLF with hourly resolution; • The proposed model outperformed the other LTLF models by providing high accuracy with MAPE of 6.54 and a confidence interval of 2.25%.	More accurate forecasts	Not appropriate for online applications
[102]	ANN MLR adaptive boosting	• This paper utilized ANN, multivariate linear regression model, and adaptive boosting model; • The results proved the superiority of these models in the SGs in terms of LF intervals that are classified into monthly, seasonal, and annual.	Superior Accuracy	Limited applications

Table 5. *Cont.*

Ref.	Used Models	Summarized Highlights	Pros	Cons
[103]	LGBM XGB MLP	• They proposed a novel hybrid computing technique for STLF. • They merged three algorithms, namely, LGBM, XGB, and MLP.	Several case studies were applied	High overhead
[104]	PLF NN LSTM	• This paper proposed a PLF technique for individual consumers to handle the variability and uncertainty of future load profiles; • They used the pinball loss method, instead of MSE, to lead the training process.	It outperforms the traditional techniques.	It needs to be compared to other AI models
[46]	PLF, ITFT, LSTM, GRU, and TFT	• This paper introduced PLF technique for time series using ITFT model; • The ITFT substituted LSTM together with GRU using the main TFT model to effectively learn LTLF.	Efficient learning of long-term dependencies using a GRU	Limited Applications
[105]	Hierarchical limitations global consuming	• This paper presented a three-step method for forecasting time series of energy usage at various levels of home aggregation; • These series were related by hierarchical limitations global consuming equaled the total local consumption.	It enhanced RMSE values	Limited to household electricity consumption data, may not generalize well to other types of data or contexts
[106]	DNN	• This paper proposed ML-based forecasting hierarchical time series; • They used DNN to generate precise and consistent predictions and to retrieve information while capturing the hierarchy's structure.	Improved accuracy of the forecasts	It may not work well for other type of data or hierarchies
[107]	An enhanced attention-based LSTM	• A new forecasting model was presented for predicting high-resolution plug-in EV load; • The model utilized an enhanced attention-based LSTM approach and a feature upscaling and downscaling algorithm for processing hierarchical high-resolution data.	Good results with real data	Working only for EV
[108]	Hierarchical time series approach	• This article presents a hierarchical time series approach to predict the load demand of a primary substation one hour ahead; • The performance of the forecasting models was evaluated using the MAPE indicator.	The ability to forecast at different levels of granularity, using the bottom-up approach	Complexity of the hierarchical structure, which may make it difficult to implement and interpret

4.5. Meta-Heuristic-Based Load Forecasting Techniques

LF is a crucial aspect of power systems management, as it allows for the efficient planning and operation of power generation and transmission. Meta-heuristic techniques are a class of optimization algorithms that have been increasingly utilized in LF due to their ability to effectively handle the complexity and uncertainty inherent in this task. These techniques include genetic algorithms, particle swarm optimization, and simulated annealing, among others. In this section, we will explore various meta-heuristic-based LF techniques and their applications in the power systems industry.

Noradin et al. [109] presented a hybrid forecasting approach that incorporated a new feature selection method and a two-stage forecast engine using Ridgelet and Elman NN. The load signal was preprocessed through feature selection before being input into the forecast engine, which utilized a novel intelligent algorithm to optimize its performance. The method was evaluated on various electricity market datasets and compared to existing algorithms, and the results demonstrated the superior accuracy of the proposed method, as measured by various error metrics such as:

$$MAPE(\%) = \frac{1}{NH}\Sigma_{t=1}^{NH}\frac{|L_{act}(t) - L_{for}(t)|}{L_{act}(t)} \times 100 \tag{1}$$

$$MAE = \frac{1}{NH}\Sigma_{t=1}^{NH}|L_{act}(t) - L_{for}(t)| \tag{2}$$

Sun et al. [110] proposed a technique for electric STLF that employed LSTM networks and a modified sine–cosine algorithm called MetaREC. First, it used LSTM networks as a specific type of RNN that can retain and transmit both short and long-term information. Four crucial parameters are determined using the sine–cosine algorithm, which relies on a logistic chaos operator and multilevel modulation factor, to overcome the inaccuracies of LSTM network predictions caused by manual parameter selection as follows:

$$X_{(t+1)}(i,j) = \begin{cases} X_t(i,j) + r_1^*(t)\sin r_2|r_3 \times P_t(i,j) - X_t(i,j)|, r_4 < 0.5 \\ X_t(i,j) + r_1^*(t)\cos r_2|r_3 \times P_t(i,j) - X_t(i,j)|, r_4 \geq 0.5 \end{cases} \tag{3}$$

Additionally, the MetaREC method demonstrated superior performance in accuracy and speed on various test functions when compared to others. Finally, the study extends the analysis to evaluate the MetaREC LSTM with back propagation NN, LSTM networks with default parameters, LSTM networks with the conventional sine–cosine algorithm, and LSTM networks with whale optimization for power LF on a real electric load dataset. The results of the simulation showed that multiple forecasts with MetaREC LSTM can effectively improve the accuracy and stability of power STLF.

Roushangar et al. [111] assessed the effectiveness of the generalized wavelet kernel extreme learning machine (WKELM) approach for predicting bed load transport rate (BLTR) in gravel-bed rivers. To enhance performance, this technique was combined with the particle swarm optimization (PSO) algorithm to identify optimal parameters for WKELM models. Various input combinations were created based on three scenarios, and results showed that scenario 2 was the most effective in measuring BLTR. The model incorporating parameters Fr, V/U*, and T had the highest level of R (0.934), NSE (0.870) and lowest value of RMSE (0.025) for the test series and demonstrated more accurate and reliable prediction ability when compared to SVM. This proposed input combination was used to predict bed load transport in different intervals of median particle size, with the results showing that the intervals of 1 to 1.4 mm produced the best predictive ability with NSE = 0.982. The study found that the V/U* parameter played a crucial role in predicting BLTR. It also compared the capabilities of traditional approaches for predicting sediment load and found that these formulas had poor results due to limitations in input–output parameters and complex conditions that govern sediment transport in natural gravel-bed rivers. The results from sensitivity analysis showed that the ratio of average velocity to shear velocity is the most influential parameter in predicting bed load. However, it should be noted that the PSO-KELM approach is data-sensitive, so more studies with a greater field data are recommended to confirm the validity of the proposed models.

Ahmad et al. [112] proposed a novel DL method for electricity LF, using a three-step approach. The first step is feature selection using a combination of XGB and decision tree according to the following formula.

$$f(s) = \begin{cases} reserve, \iff IXG[f] + IDT[f] \geq t, \\ drop, \iff IXG[f] + IDT[f] < t. \end{cases} \tag{4}$$

where f indicates the feature, IXG [f] represents the important feature calculated by XGB, and IDT[f] by the decision tree. t indicates the threshold for features selection. The second step is redundancy removal using Recursive Feature Elimination. The final step is classification and forecasting using improved versions of SVM and Extreme Learning Machine (ELM). The hyperparameters of ELM were optimized using a Genetic Algorithm, while the hyperparameters of SVM were optimized using a Grid Search Algorithm. The results showed that this improved method outperforms the most recent techniques in terms of accuracy and performance, with forecasting accuracy of 96.3% for ELM-GA and 93.25% for SVM-GC, which are 10% and 7% higher, respectively, than other techniques.

Huafeng et al. [113] introduced a framework, called multi-space collaboration (MSC), aimed at optimizing model selection. It utilized a space separation strategy to perform model selection on subspaces, increasing the likelihood of selecting the optimal model. Additionally, their framework incorporated a subspace elimination strategy that gradually eliminated subspaces with low potential as iterations progress, thus focusing more on the better parameter domains. They performed simulation and real case studies to demonstrate the effectiveness of the MSC framework. Results from test functions with known optimal solutions showed that the MSC framework outperformed traditional meta-heuristic algorithms and had strong robustness.

A quantum computing was utilized to enhance the searching capabilities of the dragonfly algorithm, referred to as QDA, by quantifying dragonfly behaviors in [114]. Additionally, the use of complete ensemble empirical mode decomposition adaptive noise (CEEMDAN) for data preprocessing improved forecasting accuracy. As a result, a new electric LF model, called the CEEMDAN-SVRQDA model, was proposed. This model combines CEEMDAN and hybridizes QDA with a SVR model to provide more accurate forecasts as in Equation (5). The proposed model was tested using two real data from Japan and United Kingdom, and it was found to perform better than other models.

$$|\psi\rangle = \beta_1|0\rangle + \beta_2|1\rangle \tag{5}$$

Ribeiro et al. [115] proposed a hybrid learning model for electric STLF based on a dual decomposition approach. This scheme combines ML-based signal decomposition techniques with metaheuristic-based hyperparameter optimization. The first decomposition approach, seasonal and trend decomposition based on locally weighted regression STLF, decomposed the time series into seasonal, trend, and residual components. The second decomposition approach, variational mode decomposition (VMD), further decomposes the STLF residual into different frequencies. The scheme was evaluated using measures such as MEA, sMAPE, overall weighted average, and the Diebold–Mariano statistical test as follows.

$$Diebold - Mariano = \frac{\frac{\sum_{i=1}^{n}[L(\epsilon_i^p) - L(\epsilon_i^c)]}{n}}{\sqrt{\frac{S^2}{n}}} S^2 \tag{6}$$

The techniques for LF that have been discussed previously and are based on metaheuristic methods can be found in the accompanying Table 6.

Table 6. Summary of meta-heuristic based load forecasting techniques.

Ref.	Used Models	Summarized Highlights	Pros	Cons
[109]	Ridgelet-NN Elman-NN	• This paper presented a hybrid forecasting approach that incorporated a new feature selection method; • Two-stage forecast engine using Ridgelet and Elman NN. • Results demonstrated superior accuracy as measured by various error metrics.	Superior accuracy of the proposed method as measured by various error metrics	It requires more computational resources than other forecasting algorithms
[110]	LSTM MetaREC RNN	• This paper proposed a technique for electric STLF that employed LSTM networks and a modified sine-cosine algorithm called MetaREC; • Results showed that multiple forecasts with MetaREC LSTM can effectively improve the accuracy and stability of power STLF.	MetaREC LSTM improves the accuracy and stability of power STLF	The proposed technique may not be generalizable to other applications
[111]	WKELM BLTR PSO	• This paper Assessed the effectiveness of the generalized WKELM approach for predicting BLTR in gravel-bed rivers; • This technique was combined with PSO algorithm to enhance performance.	Accurate and reliable prediction compared to SVM	It was not compared to other models
[112]	XGB Decision Tree RFE Improved-SVM ELM-GA	• This paper proposed a novel DL method for electricity LF using a three-step approach; • The results showed that this improved method outperforms the most recent techniques in terms of accuracy and performance.	The improved method outperforms the most recent techniques in terms of accuracy and performance	It may require more computational resources than other forecasting algorithms
[113]	MSC	• This paper introduced a framework called MSC aimed to optimize model selection; • The results showed that the MSC framework outperformed traditional meta-heuristic algorithms.	MSC framework outperformed traditional meta-heuristic algorithms	The proposed framework may be complex and difficult to implement
[114]	QDA CEEMDAN SVR	• This paper utilized quantum computing to enhance the searching capabilities of QDA algorithm; • The proposed model was tested using two real data from Japan and United Kingdom, and it was found to perform better than other models.	It was found to perform better than other models	It is data-sensitive, allowing for more studies with more field data
[115]	WKELM BLTR PSO	• This paper used a hybrid learning model based on dual decomposition approach in electric STLF; • The results were compared with single decomposed models, dual decomposed models, non-decomposed models, and the most recent models.	Accurate and reliable prediction compared to SVM	It needs to be compared to other models

5. Recommendations

This paper aims to provide a comprehensive survey of the major techniques used in LF and their applications in SGs. Despite the numerous survey papers and reviews that have already examined LF techniques from various perspectives, our paper aims to offer a more in-depth and up-to-date overview of the field. We begin by reviewing existing reviews and survey papers on the topic in a section dedicated to related work, providing readers with a broad understanding of the existing literature and the most recent techniques. Additionally, we present an overview of the current state-of-the-art techniques, including traditional techniques, clustering-based techniques, AI-based techniques, LF techniques based on time series, and meta-heuristic-based techniques. Additionally, Table 7 provides a detailed comparison of advantages and disadvantages for all LF techniques for a thorough understanding.

Based on the review of existing literature on LF techniques and their applications for SGs, it is recommended that future research focus on the following areas:

- Development of more advanced forecasting models that can handle high levels of volatility and uncertainty in load data;
- Implementation of ensemble methods, which have been shown to improve the accuracy of forecasting models;
- Investigation increasing the use of NNs, which have shown promising results in LF in recent studies;
- Exploration of the use of big data and ML techniques for LF in SGs;
- Examination of the potential benefits of integrating LF with demand response programs in SGs;
- Study of the impact of renewable energy sources on LF in smart grids and the development of models that can accurately forecast the impact of these sources on the grid;
- Development of forecasting models that can take into account the specific characteristics of different types of loads, such as residential, commercial, and industrial loads;
- Consideration of the role of distributed energy resources and their impact on LF in SGs.

Overall, it is important for future research to continue to focus on developing more accurate and reliable LF techniques for SGs, as these are crucial for the efficient and effective operation of the grid.

Table 7. Summary of advantages and disadvantages for all LF techniques.

Techniques	Advantages	Disadvantages
Traditional Load Forecasting Techniques	• These techniques are well-established and widely used in the industry; • They are relatively simple to implement and understand; • They do not require a large amount of data.	• These techniques may not be as accurate as more advanced methods; • They may not be able to handle complex or non-linear relationships in the data; • They may not be able to handle missing data or extreme events.
Clustering-Based Load Forecasting Techniques	• These techniques can identify patterns and relationships in the data that traditional methods may not detect; • They can be used to identify and forecast patterns in specific. subsets or groups of the data; • They can handle missing data or extreme events.	• These techniques may require a large amount of data to achieve high accuracy; • They may be computationally intensive to run; • They may be difficult to interpret and understand.
AI-based Load Forecasting Techniques	• These techniques can handle complex or non-linear relationships in the data; • They can be used to identify and forecast patterns in specific subsets or groups of the data; • They can handle missing data or extreme events.	• These techniques may require a large amount of data to achieve high accuracy; • They may be computationally intensive to run; • They may be difficult to interpret and understand; • These techniques may not be generalizable to other types of data.

Table 7. *Cont.*

Techniques	Advantages	Disadvantages
Time Series Load Forecasting Techniques	• These techniques are well-established and widely used in the industry; • They are relatively simple to implement and understand; • They can handle missing data or extreme events.	• This paper presented a hybrid forecasting approach that incorporated a new feature selection method; • These techniques may not be as accurate as more advanced methods; • They may not be able to handle complex or non-linear relationships in the data; • They may require a large amount of data to achieve high accuracy.
Meta-Heuristic Based Load Forecasting Techniques	• These techniques can handle complex or non-linear relationships in the data; • They can be used to identify and forecast patterns in specific subsets or groups of the data; • They can handle missing data or extreme events; • They are global optimization methods which can find optimal or near-optimal solutions.	• These techniques may require a large amount of data to achieve high accuracy; • They may be computationally intensive to run; • They may be difficult to interpret and understand; • These techniques may not be generalizable to other types of data; • They require a good initialization to find global optimal or near-optimal solutions.

6. Conclusions

LF techniques are essential for maintaining the reliability, stability, and efficiency of the smart grid SGs as they are able to predict energy demands of consumers. With the growing various of ML and DL algorithms, the challenge is to find the most suitable algorithm for forecasting electricity demands. To address this, a comprehensive survey of state-of-the-art LF techniques was conducted to showcase the various LF techniques and their applications in SGs. We included a related work section that reviewed existing reviews and survey papers on the topic. We presented an overview of the existing literature and most recent techniques, including traditional LF techniques, clustering-based techniques, AI-based techniques, LF techniques based on time series data, and meta-heuristic-based LF techniques.

We believe that the increasing advancements in AI technology, specifically ML and DL algorithms, have greatly improved the precision of demand forecasting in LF. However, there is still a need for further research to analyze and evaluate different LF techniques to identify the most accurate and appropriate techniques for use in SGs. Our findings suggest that AI-based LF techniques, including ML and NN models, have yielded the best forecast performance among the techniques studied. These techniques also achieved a higher overall (RMS) and (MAPE) compared to other applied LF techniques.

One potential suggestion for future advancements in LF for SGs applications could be the integration of ML models to enhance the accuracy and efficiency of forecasting techniques. Additionally, integration of ML models with statistical models could also improve the precision and effectiveness of forecasting techniques. Utilizing real-time data and implementing advanced sensor technology could also enhance the ability to accurately predict and respond to changes in load demand. Furthermore, incorporating distributed energy resources and considering the integration of renewable energy sources into forecasting models can also provide a more holistic and sustainable approach to LF in SGs systems.

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Abbreviations

The following abbreviations are used in this manuscript:

RTP	Real-Time Pricing
SG	Smart Grid
LF	Load Forecasting
AI	Artificial Intelligence
MLP	Multi-Layer Perceptron
PSO	Particle Swarm Optimization
FCRBM	Factored Conditional Restricted Boltzmann Machine
ARMA	Auto-Regressive Moving Average
MPC	Model Predictive Control
VSTLF	Very Short-Term Load Forecasting
EV	Electric Vehicle
GSP	Gross State Product
MLR	Multiple Linear Regression
SM	Smart Meter
ELM	Extreme Learning Machine
SVM	Support Vector Machine
MSC	Multi-Space Collaboration
RMS	Root Mean Squared
ARIMA	Auto-Regressive Integrated Moving Average
STLF	Short-Term Load Forecasting
WKELM	Wavelet Kernel Extreme Learning Machine
ANN	Artificial Neural Network
SI	Swarm Intelligence
LSTM	Long Short-Term Memory
KNN	K-Nearest Neighbors Algorithm
ToU	Time of Use
MAPE	Mean Absolute Percentage Error
RNN	Recurrent Neural Networks
SCADA	Supervisory Control And Data Acquisition
OLIN	Online Information Network
IEMD	Improved Empirical Mode Decomposition
ML	Machine Learning
MTLF	Medium-Term Load Forecasting
WNN	Wavelet Neural Network
NN	Neural Network
FOA	Fruit Fly Optimization Algorithm
PLF	Probabilistic Load Forecast
DL	Deep Learning
SCC	Spearman Correlation Coefficient
FWK	Functional Wavelet-Kernel
CHAID	Chi-squared Automatic Interaction Detector
HVAC	Heating, Ventilation, and Air Conditioning
XGB	Extreme Gradient Boosting
MLR	Multi-variable Linear Regression
SVR	Support Vector Regression
CRBM	Conditional Restricted Boltzmann Machine
LTLF	Long-Term Load Forecasting
DBN	Deep Belief Network
FL	Federated Learning
VMD	Variational Mode Decomposition
IoT	Internet of Things
LGBM	Light Gradient Boosting Machine
GRU	Gated Recurrent Units
CPP	Critical Peak Pricing

QDA	Quantifying Dragonfly Algorithm
KF	Kalman Filtering
BLTR	Bed Load Transport Rate
CLC	Closed-Loop Clustering
HLF	Hierarchical Load Forecasting
CEEMDAN	Complete Ensemble Empirical Mode Decomposition Adaptive Noise
IPFE	Inner-Product Functional Encryption
CAT	Change And Transmit

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