applied sciences

MDPI

Review

From Time-Series to Hybrid Models: Advancements in Short-Term Load Forecasting Embracing Smart Grid Paradigm

Salman Ali [1], Santiago Bogarra [1,*], Muhammad Naveed Riaz [2], Pyae Pyae Phyo [3], David Flynn [4] and Ahmad Taha [4]

[1] Department of Electrical Engineering, Universitat Politècnica de Catalunya (UPC), C. Colom 1, 08222 Terrassa, Spain; salman.ali@upc.edu
[2] Computer Vision Center (CVC), Universitat Autonoma de Barcelona (UAB), 08193 Bellaterra, Spain; nriaz@cvc.uab.cat
[3] Department of Electrical Engineering, Eindhoven University of Technology, 5611 AZ Eindhoven, The Netherlands; p.p.phyo@tue.nl
[4] James Watt School of Engineering, University of Glasgow, Glasgow G12 8QQ, UK; david.flynn@glasgow.ac.uk (D.F.); ahmad.taha@glasgow.ac.uk (A.T.)
* Correspondence: santiago.bogarra@upc.edu

Abstract: This review paper is a foundational resource for power distribution and management decisions, thoroughly examining short-term load forecasting (STLF) models within power systems. The study categorizes these models into three groups: statistical approaches, intelligent-computing-based methods, and hybrid models. Performance indicators are compared, revealing the superiority of heuristic search and population-based optimization learning algorithms integrated with artificial neural networks (ANNs) for STLF. However, challenges persist in ANN models, particularly in weight initialization and susceptibility to local minima. The investigation underscores the necessity for sophisticated predictive models to enhance forecasting accuracy, advocating for the efficacy of hybrid models incorporating multiple predictive approaches. Acknowledging the changing landscape, the focus shifts to STLF in smart grids, exploring the transformative potential of advanced power networks. Smart measurement devices and storage systems are pivotal in boosting STLF accuracy, enabling more efficient energy management and resource allocation in evolving smart grid technologies. In summary, this review provides a comprehensive analysis of contemporary predictive models and suggests that ANNs and hybrid models could be the most suitable methods to attain reliable and accurate STLF. However, further research is required, including considerations of network complexity, improved training techniques, convergence rates, and highly correlated inputs to enhance STLF model performance in modern power systems.

Keywords: short-term electrical load forecasting; time-series models; regression models; machine learning models; expert-systems-based models; metaheuristic models; hybrid models; smart grid

check for updates

Citation: Ali, S.; Bogarra, S.; Riaz, M.N.; Phyo, P.P.; Flynn, D.; Taha, A. From Time-Series to Hybrid Models: Advancements in Short-Term Load Forecasting Embracing Smart Grid Paradigm. *Appl. Sci.* **2024**, *14*, 4442. https://doi.org/10.3390/app14114442

Academic Editor: Filipe Soares

Received: 7 May 2024
Revised: 21 May 2024
Accepted: 22 May 2024
Published: 23 May 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Global electricity demand is projected to reach 26.8 kTWh by 2025, driven by population growth, urbanization, and economic expansion [1], as shown in Figure 1. Diverse resources such as water, wind, solar, fossil fuel, thermal, and nuclear power contribute to electricity generation. This increasing demand is driving up production costs. An efficient energy management system (EMS) relies on overcoming the challenges of generation, transmission, and distribution challenges. The electric grid (EG), consisting of power plants, substations, and transmission and distribution lines, connects suppliers to consumers [2]. Overloading the grid can lead to power quality issues, requiring the installation of new power plants. However, existing grids lack accurate forecasting mechanisms to predict the causes of outages and response times, creating challenges for resource allocation [3–6].

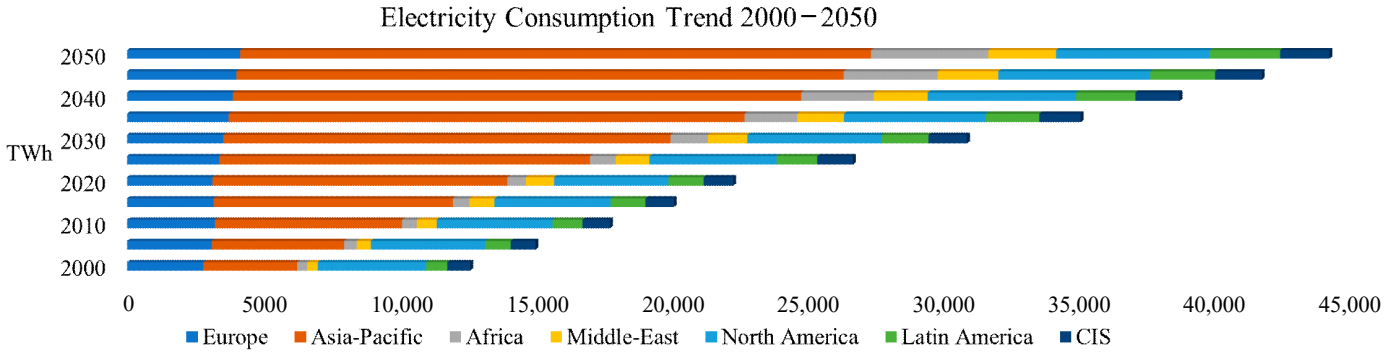

Figure 1. Electricity consumption trend 2000–2050.

Despite increasing demand due to population growth, the current electrical power system (PS) has changed little [7–9]. It suffers from visibility issues, slow mechanical switches, inadequate monitoring, and poor power management. Climate change, component failures, increasing energy demand, population growth, and fossil fuel consumption require modern grid technology. Smart grids and microgrids have emerged as critical next-generation energy infrastructures to address these challenges [10,11]. Modern smart grids with advanced metering enable fast two-way communication, optimize energy consumption, and improve grid efficiency through effective load management. They also have faster self-healing capabilities and greater resilience to disasters and cyber threats. In addition, smart grids quickly identify and resolve problems with minimal customer impact, while conventional systems are slow to respond. Finally, power flow regulation in conventional grids is severely limited compared to smart grids and microgrids [12].

Integrating distributed energy resources (DERs) address the growing demand for electricity while complicating power systems [13]. Accurate load forecasting (LF) is critical for effective grid management, especially with increasing DER integration. Emissions targets require widespread integration of renewable energy sources (RESs), as shown in the total electricity generation forecast in Figure 2. Additionally, the global trend in RES electricity generation (%) is shown in Figure 3 [1]. Reliable load data, facilitated by the Internet of Things (IoT), are essential for accurate LF. Researchers are developing innovative approaches to predict future electricity demand in modern grids [14].

The LF guides critical decisions such as dispatch, unit commitment, and fuel allocation [15]. It minimizes the gap between power production and demand, thereby reducing generation costs. Rapid changes in load consumption patterns require models that can adapt and learn from historical data. However, model validation is affected by boundary conditions and data quality issues, resulting in case-by-case adjustments. A model that lacks essential features can result in significant operational, infrastructure, financial, or maintenance losses. A reduction of only 1% in the mean absolute percentage error in load forecasting can have a significant impact on the generation side, potentially reducing generation costs by 0.1% to 0.3%, for a consequential impact of 3–5% [16].

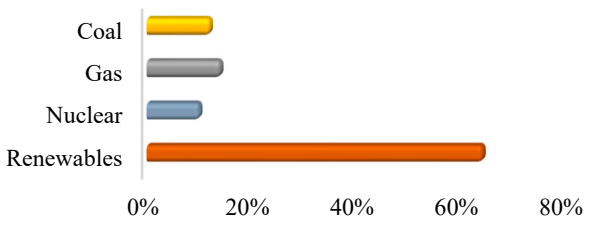

Figure 2. Electricity generation by energy source 2050 (%).

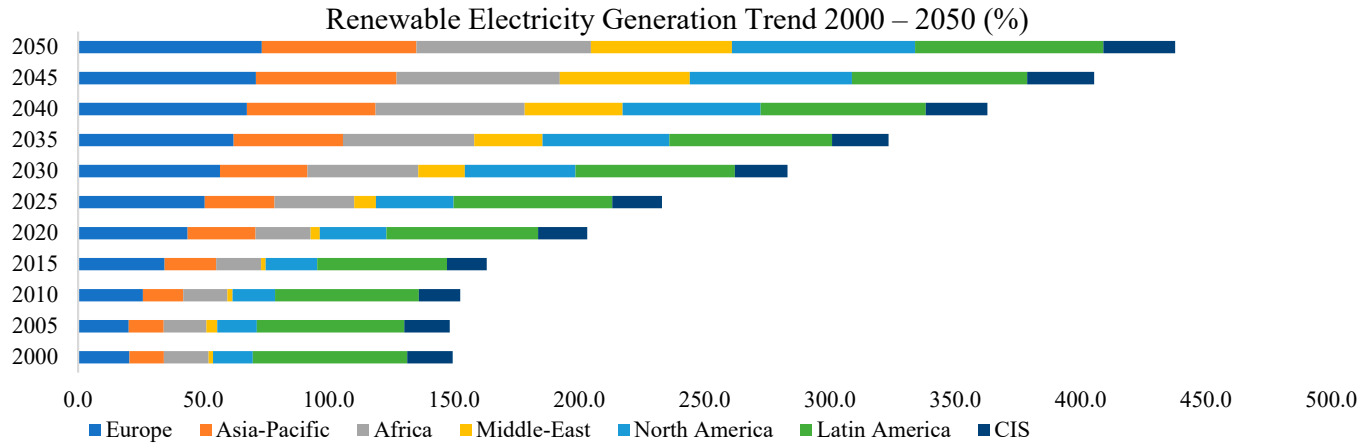

Figure 3. Renewable electricity generation trend 2000–2050 (%).

In the literature, electrical load forecasting is categorized into long-term load forecasting (LTLF), medium-term load forecasting (MTLF), short-term load forecasting (STLF), and very short-term load forecasting (VSTLF), which are discussed in detail in Section 3. However, the focus of this paper is on STLF and its associated forecasting techniques due to its importance in power utility management. STLF is critical to the efficient operation of conventional power systems, influencing dispatch plans [17], demand-side management, and generation monitoring [18]. It has a significant impact on power markets, transactions, and revenues [19]. Scholars have proposed various STLF methods [20–25], influencing power system performance [26] and resource management in modern grids [27]. STLF helps to evaluate energy trading volumes with the wholesale power market and addresses critical issues in grid management, RES optimization, and planning [28,29]. However, accurate LF in modern grids is sensitive to equipment changes and load asymmetries and requires extended time spans. Therefore, STLF is essential for modern grid operation and security.

Despite extensive efforts to improve the efficiency and economic performance of electric utilities through the development of high-precision LF models, limited research papers have focused on STLF [30]. Previous reviews have emphasized specific sectors and have examined either statistical, artificial intelligence (AI), or machine learning (ML) approaches. Additionally, previous research categorized load forecasting into methodologies or application domains. The evolving domains present challenges when existing methods cannot adapt, while computational advances enable more efficient models, often incorporating artificial neural networks (ANNs). Table in Section 2 provides a comparative analysis of STLF reviews to provide context. In light of previous reviews on STLF, the main contributions of this paper are:

1. Unlike previous reviews, it uniquely focuses on a comprehensive analysis of STLF methodologies (statistical, intelligent computing, hybrid models), considering multiple sectors to provide a broader perspective while integrating the smart grid perspective.
2. It provides a thorough background on load forecasting, emphasizing its importance, load curve characteristics, influencing factors, and categorization.
3. Addressing the evolving landscape, the paper explores STLF in smart grids, highlighting the role of smart devices and storage systems in improving accuracy for efficient energy management.
4. The study concludes with findings, research gaps, and future perspectives from a detailed literature review.

Therefore, the main contribution of this paper is to provide a comprehensive study for researchers to identify the work performed in STLF and further explore the future directions along with the role of STLF in smart grids. It lays the foundation for researchers

to identify the performance of different methodologies in different operating conditions and applications.

Section 2 outlines the methodology for a comprehensive study of STLF. Section 3 discusses the importance of load forecasting, load curve characteristics, influencing factors, and model categorization by time horizon. Section 4 discusses evaluation criteria and outlines those used in this review. Section 5 provides a tabular overview of STLF methodologies. Section 6 provides a study of STLF methodologies in smart grid applications. Section 7 analyzes models based on accuracy, time, and geographic factors. Section 8 highlights significant findings. Section 9 addresses research gaps and future directions. Section 10 concludes the study.

2. Methodology

A systematic review [31,32] of electronic resources was conducted to investigate the underlying electrical load forecasting models. Initially, different types of electrical load forecasting were searched and studied. Subsequently, the focus shifted to short-term electrical load forecasting. The initial search using the keyword "short-term electrical load forecasting" yielded 3165 results. Preliminary studies on STLF revealed key topics, including electric load demand and supply models, time-series models, exponential smoothing methods, regression models, machine learning models, expert systems, hybrid models, and smart grids. These results were further refined using the following criteria:

- Objective: Short-term electrical load forecasting.
- Keywords: Short-term electrical load forecasting, time-series models, exponential smoothing methods, regression models, machine learning models, expert systems, hybrid models, and smart grids.
- Studies covering STLF supply/demand.
- Key novel/review publications on STLF models from renowned institutions/authors.
- This review exclusively incorporates research papers published in peer-reviewed journals, excluding contributions from conference papers.

Out of 282 publications on load forecasting, 208 reviews on short-term load forecasting and demand planning, including smart grid applications, were selected for analysis. First, STLF models were categorized into statistical methods, intelligent-computation-based methods, and hybrid models. Based on this categorization of STLF models, a comprehensive study considering the contribution and performance accuracy of the reviewed papers is presented. Furthermore, the study is extended to include the role of STLF in smart grids and provides an inclusive review of STLF methodologies considering smart grid application. The results are postulated based on a comprehensive study of various state-of-the-art prediction models. Considering the influential factors to improve the performance of STLF methods, the research gaps and future directions are outlined. The methodology of the paper is presented in Figure 4. Table 1 lists relevant literature reviews of load forecasting.

Table 1. List of relevant literature reviews of load forecasting.

Reference	Year	Review Type	Remarks
[33]	1982	Systematic	Categorized modeling techniques reflect load demand. Multi-variable identification methods model load demand at key nodes in large power systems.
[34]	1987	Tutorial	Emphasized the critical role of STLF in EMS online scheduling and security operations and addressed practical implementation challenges.
[35]	2001	Methodological	Presented a comprehensive review of CI approaches to STLF in power plants without relying on traditional models. It includes eight case studies that demonstrate the effectiveness of the approach under different conditions.
[36]	2001	Critically evaluated	Evaluated skepticism of NNs in STLF in various publications, suggesting that more research on large NNs with stringent standards is needed for conclusive results.

Table 1. *Cont.*

Reference	Year	Review Type	Remarks
[37]	2015	Systematic	Reviewed and evaluated AI-based LF models, highlighting the importance of factors such as ANN architecture, input combinations, activation functions, training procedures, and exogenous variables on accuracy.
[38]	2016	Tutorial	Reviewed probabilistic LF, including research directions and LF strategies.
[39]	2017	Systematic	Organized LF techniques with a focus on scenario-specific model selection. Provided a taxonomy for model selection based on challenges.
[40]	2017	Comparative	Compared STLF using different RNN architectures.
[41]	2020	Comprehensive	Examined STLF using single, hybrid, and combined approaches.
[42]	2021	Narrative	An analysis of the residential, commercial, industrial, and off-grid sectors was reported. It highlighted the limitations of current LF models and proposed solutions.

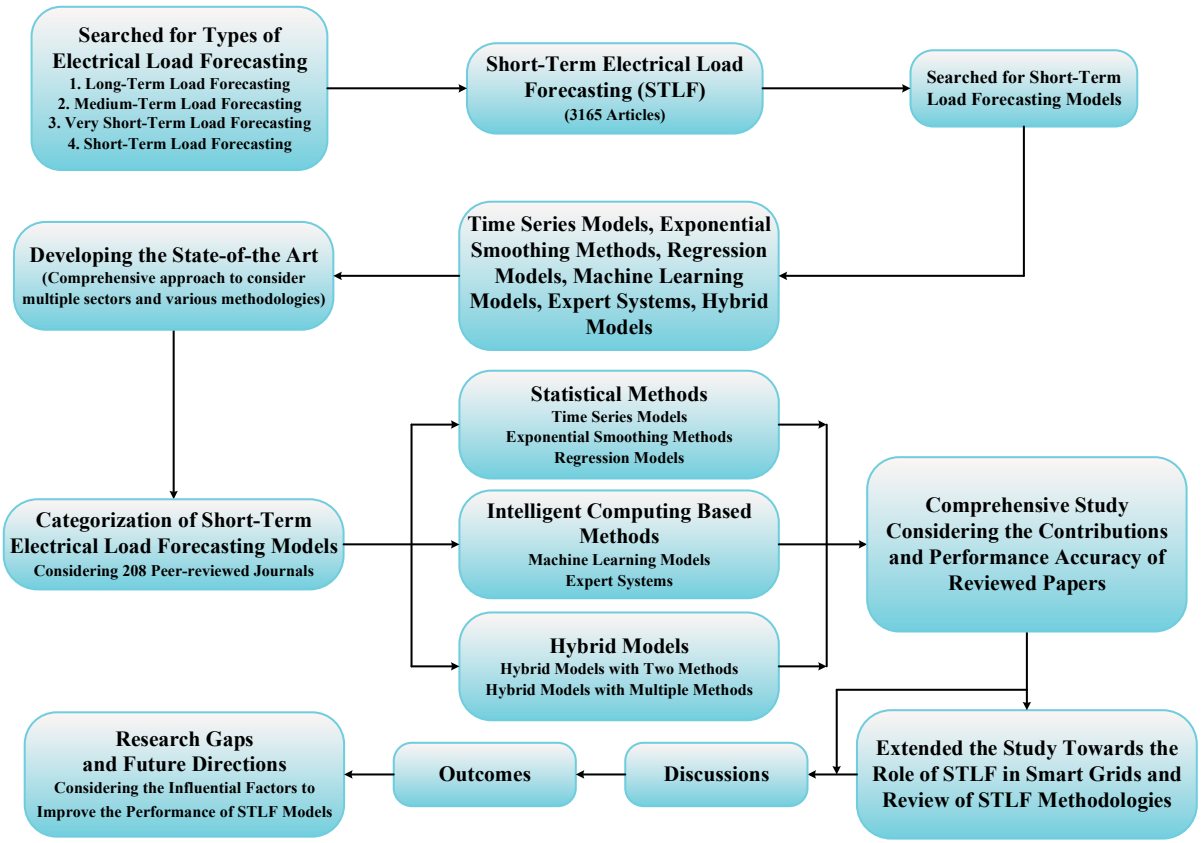

Figure 4. Methodology of the paper.

3. Load Forecasting

Load forecasting is critical for demand forecasting, power industry calculations, and non-power sector planning. Table 2 outlines the advantages of traditional and modern grid forecasting and their impact on beneficiaries. However, for reliable LF, a thorough examination of load data dynamics is essential [43]. Key elements that directly and indirectly affect LF accuracy must be carefully considered during model development. Researchers must identify relevant factors for accurate prediction of electrical consumption patterns. Table 3 briefly describes key elements that influence LF in traditional and modern power grids [44]. These influencing factors also pose challenges to the development of accurate models.

Table 2. Advantages of Traditional and Modern Power Grid Load Forecasting Along with The Impact on Beneficiaries.

Benefits	Beneficiaries						Impact on Beneficiaries
	Government	Environment	Power Utility	Industrial	Commercial	Residential	
Ahead-of-load demand	✓	-	✓	✓	-	-	Aids decision-making.
Planning and execution	✓	-	✓	✓	-	-	Plan and make decisions to avoid disruptions.
Maintaining infrastructure	✓	-	✓	✓	-	-	Prioritize infrastructure advancements.
Purchasing and conserving fuel	-	-	✓	✓	-	-	Pre-negotiation and warehouse preparation.
Resource calculation	✓	-	✓	✓	-	-	Management of spinning and non-spinning reserve.
Asymmetrical energy preparation	✓	-	✓	✓	-	-	Production facilities and uncertainties management.
Development of facilities	-	-	✓	✓	-	-	Improvements in generation and resource addition.
Continuous power supply	✓	✓	✓	✓	✓	✓	Intelligent power supply management.
Calculation of theft and loss	✓	-	✓	-	-	-	Disclosing problems that are overloading the system.
Contribution of renewable energy	✓	✓	✓	✓	✓	✓	Permits efficient integration of RESs.
IPP contribution	✓	-	✓	✓	✓	✓	Prevent cascading collapse effects.
Digitalization in industry	✓	✓	✓	✓	✓	-	Intelligent forecasting-based operational decisions.
Implementation of smart cities	✓	✓	✓	✓	✓	✓	Intelligently manage distributed energy resources.
Market bidding and investment	✓	-	✓	-	-	-	Efficient handling of bids and investments.
Decline in CO_2 emission	✓	✓	✓	✓	-	-	RES integration leads to reduction in CO_2 emission.

Table 3. Influential Factors Affecting Load Curve.

Factors	Affects
Time	Influences load patterns, requires historical data analysis [45].
Meteorology	Temperature, humidity, wind, etc. influence load consumption [46].
Region	Unique climates affect regional electricity demand, adaptation is crucial [47].
Application	Model effectiveness depends on the intended grid application [38].
Economics	Industrialization and consumer behavior [48].
Events	Pandemic and special events impact load patterns and sectors differently [49].
Past information	Historical data vital for training, model direction, and properties adaptation [50].
Data quality	Reliable data are essential for accurate LF and model performance [51].
Technology	Advancements bring greener power systems but also introduce uncertainty in LF [51].
DERs	Commercial and residential input affects LF accuracy, necessitates meter-level LF [52].

Forecasting involves input variables (past and present data), forecasting methods (analyzing trends), and output variables (future predictions). Electric load forecasting is categorized into four groups according to the distribution of time stamps (Figure 5): LTLF, MTLF, STLF, and VSTLF [53]. Different techniques, including expert systems, statistical methods, AI (e.g., ML, deep learning), and hybrid models, are used for different time domains.

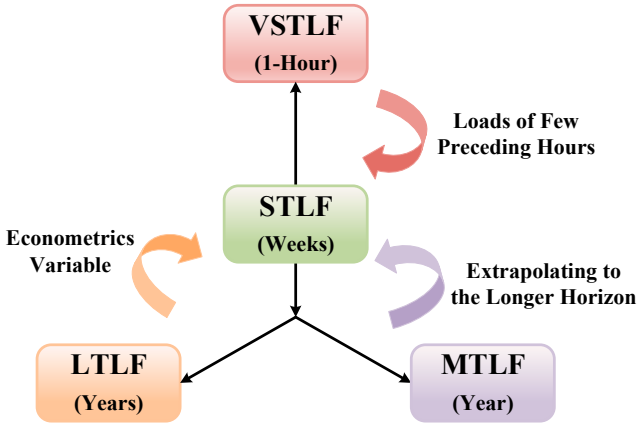

Figure 5. Classifying electrical load forecasting categories based on various time periods and the conversion process between STLF and LTLF, MTLF, and VSTLF.

LTLF addresses electrical demand planning for an extended horizon, supporting system comprehension and ensuring a reliable power supply. It enables accurate forecasting of infrastructure changes, impacting grid reliability, customer satisfaction, and utility investments [54]. MTLF includes planning for grid maintenance, considering electricity pricing, managing energy sharing agreements, and fuel preparation, typically over a month to a year horizon [55].

STLF is critical to the day-to-day management of the utility, ranging from minutes to weeks. It has a significant impact on financial savings and operational risk reduction. STLF techniques include statistical methods such as LR, ARIMA, and ES, as well as advanced approaches such as ANN, FL, SVM, RNN, and LSTM [56]. Hybrid models, such as GWDO with MMI and FCRBM, have been proposed for improved accuracy. The combination of LSTM and CNN has shown improved results [57]. Notable ML algorithms such as SVM, RF, and LSTM have been evaluated, with a combined model proposed for superior STLF [58].

Several advanced techniques have been proposed for STLF. For instance, in [59], the chimp optimization methods were coupled (CLFIF-IL-ChOA), combining iterative learning, fractal interpolation function, parameterization, and chimp optimization, which showed superior adaptability compared to other methods. A decision tree (DT) approach achieved 1.90% MAPE in predicting short-term electricity demand, reducing forecast variability [60]. A wavelet-based extreme learning machine (ELM) addressed load fluctuation challenges by automatically determining hidden neurons based on input samples [61]. A multi-layer bidirectional RNN outperformed regression methods in estimating monthly electricity consumption [62]. Hybrid models, CNN, and LSTM networks showed promise, with hybrid models performing best, followed by CNN. LSTM training was the fastest, but its performance declined with longer input sequences [63].

STLF, with its range of minutes to days, plays a central role in power utility operations and planning. It guides load control, dispatch, and secure power system operations, ensuring efficient use of different forms of generation. Accurate STLF is critical for economic dispatch and ensuring power system reliability. Accurate forecasting is critical to avoid power supply problems or inefficient resource allocation due to underestimation or overestimation of load demand. In the last decade, significant progress has been made in load accuracy [64]. This paper focuses on STLF, and Section 5 provides a comprehensive review of STLF approaches, which are categorized into statistical, intelligent-computing-based, and hybrid methodologies, which are further subdivided into subcategories.

VSTLF specializes in short-term load forecasting, ranging from minutes to an hour. It differs from other methods in that it relies on the most recent load patterns rather than multi-variable relationships. The VSTLF model can be derived from the STLF model by including loads from a few previous hours as inputs. The conversion processes between STLF, LTLF, MTLF, and VSTLF are shown in Figure 5.

4. Evaluation Criteria

Various criteria are used in the literature to evaluate the accuracy of load forecasting methods. Researchers have used various statistical metrics, with an emerging focus on probabilistic load forecasting metrics. Table 4 shows the most commonly used statistical measures in the field. Here, n denotes the sample size, x'_i denotes the model's predicted value, and x_i denotes the actual value. The second-degree loss function provided by RMSE prioritizes larger errors over smaller ones. Mean average error (MAE) is naturally measurable and is unambiguous. Mean average percentage error (MAPE) can be easily applied to both large-volume and small-volume items and is not scale dependent. However, differential error often leads to biased predictions. In typical load forecasting problems, demand at the aggregate level rarely approaches zero or is very small, so the shortcomings of MAPE, such as problems with handling small and zero denominators, are not very significant [38]. When the error distribution is anticipated to be Gaussian, reference [65] asserted that the root mean square error (RMSE) is more appropriate than the MAE; however, although this would help to elicit more information from the data, it is often ignored in the reviewed articles.

Table 4. Formulas for Evaluation Criteria.

Criterion Name	Formula
Mean Absolute Error (MAE)	$\frac{\sum_{i=1}^{n} \lvert x'_i - x_i \rvert}{n}$
Root Mean Square Error (RMSE)	$\sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i - x'_i)^2}$
Mean Average Percentage Error (MAPE)	$\frac{1}{n}\sum_{i=1}^{n} \frac{(x_i - x'_i)}{x_i}$

According to the objective of the research, the following additional variables were found in the literature:

- The largest negative and positive differences between a predicted value and the actual values are indicated by the terms maximum negative error (MNE) and maximum positive error (MPE), respectively. For some applications, these values may be more relevant than the typical error (e.g., fuel storage forecasting in a power plant).
- Relative root mean square error (rRMSE) normalizes the RMSE by dividing it by the range of actual values. This makes it easier to compare prediction accuracy across datasets of different scales.
- The coefficient of determination (R^2), which is used in the literature to measure the fit of the prediction model [66]. If R^2 is closer to 0, this indicates low predictive ability and poor fit of the data.
- Percentage error (PE) quantifies the relative discrepancy between forecasted and actual values, expressed as a percentage. It provides clarity on the direction and extent of forecast inaccuracies.
- The residual sum of squares (RSS), which represents the expected deviations from actual data values, is the sum of the squares of the residuals. It can be calculated using the RMSE. It measures how much divergence there is between the actual data and an estimated model.
- Pearson's correlation coefficient (Pearson's r) measures the linear relationship between forecasted and actual values. A high correlation indicates a robust linear relationship, indicating that the forecasting models are effectively capturing the underlying patterns.
- The standard deviation of residuals is a statistical term used to represent the difference between the standard deviations of the observed values and the anticipated values, as indicated by the points in a regression analysis.

- Bias quantifies the consistent deviation of forecasts from actual values. Positive bias indicates consistently higher forecasts, while negative bias indicates consistently lower forecasts.
- Some authors also employ quality comparisons between the time series generated by different algorithms and the real validation data [67].

Calculating these variables makes it easier to compare the results of different methods, especially by evaluating models that share identical influential factors and datasets. However, such a simple study may not be very informative, particularly when there is small variation between the methods or the dataset is not very large. In order to compare the results of an ANN, MLR, and ARIMA, the reference [48] employed Wilcoxson signed-rank and paired *t*-tests. The ANN had no real advantage over ARIMA or MLR because the *p*-values obtained were above $\alpha = 0.05$, making the results insignificant. In addition, the importance of these indicators varies depending on the parameters and datasets used. Therefore, it is difficult to compare the results of different methods. Furthermore, there is no task where all algorithms are tested on a single dataset to compare them. The accuracy of the approaches mentioned in this study project is recorded in the following parts of forecasting techniques.

To critically evaluate the effectiveness of STLF, especially within the paradigms of modern power systems and smart grids, it is essential to define evaluation metrics that reflect both quantitative and qualitative performance. These metrics provide standardized means to compare and contrast different STLF methodologies and their alignment with the operational requirements of modern power grids. Based on the literature review, the following metrics are considered in this study because most of the forecasting studies in the literature have used these metrics to evaluate the performance of their proposed algorithm.

MAPE: Offers a normalized measure of the deviation of forecasted values from actual values, allowing comparisons to across different scales of data.

RMSE: Gives higher weight to larger errors, thus being sensitive to outliers which are crucial in peak load forecasting.

MAE: Provides a direct average measure of forecasting errors, useful for understanding typical deviations in load predictions.

It should be noted that in this paper, the presented performance accuracy of each paper in Sections 5 and 6 is derived from each research paper studied. It is also important to note that developing a comparison between the methodologies is challenging because, in the literature, each research paper considers different protocols, hyperparameters, and input data for the performance analysis of an algorithm in a specific application. The tables and figures presented in Sections 5 and 6 provide a comprehensive review of the papers studied along with their performance, allowing the readers to identify the performance evaluation of each model in relation to the input data for a specific application, which could pave the way for future research.

5. Methods for Short-Term Load Forecasting

The methodologies for STLF are mainly divided into three categories: statistical methodologies, intelligent-computing-based methodologies, and hybrid methodologies. The three main categories are further divided into subcategories. Tables 5–7 present the advantages and disadvantages of statistical models, intelligent-computing-based models, and hybrid models, respectively. The purpose of presenting both advantages and disadvantages is to provide a comprehensive evaluation that allows readers to make informed decisions based on a detailed understanding of each forecasting model. The advantages are discussed to highlight the strengths and positive attributes of each forecasting model. Conversely, the disadvantages are mentioned to draw attention to the limitations, challenges, or drawbacks associated with each forecasting model. The discussion is intended to guide researchers and practitioners in selecting the most appropriate model for their specific requirements, considering both the strengths and limitations of the available options.

Table 5. Overview of Statistical Models for STLF.

Models	Advantage	Disadvantage
Time-Series Models		
ARMA	High computational speed for stationary time series.	Unable to respond immediately, resulting in a certain lag.
ARIMA	Fast computation for non-stationary time series.	Exhibits some lag and is highly sensitive to outliers.
SARIMA	Outperforms ARIMA in predicting cyclical datasets.	Lacks the advantage of exogeneous variables.
ARMAX	Combines time series and regression for optimization.	Covariate coefficients are hard to interpret.
BVAR	Manages large datasets and prior beliefs in modeling.	Sums lower-frequency data, ignores high-frequency data.
GARCH	Simple and generates volatility clustering.	Symmetrical at positive and negative prior returns.
SEGARCH	Includes autoregressive errors and GARCH variances.	Lags behind other GARCH models in performance.
EGARCH	Achieves accuracy via unconstrained likelihood maximization.	Volatility, by its very nature, is unpredictable.
Exponential Smoothing		
SES	More significance to recent observations.	Does not project trends.
DES	Projects trends.	Seasonal patterns are not recognizable.
TES	Recognizes seasonal patterns.	Captures the multiplicative aspect of seasonality.
Regression Models		
RM-W-SML		
LR	Performs remarkably well for linearly separable data.	Linearity links independent and dependent variables.
NLR	Unbiased and produces smaller residuals.	Mass computation required.
LgR	Resists overfitting, avoids feature space disturbances.	Tendency for model overfitting in linear regression.
NPR	Assumes no parametric form of predictor dependency.	Larger sample size required.
SWR	Manages large potential predictor variables effectively.	Variable selection influenced by multi-collinearity.
RM-SML		
LR	Easy implementation, extrapolation beyond dataset.	Sensitive to outliers and multi-collinearity.
IR	Improves variable relationship understanding.	Complicates model with multiple interactions.
RRM	Detects outliers in contaminated data.	Less effective with Gaussian residuals than OLS.
SWLR	Manages various potential predictor variables.	Estimates high absolute values.
MTR	Offers medium-sized functions for flexible responses.	Takes longer time to train the model.
CTR	Offers a few large leaves for coarse response function.	Model flexibility is low.
FTR	Offers several small leaves for flexible response.	Very leafy tree tends to overfit.
LSVM	Finds decision boundary in separable data.	Low flexibility, time-consuming feature selection.
QSVM	Capable of separating non-linearly separable data.	Class overlap increases with noisy datasets.
CSVM	Effective when classifier's kernel function is cubic.	Medium-level flexibility.
FGSVM	Precise class divisions with a specific kernel scale.	Flexibility decreases with the kernel scale setting.
MGSVM	Efficient with a specific kernel scale.	Classifies only medium-complexity data.
CGSVM	Makes coarse distinctions between classes.	Classifies low-complexity data effectively.
RQGPR	Fit for large datasets, smooth interpolating functions.	Tricky to detect errors in multi-dimensional data.
SEGPR	Handles large datasets in higher dimensions.	Interpretability is difficult.
M-5/2-GPR	No measure concentration issue in higher dimensions.	Effective within dataset range boundaries.
EGPR	Handles smooth functions with minimum error.	Struggles with smooth functions with discontinuities.
BT	Capable to capturing complex patterns.	May overfit if the data are noisy.
BgT	Increases with the number of learners, high flexibility.	Introduces a loss of interpretability of a model.

Table 6. Overview of Intelligent-Computing-based Models for STLF.

Models	Advantage	Disadvantage
Machine Learning Models		
ANN	Powerful prediction, discovers non-linear relations.	Low interpretability, limited scalability.
DL	Improved initial values, general purpose learning.	Training process could get stuck at bad local optima.
MLP	Higher accuracy and superior for non-linear problems.	Local minima affect training; slow convergence.
SVM	Accurate even with non-separable datasets.	Large memory utilization, high computational cost.
ELM	Fast training with good generalization.	Generality degradation and ambiguity hinder ELM.
SOM	Superior interpretation with few training samples.	Scalability issues; inputs must be vectors.
DT	Non-parametric with scalability for handling large data.	Poor prediction performance.
RNN	Processes any length of time-series data.	Slow recurrent computation.
LSTM	Addresses RNN issues with long-term memory.	High memory bandwidth demand, overfitting.
AN	Simplifies problems via numeric subdivision functions.	Elusive completeness, identifies all alternatives.
Expert Systems		
GP	Minimizes external factors, less reliance on historical data.	Unreliable prediction effects with large datasets.
FCMs	Superior error estimation index.	Sensitive to local minima, lengthy computation.
FRBS	Short development time, no design parameters required.	Difficult to recognize optimal FRBS.
FR	Mitigates LR limits, studies system's structural uncertainty.	Problematic tasks; guidelines, setting accuracy.
Metaheuristic Systems		
ABCO	Efficient for multi-variable optimization and flexibility.	Needs new fitness experiments for new factors.
AIS	Decodes and encodes information efficiently.	Limited potential of extrapolation.
GA	Does not break easily in presence of moderate noise.	Not scalable with complexity.
FA	Able to find local and global optima synchronously.	Convergence speed is low and accuracy is imprecise.
CSA	Low parameter setting and easy to implement.	Slow convergence rate.
MA	Improves fitness using local research in GA.	Complexity linked to problem's extrapolation.
GSA	Precision in solving adaptive non-linear optimization.	Slow iteration's search, post-convergence inactivity.
SAA	Evades local maxima and finds near-optimal solutions.	Sensitive to input, slow optimal solution.
HSA	Quick convergence and fewer modifiable parameters.	Needs improved parameter tuning for diverse applications.
PSO	High training speed, efficient search algorithm.	Slow convergence, global optimum search issues.
ACO	Parallelized concurrent processing and derivative free.	Uncertain convergence time.
CASO	Overcomes untimely local optimum concern of SVR.	Insufficient impact of organization variable on ant.
DE	Homogeneity around the mean compared to GA and PSO.	Unstable convergence risk, local optimum trapping.

Table 7. Overview of Key Hybrid Models for STLF.

Models	Advantage	Disadvantage
Hybrid Models		
SVM-BFGSFA	Minimum number of average value iterations.	Complexity allows optimal solution convergence.
SVM-HSA	High prediction accuracy and training speed.	Complex architecture.
SVM-FFOA	Able to quickly attain global optimum solution.	Optimal SVM parameter selection is challenging.
SVM-GA	Finds optimal values for minimal forecast errors.	Protracted real-time SVR parameter optimization.
SVM-PSO	Memory storage ability.	Early convergence, resistant to local minimization.
SVM-SAA	Non-linear mapping capability.	Training error minimization not performed.
ANN-FA	Solves local optimal shortcoming of NN.	More iterations needed with optimal parameters.

Table 7. *Cont.*

Models	Advantage	Disadvantage
ANN-CT	Models complex output/input relations.	Higher number of clusters and samples required.
ANN-NFIS	Forecasts irregular datasets.	Increased training time for complex tasks.
ANN-AIS	Fast search capability.	Limited extrapolation capability.
ANN-WT	Separates multiple load frequency components.	Dependence on frequency resolution.
ANN-PSO	Affordable computation useful in load variation.	Multiple function estimates need optimal solution.
ANN-GA	Resolves the local minima convergence issue.	GA assists ANN parameter selection complexities.
GNN-WT-GAFL	Mitigates concerns of BP and ANN algorithms.	Manual changes required for suitable fitness.
EMD-PSO-SVR	Load data decomposition capability to IMF components.	Challenges in handling non-stationary and non-linear data.
EEMD-GLM-GOA	Efficient for weight and threshold parametric solutions.	Unable to predict abnormal events and traditional parameters selection is complex.
GHSA-FTS-LS-SVM	Good computational speed utilizing a bionic algorithm with high accuracy of prediction.	Manual parameter selection.
T-C-IEMD-DBN	T-Copula enhances peak-time forecasting accuracy with DBN.	Process repetition required due to the stochastic nature of exogenous variables.
GA-NARX-NN	Less complexity with fast convergence by utilizing elitist GA.	GA parameter manual selection.
FCW-EMD & KF-BA-SVM	More prediction accuracy with improved selection and optimizing algorithm.	Incapability of learning input data temporal features.
GA-PSO-ANFIS	Fast execution time and selects predictors that notably affect the load pattern.	Predictor selection is complex.

5.1. Statistical Methods

Statistical models are preferred for STLF, which involve extensive data analysis to predict load demand [68]. Time-series datasets contain repeated measurements of a variable at regular intervals. Understanding data patterns is critical to interpreting historical behavior and making future projections. Statistical techniques include various models for data analysis, presentation, and correlation [69]. Table 5 provides an overview of statistical methods, including time-series, exponential smoothing, and regression models, and outlines their advantages, disadvantages, and levels of complexity. Table 8 summarizes key information from reviewed research articles on models based on statistical analysis [56,70,71]. The MAPE, MAE, and RMSE values presented in Table 8 are drawn from the respective studied research papers and they are not meant to draw a comparison in this paper. The purpose of presenting the performance accuracy of each paper is to offer an inclusive review for the readers to identify the performance evaluation of each model in accordance with their dataset and input parameters.

Figure 6 shows the distribution of the methods studied in Table 8, which outlines the RMSE, MAE, and MAPE according to the information reported in the respective papers.

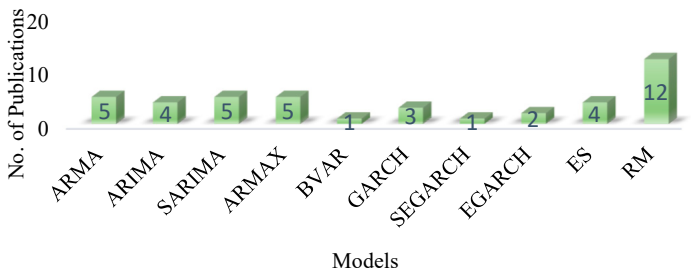

Figure 6. Statistical model distribution for STLF.

Table 8. Review Based on Statistical Analysis Methodologies for STLF. (Year: Research paper published, Data Duration: Duration of the dataset used in the research paper, Contribution: Each paper's contribution, Benchmarked Against: Studied research papers compared their proposed model with different models and load, Accuracy: Proposed model accuracy presented in research papers).

Year	Data Duration	Contribution	Benchmarked Against	Accuracy (Best-Performing Model)		
				RMSE	MAE	MAPE
ARMA						
1987 [72]	1983–1984 USA	Enhanced ARMA with polynomial regression for a non-linear extension of TFM for optimal forecasting.	ARMA, TFM, non-linear, periodic ARIMA	–	3.7	–
1994 [73]	>4 Weeks USA	Applied ARMA with WRLS algorithm for online model parameter estimation in power distribution.	Actual load	–	<2.5	–
2002 [74]	1998–2000 USA	ARMA fitted after analyzing deseasonalized data; hyperbolic distribution offers an excellent fit.	Actual load	–	1.3	–
2006 [75]	2001–2002 Turkey	Combined offline learning with online forecasting while adjusting weights to conditions.	ARMA, hybrid	–	1.6	–
2013 [70]	2008–2010 ISO-NE	ARMA-GARCH models and performance evaluation of their modifications for STLF.	ARMA-GARCH(-M) variants	7.4	0.2	14.5
ARIMA						
2000 [76]	1994–1995 CR	Introduced a non-linear statistical dependence measure; compared ANN and non-linear models.	ARIMA, ARMAX, ANN	–	–	0.8
2001 [77]	1991–1997 Iran	Proposed modified ARIMA with operator estimation; outperformed ARIMA and ANN.	ARIMA, modified ARIMA, ANN	–	–	1.98
2018 [78]	2012–2015 Australia	MARS yielded most accurate results at 0.5 h and 1.0 h horizon, while SVR performed well at 24 h horizon.	ARIMA, MARS, SVR	3.8	2.7	–
2020 [79]	2017–2018 Japan	Suggested model integrates auto-ARIMA and *K*-means for peak load reduction.	ARIMA, hybrid ARIMA	–	–	5.1
SARIMA						
2011 [80]	2004–2009 China	Proposed MA-C-WH model excels against SARIMA in seasonal adjustments and trends.	SARIMA, actual load	–	–	2.88
2012 [81]	2007–2010 China	Fourier-based residual series enhance SARIMA precision optimized by PSO. FS-SARIMA excels.	SARIMA, F-SARIMA, S-SARIMA, FS-SARIMA	4.9	–	2.19
2013 [82]	2009–2009 Italy	SARIMA-SVM model outperformed SARIMA and SVM in PV power forecasting.	SARIMA, SVM, actual data	9.4	–	2.73
2018 [83]	2012–2015 Japan	Developed interactions-SARIMAX method; enhancing predictive performance and accuracy.	SARIMA, MLR	–	–	0.7
2019 [84]	2007–2008 UK, France	Proposed KP-SVR via SARIMA with feature selection for time series.	ARIMA, SARIMA, ANN, SVR, KP-SVR	–	–	1.79
ARMAX						
2009 [85]	1998–2005 Colombia	Included exogenous variables in the models, and TSK models perform well.	ARMAX, NN, TSK	5.4	–	–
2008 [86]	2005–2005 China	HSPO-ARMAX overcomes local optimal points via genetic algorithm crossover operation.	PSO-ARMAX, HPSO-ARMAX	–	–	1.06
2011 [87]	1995–2007 Spain	Explored diverse population growth effects on electric roads for tourism planning.	ARMAX, GARCH	–	–	–

Table 8. *Cont.*

Year	Data Duration	Contribution	Benchmarked Against	Accuracy (Best-Performing Model)		
				RMSE	MAE	MAPE
2012 [88]	2006–2007 USA	ARMAX-GARCH models advance in long-horizon forecasting for MISO, USA.	ARMAX-GARCH	–	2.63	–
2018 [89]	2011 Netherlands	Developed hourly ARMAX for EDF and ILF, performed exceptionally in risk-aware activity decisions.	ARMAX-GARCHX, ILS, CAViaR, CARE	–	1.79	–
BVAR						
2008 [90]	2007 China	Utilized the Bayes method for input group selection to improve forecasting performance.	BP-NN, Bayesian-SVR	–	–	1.61
GARCH						
2010 [91]	2002 and 2006 Spain, USA	Combined ARMA and GARCH with wavelet transform for enhanced historical series.	ARIMA, ARIMA-GARCH, CNN	–	–	1.16
2005 [92]	1999–2000 Spain, USA	Proposed GARCH for deregulated electricity prices, outperforming ARIMA, enhanced by demand.	ARIMA, actual data	–	9	–
2009 [93]	2000–2002 Germany	Proposed *k*-factor GIGARCH, predicting long-memory seasonality in electricity prices.	SARIMA, GARCH	3.63	–	–
SEGARCH						
2009 [94]	1993–2007 Taiwan	Incorporated GARCH variances and autoregressive errors.	WARCH-ANN, SEGARCH-ANN	–	–	2.56
EGARCH						
2008 [95]	2007–2007 USA	Examined ARIMA and its EGARCH variant models' in-sample and out-of-sample forecasting performance.	ARIMA-EGARCH, ARIMA-EGARCH-M	–	10.5	–
2019 [96]	2009–2016 Australia, Spain	Proposed EGARCH model for accurate electricity price estimation in the Australian and Spanish markets.	ARMA and extensions	–	–	8.87
ES						
1971 [97]	1966–1967 USA	Implemented general ES for STLF, which offered operational simplicity and high accuracy.	Actual data	–	2	–
2010 [98]	2001–2006 UK, France	Extended double seasonality methods capturing intra-year, intra-week, and intra-day cycles.	SES, DES, TES, actual data	–	–	1.7
2012 [99]	2007–2009 UK, France	Explored ES methods for STLF, introduced SVD-ES, enhanced efficiency for intra-day.	ES methods, ARMA, ANN, actual data	–	–	2
2018 [100]	2011 China	Created SES-GP model, using SES smoothing for GP sequence development.	GP model, actual data	–	1.26	–
RM						
1990 [101]	1982–1985 USA	Suggested novel LR model for holiday load forecasting using binary variables.	Actual data	–	–	0.44
1998 [102]	1997 USA	Introduced NPR-based method, forecasting directly from historical data with ANN outperformance.	NPR, NPR-Static, ANN	–	2.64	3.57
2008 [103]	1999–2003 Iran	Developed hybrid NN model using novel data clustering, surpassing hybrid LR.	Hybrid LR, proposed model	–	–	1.5
2009 [104]	1970–2007 Italy	Forecasted Italy's consumption using various regression models with stationary data.	Regression models, national forecasts	–	–	–

Table 8. *Cont.*

Year	Data Duration	Contribution	Benchmarked Against	Accuracy (Best-Performing Model)		
				RMSE	MAE	MAPE
2010 [105]	2004–2008 UK	Combined time-series and ML models with filters, the LR model with PF and MF filters performs well.	Time series, machines learning	–	2.01	0.17
2010 [106]	1985–1991 1995–1998 EUNITE	Modified the SVR algorithm using LWR in risk function with Mahalanobis-based weighting. The LSWR outperformed other methodologies.	LWR, local SVR, LWSVR	–	–	1.34
2011 [107]	1974–2003 Iran	Designed experiments and proposed a conventional regression and ANN-MLP-based flexible model.	ANN-MLP, regression, actual data	–	0.01	0.03
2016 [56]	2002–2004 Poland	Mainly suggested straightforward models for daily STLF cycles using regression.	ARIMA, ES, MLP	–	–	1.35
2017 [108]	2014–2014 China	Proposed SVR for office building baseline forecasting, enhancing real-time effectiveness.	Simple average model, actual data	–	1.57	–
2018 [71]	2009–2012 SA	Incorporating non-linear trend variables and unit commitment enhances forecasting integration.	ILP, PLAQ-RM	–	–	0.81
2018 [109]	2007 and 2013 Australia, China	Developed SSVRE for precise SVR learning execution, enhancing computational accuracy.	SVR, SSVRE	0.11	–	–
2020 [110]	2009–2010 Ireland	Proposed a PAR-based model via group and distinct LF learning to address smart grid complexity issues.	SGDR, FTRLP, OSELM, PAR	–	–	1.62

5.2. Intelligent-Computing-Based Models

The intelligent-computing-based models (ICMs) are divided into machine learning and expert-system-based models. Machine learning includes 10 models, while expert-system-based models include 4 methodologies that address non-linear challenges in real-world load forecasting.

Since the mid-1980s, researchers have focused on ANNs as powerful tools for load forecasting. ANNs outperform previous methods for non-linear inputs, complex relationships, adaptive control, and pattern prediction. Unlike statistical models, ANNs map input–output relationships without complicated dependencies. Their training process retrieves non-linear relationships, allowing effective load demand prediction with the right algorithm, training data, and network structure [111].

Table 9 provides an overview of 45 machine learning models and 8 expert systems, including ANN, DL, MLP, SVM, ELM, SOM, DT, RNN, LSTM, GP, FCMs, FRBS, and FR applied in ICM for STLF. Table 6 provides overviews for machine learning and expert-system-based methods that could lead to the selection of an appropriate ICM according to the constraints. The MAPE, MAE, and RMSE values presented in Table 9 are derived from the respective research papers studied and are not intended for direct comparison in this paper [43,111–162]. The purpose of presenting the performance accuracy of each paper is to provide readers with a comprehensive review, enabling them to assess each model's performance based on its dataset and input parameters.

Table 9. Review depending on intelligent-computing-based methodologies for STLF. (Year: Research paper published, Data Duration: Duration of the dataset used in the research paper, Contribution: Each paper's contribution, Benchmarked Against: Studied research papers compared their proposed model with different models and load, Accuracy: Proposed model accuracy presented in research papers).

Year	Data Duration	Contribution	Benchmarked Against	Accuracy (Best-Performing Model)		
				RMSE	MAE	MAPE
Machine Learning Methods						
1992 [111]	1987 Taiwan	Proposed MLF-NN for STLF with an adaptive learning algorithm significantly accelerating convergence.	ANN, actual load	0.88	0.69	–
1995 [112]	1992 Greece	Introduced FNN for STLF; it performed similarly to neural networks but trained faster.	Actual load	–	2.9	–
1995 [113]	1992 China	Developed hybrid FNN for STLF using fuzzy set theory and logic.	Actual load	–	0.62	–
1995 [114]	1990 USA	Comparing adaptive NN and statistical methods for 7-day demand forecasting.	Statistical methods, actual load	–	–	6
1998 [43]	1989–1990 USA	Introduced ANN-based input variable identification, simplifying training and enabling compact ANNs.	Actual load	–	–	1.67
2002 [115]	1989–1999 Spain	Evaluated MLPs for specified classes using self-organizing maps and statistics.	Actual load	–	–	1.15
2005 [116]	1991–2001 Turkey	Utilized a feed-forward neural network for monthly, peak, and daily load forecasting.	ANN, actual load	–	–	–
2006 [117]	2000–2003 Australia	Introduced Euclidean norm-based similar day selection and proposed two ANN models.	ANN, actual data	–	–	1.3
2007 [118]	1985–1991 1997–1999 USA	Proposed autonomous NN-based STLF with Bayesian and SVM learning techniques.	BPN, gain scaling with CIS and SS	–	–	1.75
2009 [119]	2001 and 2003 USA	Used PSO methodology to modify NN weights and biases for training.	Actual data	–	–	1.98
2009 [120]	2000–2003 Iran	Developed an ideal large NN structure and connecting weights for STLF using CGA.	BP-ANN, CGA-ANN	–	–	1.46
2012 [121]	2000–2007 APEC	Utilized grey prediction for STLF, excelling with small, incomplete datasets.	BPN, SVR	–	–	3.27
2012 [122]	2001–2010 Spain	Proposed SOM neural network for STLF, optimized hourly input, and improved forecasting accuracy.	MLP, ARIMA	–	–	2.18
2013 [123]	2007 Taiwan	Combined SVR and DEKF for RBFNN, outperforming existing models in accuracy and stability.	DEKF-RBFNN, GRD-RBFNN	–	–	0.6
2013 [124]	2011–2011 Australia	Introduced MFES combining seasonal correction, EMD filter, and multi-output FFNN, overcoming limitations.	MFE, MFNN, MFES	–	–	2.42
2015 [125]	2004–2011 ISO-NE	Tested SVR, ELMs, DRNNs for STLF with common RBF networks, drawing insights.	Actual load	–	–	1.78
2015 [126]	2005, 2006, 2010, 2000–2001 Spain, Australia, USA	Suggested using a revolutionary pattern-sequence-based direct time-series LF approach. Clustering and next symbol prediction make up the two phases in the newly created SCPSNSP. The association between a specific length of a pattern sequence and its following pattern was trained using ANN.	DR, KNN, PSF	–	–	2.97

Table 9. *Cont.*

Year	Data Duration	Contribution	Benchmarked Against	Accuracy (Best-Performing Model)		
				RMSE	MAE	MAPE
2016 [127]	2010 Australia	Developed DCANN and UDCANN based on IBSM, combining supervised and unsupervised learning.	BP-ANN, FNN, LSSVM, GARCH	–	–	8.28
2016 [128]	2011–2011 Australia	Proposed innovative STLF combining BP-ANN, ANFIS, and D-SARIMA for varied data.	BP, ANFIS, D-SARIMA	–	–	1.65
2016 [129]	2010–2011 France	A neural network for LV/MV networks boosts accuracy with varied models for intra-day and daily average power change.	Time-series models, naïve model	–	3.63	10.3
2016 [130]	2011–2014 Portugal	Novel RELM combines ELM and RNN for enhanced electricity LF.	ELM, LR, GRNN	0.03	–	–
2016 [131]	2009 ISO-NE	Proposed an ensemble method using wavelet transform, ELM, and PLS regression for STLF.	Actual load, WNN, SVR, ELM	–	–	2.02
2017 [132]	2010–2012 China	Implemented MLP for LF; claimed NN yields better results in several sectors.	LR, SVR, DNN, CNN	–	–	1.41
2017 [133]	1991–2012 SK	Compared forecasting techniques for South Korea using 20 variables, laying the foundation.	SVR, Fuzzy-Rough, MLP, MLR, ARIMA	–	–	2.13
2017 [134]	2013 Australia	Proposed EMD-based ensemble DL for STLF, integrating adaptive signal processing.	SVR, ANN, DBN, RF, EMD-SVR	–	–	0.67
2017 [135]	2016 Chile	Developed SOM for microgrid planning, identifying distinct family consumption patterns.	Actual load	–	–	–
2018 [136]	2009–2010 Ireland	Proposed a novel deep RNN architecture for household LF employing both conventional and recurrent layers.	ARIMA, RNN, SVR, DRNN, PDRNN	0.45	0.25	–
2018 [137]	2011–2012 Hungary	Introduced a prediction model considering the impact of EVs on building loads.	ARIMA, SVR, BRNN, RBFNN	–	–	4.53
2018 [138]	2013–2013 2013–2013 Australia, Singapore	Created a strategy of decomposition–reconstruction by integration of singular spectrum analysis. A variety of forecasting models, including ARIMA, ES, and NNs, were used in the ensemble to estimate future values of each component using historical data.	LSSVM, CSA-SVM, GA-BPNN	–	–	0.59
2019 [139]	2016 USA	Proposed a novel approach combining the copula model and DNN for accurate STLF.	NN, SVR, ELM, R-DNN, DBN	–	–	2.36
2019 [140]	2004–2007 Texas and ISO-NE, USA	Developed the MOFTL algorithm, evaluated on benchmarks, enhancing LF accuracy when combined with ANN (MOFTL-ANN) for weight optimization.	GRNN, MOWCA, MOPSO, NSGA-II	–	–	4.59
2019 [141]	2007, 1997–1998 China, EUNITE	Combined BRNNs and DBNs for STLF to effectively capture temporal and spatial dependencies. Input is processed by BRNN forwards/backwards, then fed to DBN for high-level representation learning.	SVR, LSTM, BPNN	28.5	–	1.95
2019 [142]	2009–2010 Ireland	Suggested an LSTM network with pinball loss for probabilistic forecasting on large consumer dataset.	QRNN, QGBRT	2.18	–	–
2019 [143]	2012–2016 SA	Developed AI and DL-based LF system, examined OP-ELM and LSTM models considering weather impact.	ANFIS, OP-ELM	0.06	0.05	0.13
2019 [144]	2014–2018 Ireland	Proposed multi-scale CNN with time cognition for enhanced multi-step STLF.	DM-MS-CNN, DM-GCNN	–	–	3.74

Table 9. *Cont.*

Year	Data Duration	Contribution	Benchmarked Against	Accuracy (Best-Performing Model)		
				RMSE	MAE	MAPE
2019 [145]	2013–2013 2002–2002 China, USA	Implemented subsampling to expedite SVR modeling. Progressively constructs SVR, presenting regression surface parameters, affirming model relevance and effectiveness.	Actual data, SGA-SVR, SSVR	–	5.8	–
2020 [146]	2010, 2013, 2014 USA, Australia	Proposed a synthetic STLF using a MIMO model with LSSVM, employing DWT to split the signal and integrating GSA for optimal input selection.	ANN-MIMO, ANN-LSSVM	–	–	2.10
2020 [147]	2015–2017 SK	Introduced COSMOS, a stacking ensemble model for accurate STLF predictions.	Shallow NN, MLR, KNN, DT, DNN	–	–	6.97
2020 [148]	2013–2016 Greece	Developed an FFNN and clustering hybridization model for historical bus load.	RBFNN, GRNN, ENN	–	–	7.00
2020 [149]	2017–2018 USA	Used RNNs for STLF in commercial buildings, optimal with mid-season training.	GRU, LSTM	6.75	–	–
2020 [150]	2016–2016 China	Proposed a novel QRF model with temperature and humidity factors, involving training multiple models.	EEMD + QRF, EMD + QRF, QET	–	–	1.37
2020 [151]	2018–2019 China	Used an ensemble of HMMs trained on industrial electricity data for accurate forecasting.	SVR-RBF kernel, CNN, LSTM	–	–	7.07
2020 [152]	2003–2015 ISO-NE	Suggested MCRN for STLF, leveraging *k-d* tree algorithm and error correction.	Actual load, SVM, ELM	–	–	4.59
2020 [153]	2015–2016 China	Proposed DBM model, incorporating DSM and leveraging RBM for features.	ARIMA, LSSVM, DBN	–	–	3.86
2021 [154]	2020 UK	Suggested an online adaptive RNN for LF, continuously adapting to new patterns.	LSTM, regression algorithms	–	–	0.24
Expert Systems						
2005 [155]	1960–1990 SK	The FLR model applies Tanaka's fuzzy arithmetic for weekend holiday forecasting.	Actual load, NN-Fuzzy interface	–	3.57	–
2008 [156]	2002–2004 Canada	TSK fuzzy system predicts OEM peak price, compared to statistical methods.	ARMAX, ANN	0.08	–	–
2009 [157]	2000–2007 Jordan	A new fuzzy logic controller enhances LF accuracy and processing efficiency.	Actual load	–	–	2.2
2012 [158]	2000–2002 Iran	Developed Interval Type-2 FLS (IT2-FLSs) to improve LF accuracy by handling uncertainties in real datasets.	Traditional Type-1 TSK-based FLS	0.16	–	–
2014 [159]	2005–2007 ISO-NE	Fuzzy interaction regression for STLF outperforms other fuzzy and MLR models.	Multiple fuzzy regression, MLR	–	–	3.68
2015 [160]	2014 India	A novel weekday STLF algorithm combines WT, adaptive GA, fuzzy system, and GNN.	ANN, GNN	0.05	–	–
2018 [161]	2010–2012 Slovenia	An adaptive fuzzy model improves day-ahead STLF using recursive clustering and identification.	Gustafson–Kessel clustering, SARIMA	–	–	0.13
2020 [162]	2009–2010 Ireland	Fuzzy clustering and a crow optimization *K*-means algorithm improve large-scale user clustering accuracy.	RF, LSSVM, multiple hybrid models	–	–	1.63

5.3. Hybrid Models

Researchers have increasingly turned to hybrid models for STLF to improve accuracy and minimize error. These models combine multiple methodologies, leveraging the strengths of each approach. SVM and ANN are key contributors, with SVM excelling in unstructured data and ANN demonstrating adaptive learning from training data. Hybrid models offer improved forecasting results, particularly those that combine SVM and ANN. Table 10 provides a comprehensive overview of 64 research articles on various hybrid models, including SVM, ANN, LSTM, MLP, BPNN, expert systems, and metaheuristic methodologies. Hybrid models in STLF can include single-stage or multiple-stage models, each addressing specific problem-solving objectives. Single-stage models are basic, while multiple-stage models independently use different machine learning methods to address different problems. Figure 7a illustrates the basic organization, and Figure 7b depicts the structure, of multiple-stage hybrid models [163]. The MAPE, MAE, and RMSE values presented in Table 10 are sourced from the respective research papers studied and are not intended for direct comparison in this paper [164,165]. The purpose of presenting these performance metrics is to provide readers with a comprehensive review, allowing them to evaluate each model's performance based on its dataset and input parameters.

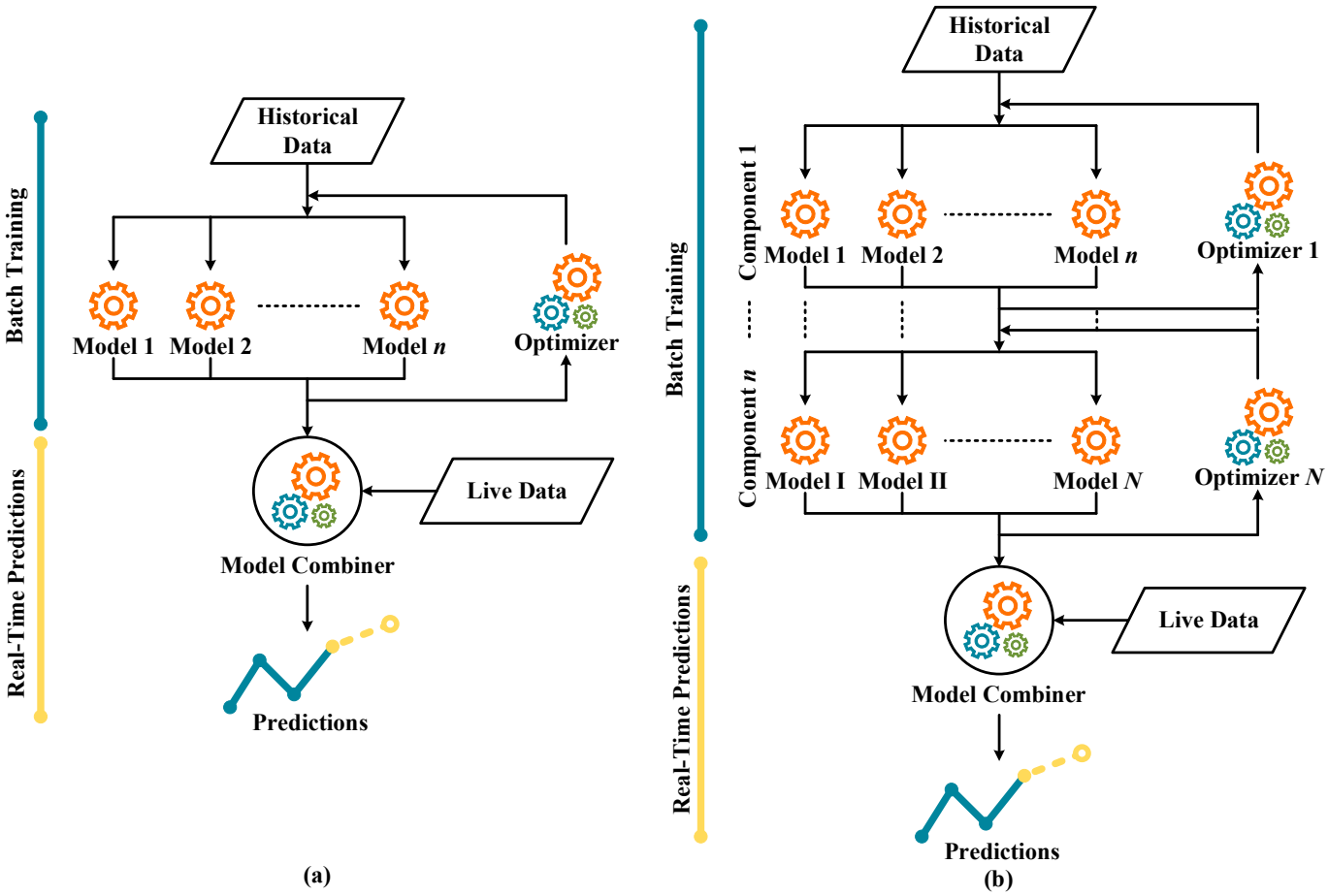

Figure 7. (**a**) Single-phase hybrid framework. (**b**) Multiple-phase hybrid framework.

Table 10. Review Based on Hybrid Methodologies for STLF. (Year: Research paper published, Data Duration: Duration of the dataset used in the research paper, Contribution: Each paper's contribution, Benchmarked Against: Studied research papers compared their proposed model with different models and load, Accuracy: Proposed model accuracy presented in research papers).

Year	Data Duration	Contribution	Benchmarked Against	Accuracy (Best-Performing Model)		
				RMSE	MAE	MAPE
Hybrid Methodologies						
1995 [164]	1993–1994 SK	Hybrid model integrates ANNs and fuzzy expert systems for STLF.	Actual load, ES	–	–	1.3
2002 [166]	1997–1999 India	ANN model for peak load demand forecasting using the Levenberg–Marquardt BP algorithm.	Levenberg–Marquardt BP, quasi-Newton BP,	–	–	2.87
2003 [167]	1993–1994 SK	Proposed GA with new operations to optimize FNN for De Jong's functions.	Actual load, GA	–	–	1.56
2004 [168]	2001–2001 1998–1999 USA	Hybrid STLF technique combines LR and ANN for improved data load forecasting.	ANN, LR	–	–	0.62 0.43
2005 [169]	1998–2002 Belgium	STLF model utilizes periodic time series and autoregression for load forecasting.	Actual load	–	–	<3
2005 [170]	1995–1997 Japan	Proposed fuzzy logic to correct neural network output for improved load forecasting.	Actual load, NN	–	–	1.71
2006 [171]	2000 Taiwan	Hybrid FNN with CGA and SA optimizes LF parameter choices.	ANN, FNN, GA-ANNN	–	–	1.96
2008 [172]	2006 Australia	Developed GRNN-based STLF model integrates prices, load, and weather data.	ANN-Fuzzy, ARMA	–	–	1.85
2009 [173]	1988–1992 USA	Hybrid forecast method combines WT, NN, and evolutionary algorithm (EA) for load prediction.	Actual load, single SVM	–	–	2.02
2009 [174]	1997–1999 EUNITE	Hybrid genetic algorithm (HGA) optimizes SVR parameters for accurate electricity load forecasting.	GA-SVR, actual load	7.73	–	0.76
2010 [175]	2004–2006 Mongolia	SVM and ACO combined for efficient STLF and improved performance.	Actual load, ANN, SVM	–	–	1.98
2013 [176]	2008–2009 2003–2004 Iran, Australia	Two-step algorithm for STLF: WT and an ANN for primary forecasting, second step uses similar-hour method and ANFIS to enhance the results.	WNN, RBFNN, ANFIS	–	1.60	–
2013 [177]	2012 Australia	Separate forecast of seasonal and trend components; evaluated using statistical tests.	Actual load, RBFs, regression models	–	–	2.09
2013 [178]	2010–2010 China	Utilized harmony search with LS-SVM for the STLF model, GRNN analyzed influencing factors.	BPNN, LS-SVM, PSO, HS	–	–	1.76
2013 [179]	1994–1994 Greece	Introduced CB-FWNN model utilizing multiplication of WNN and multi-dimensional Gaussian activation functions, with fuzzy subtractive clustering and Gaussian mixture models employed for pre-processing.	ABPA, ANFIS, RBF	3.31	–	0.87
2014 [180]	2004 2010 USA, Iran	New STLF model combines WT and GP, improving accuracy through PSO.	Improved SSA, SSA-Recurrent algorithm	–	1.96	3.12
2014 [181]	– Iran	Combines BP method (to determine suitable weighting and biasing factor parameters) and MFA for better LF.	ANN, ANN-GA, ANN-PSO, ANN-FA	2.03	–	–

Table 10. *Cont.*

Year	Data Duration	Contribution	Benchmarked Against	Accuracy (Best-Performing Model)		
				RMSE	MAE	MAPE
2015 [182]	2008–2013 ISO-NE	BNN for selected inputs through correlation analysis and ℓ2-norm and DWT for improved daily LF.	ANN, SSA-SVR	–	–	0.19
2015 [183]	1999–2010 Italy	Proposed semantic-aware genetic programming for STLF, outperforming existing methods in south Italy.	LR, RBFNN, SVM	–	–	–
2015 [184]	2013–2013 China	New STLF method: WT removes errors, LSSVM optimized by fruit fly optimization algorithm for parameter selection.	WT-LSSVM, FOA-LSSVM, PSO-LSSVM	–	–	1.07
2016 [185]	2009–2010 ISO-NE	STLF with improved ELM, Levenberg–Marquardt, and partial least square regression for accuracy.	WNN, MLR, RBFNN	–	–	0.21
2016 [186]	2014, 2010, 2013 USA, Australia	Proposed hybrid algorithm integrates conditional feature selection, LSSVM, and wavelet packet signal decomposing for price/load forecasting.	ANN-MIMO, LSSVM-MIMO	–	–	2.11
2016 [187]	2012–2014 Algeria	Suggested adaptive two-stage model excels in daily peak LF.	HWT, BPNN, NARX	–	–	1.64
2016 [188]	2015–2015 Taiwan	Novel time-series LF model combines SARIMA and MetaFA-LSSVR models to handle non-linear data.	SARIMA, MetaFA-LSSVR	–	0.03	14.8
2016 [189]	2013 USA	Hybrid approach combining data-driven techniques and physics-based models for LF energy consumption.	ANN, SVR, LSSVM, GPR, GMM	–	–	8.16
2016 [190]	2006–2010 Greece	Modified ANN combined with clustering improves STLF accuracy for Greek interconnected system buses.	Actual load, FF-ANN	–	–	3.5
2016 [191]	2006–2008 Australia	Model with multiple seasonality, ANNs, non-positive constraint theory, and BFGSFA improves performance.	ARIMA, random walk, WNN, BPNN	–	–	0.85
2016 [192]	2014–2014 China	Hybrid EMD-PSO-SVR model: EMD decomposes data, SVR for individual forecasting, PSO for parameter selection.	SVR, EMD-SVR, PSO-SVER	0.06	0.04	2.75
2017 [193]	2012–2014 USA	SDA predicts hourly electricity prices, with RS-SDA outperforming other day-ahead models.	NN, MARS, SVM, SDA, RS-SDA	–	–	2.47
2017 [194]	2008 ISO-NE	A weak-ahead LF with FFNN of three layers optimized by global best PSO.	Actual load, BPNN, LMNN, PSONN	–	–	1.41
2017 [195]	2016 China	Combined WD, second-order GNN with ADF test to increase STLF accuracy.	WD-ELMAN, GNN	–	–	2.40
2018 [196]	2013–2015 India	Proposed STLF model considers regional climate using grasshopper optimization for SVM.	GA-SVM, PSO-SVM	–	–	1.4
2018 [197]	2015–2015 Taiwan	Article reviewed various ML techniques and emphasized the accuracy of hybrid models.	ANN, bagging ANN	–	0.03	15.7
2018 [198]	2015–2016 China	Combined RF with EEMD where EEMD decomposes data, which are analyzed in time–frequency domain.	EEMD-BPNN, EEMD-LSSVM	–	–	4.45
2018 [199]	2011–2012 Spain	Proposed 3-stage hybrid model utilizing wavelet and Kalman machines and Kohonen self-organizing map for load forecasting.	ARIMA, FNN, WNN	–	17.6	–
2018 [200]	2014 USA	Introduced a 2-step hybrid optimization using the grid traverse algorithm and PSO for superior SVR load LF.	ARIMA, GA-SVM, ANN	–	–	2.53
2018 [201]	2013–2015 Australia	A hybrid approach using DWT, EMD, and RVFL for enhanced forecasting.	Actual load, ANN	–	–	2.08

Table 10. *Cont.*

Year	Data Duration	Contribution	Benchmarked Against	Accuracy (Best-Performing Model)		
				RMSE	MAE	MAPE
2018 [202]	2014–2015 China	Considering multiple decomposition factors: FCW (select dense days), EMD (decompose into IMF series), BA (optimize SVM parameters), and KF (fine tuning) to optimize SVM, the hybrid model was developed.	Multiple hybrid models	–	–	1.91
2019 [203]	2017 SK	A CLD-based STLF with LSTM using similar-day and pilot signals.	WNN, MFWNS, AGG, DTLP, CLD	–	–	3.38
2019 [204]	2 months China	Proposed hybrid GA-PSO-BPNN for STLF, overcoming local optimum in predictions.	GA-BPNN, PSO-BPNN	–	–	1.25
2019 [205]	2014 Australia	Hybrid PSO and GSA for optimal weight determination in STLF models, increasing prediction accuracy.	BPNN, WNN, SVM	–	–	0.79
2019 [206]	2017 China	Introduced DRL algorithm, DDPG with autoencoder for improved HVAC energy prediction.	BPNN, BSAS-BPNN, SVM, BSAS-SVM	–	3.47	–
2019 [207]	2018 Australia	Proposed EEMD-ELM-GOA hybrid model for accurate 1-step-ahead LF, using grasshopper optimization.	WD-ELM, EMD-ELM, EEMD-ELM	–	–	0.46
2019 [208]	2010, 2009, 1988–1992 Australia, USA	Developed Elman NN-based forecast engines with feature selection, ESSO optimized parameters.	ARIMA, SVR, RBFNN, WT-RBFNN	3.11 1.34	–	1.43 1.31
2019 [209]	2014–2016 China	Suggested GA-PSO-ANFIS for STLF utilizing binary genetic algorithm to eliminate less predictive features.	NN, ARIMA	–	–	6.78
2020 [210]	2003–2006 ISO-NE	Introduced E-ELITE, a 2-layer NN framework based on a three-stage methodology with optimized structure.	ANN, SIWNN, GP, SSA-SVR, ELITE	–	–	1.18
2020 [211]	2019 Tanzania	Proposed LSTM with pinball loss for probabilistic forecasting in consumer studies.	ANN-, ARIMA-, LSTM-, SVM-AD	0.69	–	–
2020 [212]	2017 Australia	A pre-processing method using CEEMD and SSA for LF, then combined with RBF, GRNN, and ELM models.	BP, GRNN, RBF, ELM, SVR, WNN	–	–	1.74
2020 [213]	2017 Singapore	Hybrid model enhances SVM accuracy with intelligent feature selection and optimization.	GRP-SecRPSO-SVM, mRMR-WGRP	–	–	0.04
2020 [214]	– Egypt, Canada	Novel STLF models with clustering, WNN, and ANN exhibit high accuracy.	ANN-WNN, ANN-KF, WNN-KF	0.02	–	1.83
2020 [215]	2010–2015 China	Developed using specific ratios and SVR optimized with improved adaptive genetic algorithm (IAGA).	ELM, WNN, BPNN, RBFNN	20.3	20.4	–
2020 [216]	2011–2016 Canada	Model combined wavelet packet transform and multi-layer NNs, utilizing the Levenberg–Marquardt algorithm.	NN, traditional WT-NN, actual load	–	–	1.52
2020 [217]	2010–2012 2014–2018 Greece	Proposed fuzzy clustering for ensemble predictions using novel RBFNN architecture, analyzed using CNN.	Actual load, ML-SVM, fuzzy RBFNN	–	–	3.66
2020 [218]	2016 China	Hybrid approach; EMD to decompose load data, PSO to optimize ANFIS model (EMD-PSO-ANFIS).	PSO-ANFIS, BPNN, ARIMA	–	–	9.86
2020 [219]	2013–2017 Australia	EGA-STLF employs Bi-GRU, attention mechanism, and distributed representation for LF.	SVR, MLP	–	–	3.06
2021 [220]	2016–2019 ISO-NE	Developed DBNN with Markovian dynamic topology to enhance network resilience to attacks.	DBN, DDBN	–	–	2.05

Table 10. *Cont.*

Year	Data Duration	Contribution	Benchmarked Against	Accuracy (Best-Performing Model)		
				RMSE	MAE	MAPE
2021 [221]	2006, 2018, 2002, 2009 ISO-NE	Proposed method includes wavelet transform, feature selection, and LSTM networks to enhance load and price prediction accuracy.	Multiple hybrid models	–	–	0.93 4.38 2.2 2.67
2021 [222]	2015–2016 2005–2006 China, USA	Combined improved FCMs, RF, and DNNs, addressing historical load data disparity for better load profiling.	Actual load, multiple hybrid models	–	–	0.03 0.08
2021 [223]	2017, 2018–2021 ISO-NE, China	Hybrid NN constituting CNN and bidirectional GRU (CNN-BiGRU) using multi-model fusion.	CNN-NN, CNN-GRU, CNN-LSTM	–	–	4.22 5.08
2022 [224]	2012–2013 2003–2014 ISO-NE, China	Model with improved TCN and DenseNet, incorporating correlation analysis and self-attention.	Multiple hybrid models	–	–	0.91 0.87
2022 [225]	2017–2021 Australia	Integrated WNN and self-adaptive momentum factor (SAMF) for accurate and stable forecasting.	Multiple hybrid models	–	–	0.79 1.08
2023 [226]	2006–2010 Australia	Based on ResNet and LSTM, a hybrid model to enhance STLF performance, ResNet used to extract data features.	MLR, ResNat, CNN-LSTM, ResNet-LSTM	–	–	0.61
2023 [66]	2016–2016 2009–2009 USA, Denmark	Model consisting of SVM, BPNN, GRNN predictors, and deep ensemble model. The predictors' performance was optimized using GA and the bat algorithm.	BPNN-PSO, ELM-GA, RBF	0.01	–	–
2023 [165]	2015–2017 Switzerland	Researched feed-forward LSTM, introducing HFSM for optimal feature selection.	LSTM, CNN, FC, HFSM-LSTM	–	–	2.21

6. Smart Grid

The smart grid, an advanced power network capable of automatic control of electricity and information exchange between utilities and consumers, offers significant advantages over conventional grids for STLF [227–229], as detailed in Table 11. The initial step towards smart grids is the integration of smart meters by utilities [230,231], as they play a central role in the use of data for the smart grid network paradigm [232].

In the realm of smart grids, the integration of second-life batteries alongside innovative technologies such as vehicle-to-grid (V2G) and microgrid technologies further enhances adaptability and resilience. V2G, which enables bidirectional energy flow between electric vehicles and the grid, contributes to flexibility and stability [233,234]. The integration of second-life batteries and V2G plays a crucial role in STLF within smart grids. This synergy affects the stable operation of the smart grid, addressing evolving load forecasting needs and ensuring efficient energy management. Numerous models address the impact of additional EV charging on distribution systems [235–237]. Microgrids improve reliability with their localized power generation and distribution [238,239]. In the dynamic smart grid environment, electrical consumption patterns are constantly evolving due to a variety of factors, including weather, processes, activities, and events. Unlike cyclical patterns, these changes manifest themselves unevenly throughout the day. In the smart grid environment, the smart switches are an integral part that significantly improve the accuracy of load

forecasting. Their precise control and monitoring of devices provide critical data that optimize load forecasts for efficient grid management.

Table 11. Comparative advantages of smart grid systems in enhancing STLF over traditional power grid.

Advantages	Smart Grid System: Advantages for STLF	Traditional Power Grid: Limitations in STLF
Energy efficiency	Improved load forecasting accuracy through real-time data monitoring and adaptive control systems.	Reduced forecasting precision due to limited visibility and control capabilities.
Reliability	Self-healing mechanisms minimize forecasting disruptions, leading to more reliable load predictions.	Increased forecasting errors due to slower fault detection and recovery capabilities.
Renewable integration	Advanced integration of renewable sources allows for improved prediction of variable load patterns.	Difficulty in predicting load due to limited renewable integration and fluctuating generation profiles.
Demand response	Real-time demand response improves load forecasting by adjusting for immediate consumption changes.	Challenges in managing peak demand lead to less accurate load forecasting.
Fault detection	Quick detection of system anomalies allows for rapid adjustments in load forecasting.	Longer reaction times to faults hinder accurate load forecasting.
Grid security	Enhanced security features protect forecasting systems from external threats.	Vulnerability to cyber disruptions leads to compromised load forecasting accuracy.
Data analytics	Utilization of sophisticated analytics for predictive load modeling and optimization.	Basic data processing capabilities restrict the refinement of forecasting models.
Flexibility	Agile grid infrastructure supports evolving forecasting models for dynamic load patterns.	Rigid grid design limits the ability to adapt forecasting models to changing load profiles.

The continuous data streams in smart grids challenge traditional machine learning models, rendering them inadequate when confronted with new and unknown parameters influencing consumption patterns [240]. Table 12 succinctly outlines the differences between traditional and adaptive learning models and provides key insights for addressing the evolving load forecasting needs in smart grids. It serves as a comprehensive summary of pertinent information gleaned from the reviewed research articles on STLF in the context of smart grids.

Table 12. Outline of the distinctions between traditional and adaptive learning models.

Aspect	Traditional Models	Adaptive Learning Models
Deterioration in forecasting	Suffers with variable inputs, negatively affecting energy management forecasts.	Retains precision and accuracy even after changes in parameters, application, and sectors.
Impact of parameter changes	Significant impact; model limitations and errors in results.	Minimal impact; adapts to changes dynamically without significant errors.
Nature of data modeling	Models static data; cannot capture dynamic changes in input parameters.	Adapts to dynamic changes; self-regulatory for updates in parameters, features, and patterns.
Automated model updates	Lacks automatic updates; tuning cannot be performed in real time.	Automatically updates with new features and patterns in real time, ensuring accuracy.
Adaptability approach	Static; lacks self-regulation.	Semi- and fully adaptive approaches; dynamically adjusts with fundamental improvements.
Impact on operations and costs	May cause losses of millions due to poor forecasts and operational challenges.	Ensures stability, reducing operational costs and potential losses.

The smart grid incorporates diverse distributed generation modalities and increases system availability and resiliency by integrating diverse energy resources. While this complexity presents challenges, it also offers a unique opportunity to propel the energy industry into a realm of reliability, availability, and efficiency that promotes intelligent

power systems. In this context, accurate electric load forecasting is crucial for anticipating future demand in smart grids. Figure 8 illustrates a hierarchical structure that underscores the importance of research in this area for the sustainable advancement of smart cities and smart grids that contribute to efficient electrical power generation and management.

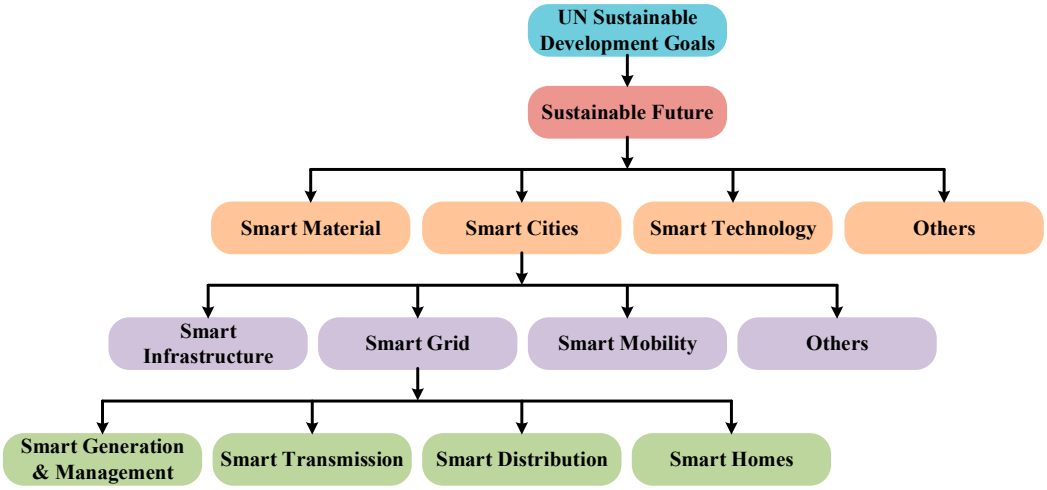

Figure 8. Hierarchical structure highlighting the target areas in smart grid.

Since the smart grid depends on accurate and efficient load forecasting, electric load forecasting is treated as a critical operational task. In the smart grid and distributed generation environment, STLF is an important factor in the day-to-day operations and planning of an electric utility and a critical component of an energy management system. Several STLF techniques have been discussed in previous sections; however, this section focuses solely on the STLF studies related to smart grids due to their importance in modern power grids. Table 13 presents the most relevant information from the reviewed STLF research articles related to smart grids [52,136,241,242]. The MAPE, MAE, and RMSE values shown in Table 13 are taken from the respective research papers and are not intended for direct comparison in this review. The purpose of presenting these performance metrics is to provide readers with a thorough overview, enabling them to assess each model's performance based on its specific dataset and input parameters.

Table 13. Review of STLF Methodologies in smart grid application. (Year: Research paper published, Data Duration: Duration of the dataset used in the research paper, Contribution: Each paper's contribution, Benchmarked Against: Studied research papers compared their proposed model with different models and load, Accuracy: Proposed model accuracy presented in research papers).

Year	Data Duration	Contribution	Benchmarked Against	Accuracy (Best-Performing Model)		
				RMSE	MAE	MAPE
2014 [241]	2009–2010 Ireland	Introduced a novel clustering-based approach, enhancing short-term intra-day household LF performance using smart meter data.	FWK, CFWK	–	–	–
2014 [243]	2012 Poland	Proposed accurate STLF at individual household level, enhancing smart meter intelligence for better customer understanding and cost management.	ANN, SVM	–	–	–
2015 [244]	2012–2013 USA, Ireland	Enhanced system-level load forecasting using clustering based on household smart meter data for improved grid efficiency.	Actual load	–	–	3.68

Table 13. *Cont.*

Year	Data Duration	Contribution	Benchmarked Against	Accuracy (Best-Performing Model)		
				RMSE	MAE	MAPE
2015 [245]	2011–2013 Portugal	Improved solar power forecasting using VAR framework for smart grid efficiency.	VAR, VARX	8.5	–	–
2016 [246]	2009–2010 Ireland	Boosted additive quantile regression increases probabilistic LF, particularly advantageous for disaggregated demand predictions.	Unconditional quantiles, conditional quantiles, additive models	–	–	–
2016 [247]	2014 SK	Examined a big-data-driven EV charging demand LF model, integrating real-world traffic data, aiding power system planning and infrastructure decisions.	Actual data	–	–	–
2017 [248]	2011–2013 USA	Sparse coding increases individual household LF accuracy by 10% over classical methods.	ARIMA, Holt–Winters, group sparse	–	–	20.6
2017 [249]	2008 UK	Seer grid offers a 2-level energy prediction framework utilizing smart meter data, minimizing privacy–utility trade-offs for smart grids.	SARMA, SVM, actual data	–	–	–
2018 [250]	2009–2010 Ireland, Australia	Novel ensemble method utilizing hierarchical clustering for improved aggregated LF with fine-grained subprofiles.	Actual data, individual forecast	–	–	5.08
2018 [52]	- Canada	LSTM-based deep learning framework advances residential LF, leveraging appliance consumption sequences for better accuracy.	LSTM, FNN, KNN	–	–	4.24
2018 [251]	2013–2016 2009–2010 ISO-NE	Introduced CQRA for probabilistic LF, achieving superior ensemble performance and effectively minimizing pinball loss.	BI, NS, MED, SA, WA, QRA variants	–	–	–
2018 [136]	2009–2010 Ireland	Developed a novel pooling-based deep RNN for household load forecasting, overcoming overfitting challenges effectively.	ARIMA, SVM, deep RNN, pooling-based deep RNN	–	–	–
2018 [252]	2012–2014 Israel	Offered sliding-window-based ARIMA algorithms integrating non-seasonal and seasonal time-series models for accurate STLF using smart meter data.	Four sliding-window-based ARIMA models	–	–	9.05
2019 [253]	2010–2013 Australia	Pioneered Bayesian deep-learning-based LSTM for superior probabilistic net LF, leveraging subprofile clustering and PV visibility.	MLR, QR, QRF, LSTM	17.2	13.9	0.09
2019 [254]	2015–2016 China	A parallel gradient boosting decision tree algorithm for EV schedulable capacity forecasting was developed, outperforming other methods in accuracy and efficiency in big data environments.	SCC-PGBDT, SCC-PRF, SCC-PKNN, SDC-PGBDT, SDC-PRF, SDC-PKNN	3.99	–	3.97
2019 [255]	2009–2010 Ireland	A novel clustering-based approach for efficient LF and demand-side management using smart meter data demonstrated improved accuracy and reduced computational burden.	MLR, ANN	–	–	4.64
2020 [256]	2009–2010 2010–2014 Ireland, Australia	Multi-task Bayesian NN improves probabilistic LF, offering superior accuracy and addressing over-fitting challenges in deep learning for smart grids.	SVR, GBRT, RF, PLSTM	0.74 0.81	0.44 0.52	–
2020 [257]	2010 Ireland	Machine-learning-based LF with expert aggregation for improved accuracy by exploiting smart meter data in smart grid management.	SSWA, MSWA, 2S-MSWA	21.1	14.2	5.5

Table 13. *Cont.*

Year	Data Duration	Contribution	Benchmarked Against	Accuracy (Best-Performing Model)		
				RMSE	MAE	MAPE
2020 [258]	2013 UK	Efficient hierarchical clustering using dissimilarity measures captures diverse household consumption patterns in smart meter data.	ACORN-Grouped	–	–	–
2020 [259]	2013 Australia	Proposed a CNN-LSTM hybrid for individual household STLF, outperforming state-of-the-art models.	LSTM, BPNN, KNN, ELM	–	–	40.3
2020 [260]	2017 SK	Developed a hybrid DL scheduling algorithm for smart grids, improving accuracy and processing time efficiency.	Ring buffer, class-means *K*-means, CosSim, incremental DL	0.09	–	–
2020 [261]	2017 USA	Introduced ST-BTMLPVF problem, developed ST-GAE and STGDL optimization for accurate BTM load and PV forecasting.	SVR, GRU, LSTM, DRNN	0.19	0.13	8.01
2020 [262]	2012–2016 Czech Republic	Offered a DRNN Bi-LSTM model for accurate STLF, enhancing microgrid operational scheduling effectiveness.	RNN, FFNN, Copula-DBN, CNN-RNN, D-CNN	–	–	1.18
2020 [263]	2016–2018 Australia	Combining best-basis stationary wavelet packet transform and Harris-hawk-optimization-based feed-forward NN model for STLF in microgrids, significantly outperforming existing models.	PSO-ANN, PSO-LSSVM, BPNN	–	–	0.48 1.27 1.43 1.02
2021 [264]	2012 Australia	Optimized accuracy in aggregated baseline load estimation under high behind-the-meter PV penetration using a 2-stage decoupled approach.	Low5of10, High5of10, Mid4of6, MLR, SVR	–	–	26.5
2021 [265]	2016–2018 China	Proposed bottom-up method for HV load forecasting, achieving superior accuracy and narrow intervals, aiding grid management.	Bottom-up, ES method, BELM	0.32	2.47	2.48
2021 [266]	2017–2019 Spain	Proposed parallel processing for fast, accurate STLF, favoring decision tree over other models.	DT, LR, NN, SVR, RF, GBRT	–	–	10.9
2021 [267]	2012 USA	Examined graph ANN for spatial–temporal STLF, achieving significant gains over traditional methods, and proposed self-adaptive models.	FC-LSTM, CNN-GRU	–	0.97 0.59 0.58	4.53 6.36 6.5
2021 [268]	2010–2014 Australia	Introduced a novel multi-task multi-information fusion DL framework, outperforming state-of-the-art methods in forecasting accuracy.	SVR, XGBoost, pooling-based deep RNN, CNN-LSTM, M-LSTM	–	0.14	–
2021 [269]	UK 2019	A CNN-LSTM time-series LF model for V2G services was developed, demonstrating improved predictive capability over regression models and adaptability to market events, crucial for service reliability.	CNN-LSTM, actual load	–	21.9	–
2022 [270]	2011–2014 UK	A hybrid scheme balancing perturbation and cryptography ensures efficient and privacy-preserving smart meter data publishing.	DDF, LDF, raw data	–	–	3.3
2022 [271]	2019 USA	Efficient reduced model leverages hierarchical dimension reduction for scalable and accurate STLF using fine-resolution smart meter big data.	Cluster-based approach, aggregated model, reduced model	0.8	–	–
2022 [272]	2013 UK	FL using LSTM and FL + HC optimize residential load forecasting with improved accuracy and computational efficiency.	FL, FL + HC, FL + HC → LFT	0.02	–	–

Table 13. *Cont.*

Year	Data Duration	Contribution	Benchmarked Against	Accuracy (Best-Performing Model)		
				RMSE	MAE	MAPE
2022 [273]	2020–2021 Taiwan	A CNN-Bi-GRU hybrid model was developed for short-term 3-phase LF in smart solar microgrids, outperforming traditional models.	RNN, LSTM, GRU, Bi-LSTM, Bi-GRU	–	0.03	–
2022 [274]	2013 Canada	Presented a superior STPLF methodology using DPMM, MCMC, and ensemble learning, surpassing benchmarks in uncertainty modeling.	CKDE, ARIMA, QRTE, CED	–	–	–
2022 [275]	2019 UK	Explored the potential of electric vehicle batteries in home energy management systems, offering optimal designs and insights.	Actual load	–	–	–
2022 [276]	2016–2019 Panama	Addressed STLF for smart grids, emphasizing the significance of deep learning in achieving superior accuracy, as evidenced in Panama case study.	DLR, Bi-LSTM, GRU, SVR, XGB, AdaBoost, random forest	–	–	2.9
2022 [277]	2018 India	Developed a pooling-based DL algorithm, utilizing Copula function and Hankel matrix, significantly enhancing EMS forecasting accuracy.	SVM, DBN	2.86 2.46	–	–
2023 [278]	2022 India	Introduced an IoT-based STLF model for electric power consumption and RES generation, enhancing demand-side management in smart buildings.	Decision tree regression, random forest regression	–	–	0.55
2023 [279]	2022 Iraq	An innovative IoT-based smart meter with high data rates was developed, featuring cloud-based storage and energy estimation, contributing to smart grid structure.	Actual load	–	–	–
2023 [227]	2010–2013 Australia	Examined privacy-preserving and communication-efficient federated learning for net metering, combining hybrid DL predictor, IPFE, and CAT for superior results.	CNN, LSTM, CNN-LSTM	0.57	0.32	–
2023 [280]	2009–2010 Ireland	Offered flexible probabilistic LF approach using Bernstein polynomial stabilizing flow, demonstrating superior performance over Gaussian and QR-based methods, especially in low-data scenarios.	Fully connected NN, dilated 1D convolution NN	–	–	–
2023 [281]	2018 USA	Customized pricing scheme for an electricity market, enhancing the agent's profit by 4% to 130% compared to uniform pricing utilizing LSTM, considering BTM PV and energy storage.	Actual load	17.8	–	1.31
2023 [242]	2009–2010 Ireland	Proposed a global modeling framework for LF in distribution networks, outperforming local models and offering scalability and efficiency.	MLR, LSTM, N-BEATS, *K*-means LSTM	–	0.80	8.26

7. Discussion

7.1. Accuracy

Power generation and distribution infrastructure decisions rely on accurate STLF. Evaluation metrics such as RMSE, MAE, and MAPE are considered in this study. Different models use diverse variables and datasets, making direct comparison challenging, which can only be performed by comparing models that use similar influencing factors and datasets. This study presents precision results (Tables 8–10), taking into account the specific objectives of each model for clarity. This study found that ICM approaches outperformed statistical methods. Combining statistical methods with RM, metaheuristic models, ES, and ANN models improved accuracy. Hybrid approaches generally outperformed ICM

methods. The choice of forecasting method depends on the learning difficulty and data availability, while the performance of the forecasting model depends on the size of the dataset. The STLF using ICM includes methods such as SNN and SVMs. The dataset size affects the performance of ANNs and SVMs, with larger datasets improving generalization. The fuzzy logic adapts to uncertainty, while genetic algorithms optimize parameters; their effectiveness depends on the diversity of the dataset. Ensemble methods benefit from larger datasets for model diversity. Deep learning models such as RNNs and LSTMs require substantial data for effective training. Hybrid models combine techniques, and the dataset size also influences their performance. The analysis showed that certain hybrid models achieve MAPE values below the 3% threshold, indicating a high level of accuracy in load prediction. This accuracy has a direct impact on the grid's ability to effectively balance supply and demand, thereby reducing the frequency of load shedding events and the reliance on peaking power plants. Careful pre-processing and validation are critical for a reliable STLF model in power systems.

7.2. Time Analysis

The study of forecasting models, initiated in 1971, has experienced remarkable growth, with a surge in electrical load forecasting models after 1995. The implementation of the Kyoto Protocol in 2005 further stimulated model development. In particular, 87% of the models were developed in the last 19 years. While STLF models slightly declined after 2020, hybrid STLF models showed consistent growth. Machine learning gained prominence in the 1990s, with a notable increase in both statistical and machine learning techniques after 2007. The use of metaheuristic techniques in forecasting increased after 2009. Despite the increased accuracy of intelligent computing techniques, hybrid models have seen a more significant increase in the last eight years.

7.3. Geographical Extent

In the context of STLF, geographic scope plays a critical role in shaping the performance efficiency of forecast models. The case sensitivity of a forecasting model becomes evident as the same methodology may yield different performances in distinct locations or countries due to factors such as temperature, humidity, windspeed, rainfall, and cloud cover. In particular, variations in climatic conditions lead to dynamic patterns in energy consumption, highlighting the need for adaptive and location-specific forecasting models. This nuanced understanding enhances our appreciation of the complex interplay between geographical characteristics and forecast accuracy and further emphasizes the case sensitivity inherent in STLF. Out of 196 countries [282], 44 nations, including the USA and China, have contributed to STLF models and datasets. Collaborative efforts from organizations such as EUNITE and APEC have further enriched the dataset (Figure 9), underscoring the global commitment to STLF research. There are six countries in North Africa, of which only Egypt and Morocco have presented studies based on their datasets.

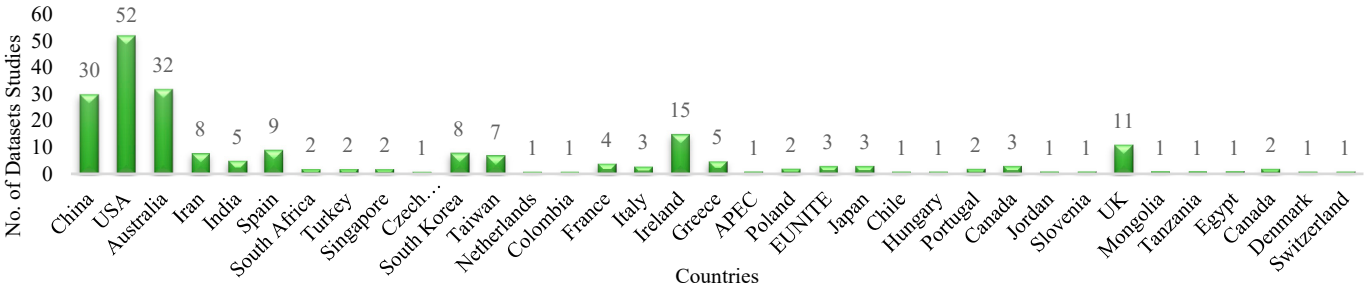

Figure 9. Country-wise models developed and datasets utilized in STLF.

Tanzania is the only East African country out of 19 working on STLF, while 4 out of 6 East Asian countries are involved. India and Iran are notable contributors in South Asia. In West Asia, Turkey, Tanzania, and Jordan are actively developing models. In Western Europe, Spain, the Netherlands, France, Italy, Ireland, Denmark, Switzerland, and Portugal conduct STLF research. In Eastern Europe, the Czech Republic, Greece, Poland, Hungary, and Slovenia are notable. Colombia and Chile are the leaders in South America. Developed regions such as the United States, Canada, Australia, and Japan are actively involved in developing electric load forecasting datasets and implementing various STLF models, in addition to the collaborative efforts of EUNITE and APEC.

7.4. Robustness and Reliability

The robustness of a model, particularly its capacity to consistently perform under variable conditions, is of paramount importance in the context of the smart grid paradigm. The findings demonstrate that machine learning models with self-correcting capabilities exhibit a notable improvement in error consistency. This robustness signifies a reliable performance, which is crucial for maintaining grid stability and ensuring an uninterrupted power supply.

7.5. Computational Efficiency and Its Impact

The computational efficiency of STLF models has significant implications for their deployment in smart grids. Models exhibiting rapid computation times are of paramount importance for real-time analytics and immediate load adjustment, which are central to the dynamic demand-response mechanisms in smart grids. The analysis indicates that while there is a trade-off between speed and complexity, the employment of efficient algorithms can mitigate this, enabling fast and reliable forecasting.

7.6. Implications of Scalability

In the context of the expansion of modern grid networks, scalability represents a crucial feature for STLF models. The analysis indicates that models designed with scalability in mind are capable of handling increasing volumes of data from diverse sources without a significant loss in performance. This scalability is of great importance in adapting to the growth of the smart grid infrastructure and the integration of distributed energy resources.

7.7. Policy and Future Research

The analysis of STLF models not only affects the technical management of modern grid networks but also has policy implications. The formulation of accurate forecasts enables the formulation of more efficacious policy decisions pertaining to energy conversion, demand-side management, and investment in infrastructure. Moreover, the results of this analysis can inform future research in the development of models that are not only precise but also incorporate features such as adaptability and resilience against anomalies in data, which are crucial for the next generation of modern power grids and smart grids.

8. Outcomes

The following is a list of the principal outcomes postulated following a detailed examination of the various state-of-the-art predictive models presented in the previous sections:

- The forecasting time, weather conditions, and system economy all have a significant impact on the accuracy of a given load forecasting model.
- To assess the reliability of a hybrid or single predictive model's reliability, the values of MAE, RMSE, and MAPE can be employed.
- A multitude of articles consider a plethora of climatic variables based on the specific application and location in question, rendering the use of standard variables irrelevant for LF, as the LF fails to account for them.

- Geographical factors, such as temperature and humidity, render the STLF case sensitive, with location-specific variations impacting model performance and accuracy.
- Correlational analysis of the load-forecasting-related elements has a significant impact on the model's accuracy. Any alterations to the region will have a detrimental effect on the model's accuracy, given that these correlations are similarly dependent on the region in question.
- By incorporating econometric variables, loading data, or statistical processes, the values derived from STLF can be approximated to those of MTLF or LTLF.
- The ELM offers expedient training, the fuzzy C-means method offers a superior error analysis index, FRBS has the capacity to approximate all variables, and MLP and LSTM have the most precise classification of the single methods listed.
- From a literature perspective, the combination of various single predictive methods for load forecasting, such as ANN, SVM, or LSTM-based double predictive models, has demonstrated enhanced outcomes.
- In various studies, a variety of clustering techniques were employed, with *K*-means demonstrating superior performance.
- In load forecasting models, optimization strategies were employed with great frequency. Nevertheless, the GA and PSO techniques were predominantly applied due to their superior crossover and mutation performance and optimal fitness.
- The STLF plays a pivotal role in optimizing smart grid operations, particularly in the context of integrating advanced technologies such as smart meters, V2G, and second-life batteries.
- The use of smart meters provides valuable data for STLF, thereby enhancing forecasting accuracy.
- The integration of second-life batteries introduces a new level of adaptability, improving the stability and overall performance of the smart grid.

In summary, the comprehensive analysis highlights the significance of each model's performance in a practical setting and its potential to contribute to the advancement of modern grid technology. It is of the utmost importance to continue refining and evaluating these models in order to achieve the ultimate goal of a fully intelligent power grid system.

9. Research Gaps and Future Directions

This section presents our findings, which identify the current research needs and potential future directions of STLF. This information is derived from synthesizing findings across multiple studies. Its inclusion is intended to highlight areas where further research is warranted based on the identified gaps in the current state of knowledge. The methodology employed to identify these research gaps is based on a comprehensive examination of the existing literature. The summarized view of research gaps and future direction is presented in Table 14.

Table 14. Summarized view of research gaps and future direction.

Research Gap	Future Direction
Time-of-use considerations	Explore the incorporation of time-of-use factors into STLF models, with a particular focus on the impact of varying electricity demand patterns during different times of the day.
Edge computing applications	The potential of edge computing in STLF to enhance local processing capabilities, reduce dependencies on centralized systems, and improve forecasting accuracy should be explored.
Consistency in LF models	Incorporate meteorological, economic, and regional data for correlational analysis in future STLF models.
LF in isolated grid sectors	Conduct additional research and design custom parameters to address the prediction challenges in isolated grid sectors.
Model adaptability concerns	Develop adaptability STLF models capable of adjusting to diverse generation modalities and varying circumstances.

Table 14. *Cont.*

Research Gap	Future Direction
Demand-side management	The integration of LF into consumer demand-side management plans has the potential to enhance the quality of the power system. Such integration may result in more economical power use, lower prices, and increased system reliability.
Anomaly detection in LF	Anomaly detection in LF is underexplored, despite the complexities introduced by smart grids. The development of models capable of anticipating and detecting anomalies could enhance the accuracy of the results obtained.
Evolutionary and metaheuristic optimization techniques	Combining evolutionary and metaheuristic optimization techniques can enhance the learning capabilities of ANNs, thereby improving the accuracy of their outputs. The hybridization strategy warrants investigation for better forecasting.
Lack of STLF analysis in developing countries	The lack of STLF analysis in developing countries is due to data availability issues. It is of the utmost importance to improve data collection methods and to explore alternative data sources in order to achieve more accurate forecasting in these regions.
Uncertainty quantification	A research gap exists in the field of uncertainty quantification for STLF. Further methodologies should provide probabilistic forecasts and quantify uncertainty through scenario analysis, ensemble forecasting, and other appropriate techniques.
STLF integration with smart technology	Integration of STLF with smart technology can enhance power systems, leading to smart grids, buildings, and microgrids. It improves energy efficiency, reduces costs, and enhances system reliability.
Data imputation techniques	The gaps in STLF caused by missing data points must be researched and the implementation of effective data imputation techniques must be carried out.
Transferability across regions	Assess the transferability of STLF models across different regions, considering variations in power system structure, climate, and load behaviors.
Grid resilience considerations	Explore how STLF models can contribute to grid resilience by incorporating factors related to grid robustness and adaptability in the forecasting process.
Privacy-preserving forecasting	Development of privacy-preserving techniques for STLF models is important, ensuring that sensitive data are protected while still allowing for accurate forecasting.

10. Conclusions

The most crucial aspect of power system operations is the forecasting of short-term electrical loads. It provides the foundation for a multitude of power distribution and management decisions. Consequently, the accuracy and precision of such forecasts are of paramount importance to decision-makers in the power sector. This study presented a comprehensive analysis of various STLF models that were applied to databases from different geographic locations and connected to several distinct power system subsectors, including smart grids. Researchers have developed a variety of prediction models to improve the efficacy of the current forecasting techniques, given the necessity for regular and accurate assessments of fluctuating factors in order to accurately predict electrical load. To provide a comprehensive analysis of the most prominent STLF models, this research classified them into three general categories: statistical approaches, methods based on intelligent computing, and hybrid models. A comprehensive tabular review was initially presented on statistical methodologies and intelligent-computing-based methods. The two aforementioned categories were then subdivided into a specific analysis of cutting-edge hybrid models. Subsequently, the significance of STLF in the context of smart grids was evaluated. The advent of smart grids in modern power systems, their integration with smart meters, and innovations such as V2G and second-life batteries have introduced a novel dimension to STLF. V2G enables bidirectional energy flow between EVs and the grid, thereby enhancing flexibility and resilience. Furthermore, the incorporation of second-life batteries contributes to the stability and adaptability of the grid. As electric consumption patterns continue to evolve in the dynamic smart grid environment, these advancements present challenges for conventional machine learning models. A number of challenges, including meteorological and production-related factors, can affect the accuracy of load

forecasting. The necessity for models that can adapt to changes in characteristics over time is of paramount importance, as traditional models become obsolete in dynamic, real-time environments. A number of studies have been conducted on STLF models related to smart grids, smart buildings, and V2G applications. The development of energy storage systems based on second-life batteries could be facilitated by the use of accurate STLF, which would assist in maintaining the stability of the smart grid during periods of fluctuating renewable energy resources. In order to assist researchers in selecting the most appropriate models for load prediction, the performance accuracy of each study is presented in terms of MAE, RMSE, and MAPE values.

The output of several fundamental time-series models, such as ARIMA and ARMA, indicates that more complex predictive models are necessary to enhance forecasting accuracy. The models must be capable of detecting sudden changes in the electric load data during peak hours. This study also examined a range of intelligent-computing-based approaches for STLF applications. Furthermore, it has been observed that neural network techniques have been utilized to varying degrees of efficacy in a multitude of electrical load forecasting research fields. The findings of a comprehensive review of intelligent-computing-based methodologies demonstrate a clear shift towards enhancing the training capability of neural networks, with the objective of achieving more promising results of the STLF model than those obtained through conventional techniques. In addition, a range of hybrid forecasting techniques have been employed with the objective of enhancing forecast accuracy. It has been demonstrated in the literature that the combination of two or more predictive models can create hybrid models with the required accuracy. In several hybrid methodologies, the widely used BPNN training algorithm is utilized to train the NN, yet these approaches do not fully resolve the aforementioned issues. In order to achieve an efficient power system utility, whereby the demand load can be forecast with a minimum error percentage, it has been demonstrated that SVM, ANN, LSTM, and their pertinent models have excellent prospects.

Recent research has demonstrated that the heuristic search and population-based optimization learning algorithms of ANN for STLF produce superior outcomes compared to conventional neural networks. Nevertheless, the efficacy of an ANN-based forecast model can be enhanced by addressing shortcomings such as the reliance on initial weight values, local minima problems, inadequate network generalization, and slow convergence. The findings of the research have been included to provide readers with a comprehensive understanding of modern predictive models, which can be utilized in the selection of a specific model for the development of new hybrid forecasters in accordance with the characteristics of the individual approaches. Future research will focus on the design and comparison of hybrid models with three or more approaches to address the shortcomings of the current forecasters. Previous studies have demonstrated that hybrid models with more than two methods have a significant advantage over single or double models. It is thus concluded that several factors, including network complexity, an improved training algorithm, convergence rate, and the selection of highly correlated inputs for the forecast model, need to be addressed in addition to enhancing the prediction accuracy of forecasting models.

Author Contributions: Literature review, conceptualization: S.A., S.B. and A.T.; Implementation and investigation of the research: S.A., S.B., M.N.R. and A.T.; Writing—original draft preparation: S.A.; Writing—review and editing: S.A., S.B., M.N.R., P.P.P., D.F. and A.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

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

Abbreviations

EMS	Energy Management System
EG	Electric Grid
RESs	Renewable Energy Sources
STLF	Short-Term Load Forecasting
RNNs	Recurrent Neural Networks
ELM	Extreme Learning Machine
DSM	Demand-Side Management
LF	Load Forecasting
EDF	Electricity Demand Forecast
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ICM	Intelligent-Computing-Based Model
ANN	Artificial Neural Network
GRU	Gated Recurrent Unit
DNN	Deep Neural Network
ML	Machine Learning
EVs	Electric Vehicles
LTLF	Long-Term Load Forecasting
MTLF	Medium-Term Load Forecasting
VSTLF	Very Short-Term Load Forecasting
ABPA	Adaptive Back Propagation Algorithm
MARS	Multi-Variate Adaptive Regression Spline
LR	Linear Regression
TD-CNN	Time-Dependent Convolutional Neural Network
C-LSTM	Cycle-Based Long Short-Term Memory
MLP	Multi-Layer Perceptron
GA	Genetic Algorithm
NARX-NN	Non-Linear Autoregressive with Exogenous Inputs Neural Network
EMS	Energy Management System
ES	Exponential Smoothing
MMI	Modified Mutual Information
FCRBM	Factored-Conditional-Restricted Boltzmann Machine
DT	Decision Tree
NLR	Non-Linear Regression
LSSVM	Least Squares Support Vector Machine
OSELM	Online Sequential Extreme Learning Machine
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
ARIMA	Autoregressive Integrated Moving Average
SARIMA	Seasonal Autoregressive Integrated Moving Average
SARIMAX	Seasonal Autoregressive Integrated Moving Average with Exogeneous Input
BVAR	Bayesian Vector Autoregressive
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
SEGARCH	Seasonal Exponential Form of Generalized Autoregressive Conditional Heteroskedasticity
WNN	Wavelet Neural Network
WARCH	Winters Model with Exponential Form of Generalized Autoregressive Conditional Heteroskedasticity
SES	Single Exponential Smoothing
DES	Double Exponential Smoothing
TES	Triple Exponential Smoothing
RM	Regression Model
SVD-ES	Singular Value Decomposition-Based Exponential Smoothing
PS	Power System
FFNN	Feed-Forward Neural Network
DERs	Distributed Energy Resources
BFGS	Broyden–Fletcher–Goldfarb–Shanno
NNs	Neural Networks
PF	Particle Filter
MF	Multi-Component Forecast
LWR	Locally Weighted Regression
LWSVR	Locally Weighted Support Vector Regression
NPR	Non-Parametric Regression
RMSPE	Root Mean Square Percentage Error
MLR	Multiple Linear Regression
ILP	Integer Linear Programming
PLAQ-RM	Partially Linear Additive Quantile Regression Model
SSVRE	Subsampled Support Vector Regression Ensemble
PAR	Passive Aggressive Regression
SGDR	Stochastic Gradient Descent Regressor
FTRLP	Follow-the-Regularized-Leader-Proxima
ARMA	Autoregressive Moving Average
PSO	Particle Swamp Optimization
MLF-NN	Multi-Layer Feedforward Neural Network
BPNN	Back Propagation Neural Network
ENN	Evolving Neural Network
SVMSA	Support Vector Machines with Simulated Annealing
GRNN	General Regression Neural Network
FNN	Fuzzy Neural Network
MRA	Multiple Regression Analysis
ADE-BPNN	Adaptive Differential Evolution with BPNN
WEFuNN	Weighted Evolving Fuzzy Neural Networks
RBFNN	Radial Basis Function Neural Network
DEKF-RBFNN	Dual Extended Kalman Filter RBFNN
GRD-RBFNN	Gradient Decent RBFNN
DCANN	Dynamic Choice Artificial Neural Network
UDCANN	Updated Dynamic Choice Artificial Neural Network
IBSM	Index of Bad Samples Matrix
DRNNs	Deep Recurrent Neural Networks
D-SARIMA	Difference Seasonal Autoregressive Integrated Moving Average
MFES	Multi-Output FFNN with EMD-Based Signal Filtering and Seasonal Adjustment
MFNN	Multi-Output Feed-Forward Neural Network
MFE	Multi-Output FFNN with EMD-Based Signal Filtering
RBF	Radial Basis Function
PDRNN	Pooling-Based Recurrent Neural Network
KNN	K-Nearest Neighbor
CLD	Characteristic Load Decomposition
EMD-SVR	Empirical Mode Decomposition-Based Support Vector Regression
IR	Interactions Regression
SWLR	Step-Wise Linear Regression
DDBN	Distributed Deep Belief Network
OLS	Ordinary Least Square

RM-W-SML	Regression Models without Utilizing Supervised Machine Learning
RM-SML	Regression Models Utilizing Supervised Machine Learning
MTR	Medium Tree Regression
LgR	Logistic Regression
SWR	Step-Wise Regression
RRM	Robust Regression Model
CTR	Coarse Tree Regression
DL	Deep Learning
SOM	Self-Organizing Map
FTR	Fine Tree Regression
LSVM	Linear Support Vector Machine
QSVM	Quadratic Support Vector Machine
FGSVM	Fine Gaussian Support Vector Machine
MGSVM	Medium Gaussian Support Vector Machine
CGSVM	Coarse Gaussian Support Vector Machine
RQGPR	Rational Quadratic Gaussian Process Regression
SEGPR	Squared Exponential Gaussian Process Regression
M-5/2-GPR	Matern 5/2 Gaussian Process Regression
EGPR	Exponential Gaussian Process Regression
BT	Boosted Tree
BgT	Bagged Tree
OP-ELM	Optimally Pruned Extreme Learning Machine
LSTM	Long Short-Term Memory
AN	Abductive Network
GP	Grey Prediction
FCMs	Fuzzy C-Means
FR	Fuzzy Regression
AIS	Artificial Immune System
GA	Genetic Algorithm
FA	Firefly Algorithm
MA	Memetic Algorithm
GSA	Gravitational Search Algorithm
SAA	Simulated Annealing Algorithm
ACO	Ant Colony Optimization
CASO	Chaotic Ant Swarm Optimization
SVM-BFGSFA	SVM and Broyden–Fletcher–Goldfarb–Shanno Firefly Algorithm
SVM-HAS	SVM and Harmony Search Algorithm
SVM-FFOA	SVM and Fruit Fly Optimization Algorithm
SVM-GA	SVM and Genetic Algorithm
SVM-PSO	SVM and Particle Swarm Optimization
SVM-SAA	SVM and Simulated Annealing Algorithm
ANN-CT	ANN and Clustering Techniques
ANN-NFIS	ANN and Neural Fuzzy Interference System
ANN-WT	ANN and Wavelet Transform
ANN-GA	ANN and Genetic Algorithm
GNN-WT-GAFL	Generalized Neural Network-Wavelet Transform-Genetic Algorithm With Fuzzy Logic
ResNet	Residual Neural Network
CGA	Chaos-Search Genetic Algorithm
MFWNS	Meteorological-Forecast-Based Weighted Nearest Similar Day Method
AGG	Aggregated Load with Measurement of One Node
DTLP	Data-Type Conditioned Linear Prediction
MIMO	Multiple-Input Multiple-Output
DWT	Dyadic Wavelet Transform
R-DNN	Recurrent Deep Neural Networks
RF	Random Forest
RELM	Recurrent Extreme Learning Machine
CSVM	Cubic Support Vector Machine
FTL-ANN	Follow the Leader ANN
MOFTL	Multi-Objective Follow the Leader
MOWCA	Multi-Objective Water Cycle Algorithm
MOPSO	Multi-Population Coevolution-Based Multi-Objective Particle Swarm Optimization
NSGA-II	Non-Dominated Sorting Genetic Algorithm
SVM	Support Vector Machine
DR	Dynamic Regression
PSF	Pattern Sequence-Based Direct Time-Series Forecasting
SCPSNSP	SOM Cluster Pattern Sequence-Based Next Symbol Prediction Method
CSA-SVM	Support Vector Machine Optimized By Cuckoo Search Algorithm
GA-BPNN	Genetic Algorithm-Based Back Propagation Neural Network
TCMS-CNN	Multi-Scale Convolutional Neural Network with Time Cognition
DM-MS-CNN	Direct Multi-Step Multi-Scale CNN
DM-GCNN	Direct Multi-Step Genetic CNN
FRBS	Fuzzy Rule Base System
CIS	Correlation-Based Input Selection
ABCO	Artificial Bee Colony Optimization
QGBRT	Quantile Gradient Boosting Regression Tree
CSA	Cuckoo Search Algorithm
BRNN	Bidirectional Recurrent Neural Network
SIWNN	Similar Day-Based Wavelet Neural Network
SSA-SVR	Singular Spectrum Analysis-Based Support Vector Regression
ANN-FA	ANN and Firefly Algorithm
HMM	Hidden Markov Model
MCRN	Multi-Column Radial Basis Function Neural Network
CEEMD	Complementary Ensemble Empirical Mode Decomposition
SecRPSO	Improved PSO with Second-Order Oscillation and Repulsive Force Factor
WGRP	Weighted Gray Relation Projection Algorithm
mRMR	Minimal Redundancy Maximal Relevance
QRF	Quantile Regression Forest
QET	Quantile Extra Tree
ANN-AIS	ANN and Artificial Immune System
ANN-PSO	ANN and Particle Swarm Optimization
FLR	Fuzzy Linear Regression

EMD-PSO-SVR	Empirical Mode Decomposition-Particle Swarm Optimization-Support Vector Regression
EEMD-GLM-GOA	Ensemble Empirical Mode Decomposition-Extreme Learning Machine-Grasshopper Optimization Algorithm
GHSA-FTS-LS-SVM	Global Harmony Search Algorithm-Fuzzy Time Series-Least Squares-Support Vector Machine
T-C-IEMD-DBN	T-Copula-Improved Empirical Mode Decomposition-Deep Belief Network
FCW-EMD & KF-BA-SVM	Fuzzy Combination Weight-Empirical Mode Decomposition And Kalman Filtering-Bat Algorithm-Support Vector Machine
GA-PSO-ANFIS	Genetic Algorithm-Particle Swarm Optimization-Adaptive Neuro Fuzzy Inference System
WRLS	Weighted Recursive Least Squares
BNN	Bayesian Neural Network
PSO-ARMAX	Particle Swarm Optimization-ARMAX
HSPO-ARMAX	Hybrid ARMAX Model Based on Evolutionary Algorithm and Particle Swarm Optimization
TSK	Takagi–Sugeno–Kang Models
ILS	Iterative Least Square
TFM	Transfer Function Model
CAViaR	Conditional Autoregressive Value at Risk
CARE	Conditional Autoregressive Expectile
HFSM	Holistic Feature Selection Method
MA-C-WH	Moving Average Combined Hybrid Model and Adaptive Particle Swarm Optimization Algorithm
KP-SVR	Kernel-Penalized SVR
APEC	Asia Pacific Economic Cooperation
CR	Czech Republic
SK	South Korea
ISO-NE	ISO New England
SA	South Africa
VARX	VAR with Exogenous Variables
MSWA	Multi-Scale Weighted Aggregation
ACORN	Geo-Demographic Characteristics of a Household
DDF	Distributed Differential Privacy
FL	Federated Learning
LFT	Local Fine-Tuning
RBM	Reconciled Boosted Model
FWK	Functional Wavelet-Kernel Approach
ST-BTMLPVF	Spatiotemporal Behind-the-Meter Load and PV Forecasting
STGDL	Spatiotemporal Graph Dictionary Learning
CKDE	Conditional Kernel Density Estimation
CED	Conditional Empirical Distribution
MCMC	Markov Chain Monte Carlo
CQRA	Constrained Quantile Regression Averaging
NS	Naïve Sorting
SA	Simple Averaging
IPFE	Inner-Product Functional Encryption
CGAE	Convolutional Graph Autoencoder
ST-GAE	ST-graph Autoencoder
BTM	Behind-the-Meter
V2G	Vehicle-to-Grid
SDC	Schedulable Discharge Capacity
PGBDT	Parallel Gradient Boosting Decision Tree
KF	Kalman Filter
IT2-FLSs	Interval Type-2 Fuzzy Logic Systems
IMF	Intrinsic Mode Function
SDA	Stacked Denoising Autoencoder
GA-NARX-NN	Genetic Algorithm-Non-Linear Autoregressive with Exogenous Input-Neural Network
MetaFA	Metaheuristic Firefly Algorithm
GMM	Gaussian Mixture Model
BFGSFA	Broyden–Fletcher–Goldfarb–Shanno Firefly Algorithm
DenseNet	Densely Connected Convolutional Network
LSSVR	Least Square Support Vector Regression
RVFL	Random Vector Functional Link Network
DDPG	Deep Deterministic Policy Gradient
BSAS	Beetle Swarm Antennae Search
DRL	Deep Reinforcement Learning
ESSO	Enhanced Shark Smell Optimization
GNN	Grey Neural Network
CB-FWNN	Clustering-Based Fuzzy Wavelet Neural Network
WD	Wavelet Decomposition
TCN	Temporal Convolutional Network
EUNITE	European Network on Intelligent Technologies
PKNN	Parallel *K*-Nearest Neighbors
CGA-ANN	Continuous Genetic Algorithm ANN
VAR	Vector Autoregression
SSWA	Single Scale Weighted Aggregation
2S-MSWA	Two-Step Multi-Scaled Weighted Aggregation
PLSTM	Pooling-Based LSTM
LDF	Local Differential Privacy
HC	Hierarchical Clustering
BELM	Bootstrap-Based Extreme Learning Machine Method
LQREC	Linear Quantile Regression and Empirical Copula-Based Day-Ahead HPLF Method
CFWK	Clustering-Based Improvement of FWK
ST-GAE	Spatiotemporal Graph Autoencoder
CNN-Bi-GRU	Convolution Neural Network Bidirectional Gated Recurrent Unit
QRTE	Quantile Regression Tree Ensemble
DPMM	Dirichlet Process Mixture Model
STPLF	Short-Term Probabilistic Load Forecasting
BI	Best Individual
MED	Median Value
WA	Weighted Averaging
CAT	Change and Transmit
ST-BTMLPVF	Spatiotemporal Behind-the-Meter Load and PV Forecasting
STGDL	Spatiotemporal Graph Dictionary Learning
M-LSTM	Multi-Task LSTM
SCC	Schedulable Charge Capacity
GBDT	Gradient Boosting Decision Tree
PRF	Parallel Random Forest

References

1. Global Energy & Climate Outlook 2050. Available online: https://eneroutlook.enerdata.net/forecast-world-electricity-consumption.html (accessed on 18 April 2023).
2. Zhao, B.; Zeng, L.; Li, B.; Sun, Y.; Wang, Z.; Pansota, M.; Xi, P. Collaborative Control of Thermostatically Controlled Appliances for Balancing Renewable Generation in Smart Grid. *IEEJ Trans. Electr. Electron. Eng.* **2019**, *15*, 460–468. [CrossRef]
3. Berk, K.; Hoffmann, A.; Müller, A. Probabilistic Forecasting of Industrial Electricity Load with Regime Switching Behavior. *Int. J. Forecast.* **2018**, *34*, 147–162. [CrossRef]
4. Cancelo, J.R.; Espasa, A.; Grafe, R. Forecasting the Electricity Load from One Day to One Week Ahead for the Spanish System Operator. *Int. J. Forecast.* **2008**, *24*, 588–602. [CrossRef]
5. Djukanovic, M.; Ruzic, S.; Babic, B.; Sobajic, D.J.; Pao, Y.-H. A Neural-Net Based Short Term Load Forecasting Using Moving Window Procedure. *Int. J. Electr. Power Energy Syst.* **1995**, *17*, 391–397. [CrossRef]
6. Soares, L.J.; Medeiros, M.C. Modeling and Forecasting Short-Term Electricity Load: A Comparison of Methods with an Application to Brazilian Data. *Int. J. Forecast.* **2008**, *24*, 630–644. [CrossRef]
7. Hu, R.; Wen, S.; Zeng, Z.; Huang, T. A Short-Term Power Load Forecasting Model Based on the Generalized Regression Neural Network with Decreasing Step Fruit Fly Optimization Algorithm. *Neurocomputing* **2017**, *221*, 24–31. [CrossRef]
8. Kavousi-Fard, A.; Samet, H.; Marzbani, F. A New Hybrid Modified Firefly Algorithm and Support Vector Regression Model for Accurate Short Term Load Forecasting. *Expert Syst. Appl.* **2014**, *41*, 6047–6056. [CrossRef]
9. Zeng, N.; Zhang, H.; Liu, W.; Liang, J.; Alsaadi, F.E. A Switching Delayed PSO Optimized Extreme Learning Machine for Short-Term Load Forecasting. *Neurocomputing* **2017**, *240*, 175–182. [CrossRef]
10. Gungor, V.; Sahin, D.; Kocak, T.; Ergut, S.; Buccella, C.; Cecati, C.; Hancke, G. Smart Grid Technologies: Communication Technologies and Standards. *Ind. Inform. IEEE Trans.* **2011**, *7*, 529–539. [CrossRef]
11. Alavi, S.A.; Mehran, K.; Vahidinasab, V.; Catalão, J.P.S. Forecast-Based Consensus Control for DC Microgrids Using Distributed Long Short-Term Memory Deep Learning Models. *IEEE Trans. Smart Grid* **2021**, *12*, 3718–3730. [CrossRef]
12. Clark, R.; Hakim, S. *Cyber-Physical Security: Protecting Critical Infrastructure at the State and Local Level*; Springer: Berlin/Heidelberg, Germany, 2017; ISBN 978-3-319-32822-5.
13. Liang, Y.; Niu, D.; Hong, W.-C. Short Term Load Forecasting Based on Feature Extraction and Improved General Regression Neural Network Model. *Energy* **2019**, *166*, 653–663. [CrossRef]
14. Fan, G.-F.; Peng, L.-L.; Hong, W.-C. Short Term Load Forecasting Based on Phase Space Reconstruction Algorithm and Bi-Square Kernel Regression Model. *Appl. Energy* **2018**, *224*, 13–33. [CrossRef]
15. Bunn, D.W. Forecasting Loads and Prices in Competitive Power Markets. *Proc. IEEE* **2000**, *88*, 163–169. [CrossRef]
16. Singh, P.; Dwivedi, P.; Kant, V. A Hybrid Method Based on Neural Network and Improved Environmental Adaptation Method Using Controlled Gaussian Mutation with Real Parameter for Short-Term Load Forecasting. *Energy* **2019**, *174*, 460–477. [CrossRef]
17. Sulla, F.; Koivisto, M.; Seppänen, J.; Turunen, J.; Haarla, L.C.; Samuelsson, O. Statistical Analysis and Forecasting of Damping in the Nordic Power System. *IEEE Trans. Power Syst.* **2015**, *30*, 306–315. [CrossRef]
18. Raña, P.; Vilar, J.; Aneiros, G. On the Use of Functional Additive Models for Electricity Demand and Price Prediction. *IEEE Access* **2018**, *6*, 9603–9613. [CrossRef]
19. Liu, D.; Zeng, L.; Li, C.; Ma, K.; Chen, Y.; Cao, Y. A Distributed Short-Term Load Forecasting Method Based on Local Weather Information. *IEEE Syst. J.* **2018**, *12*, 208–215. [CrossRef]
20. Hernández-Callejo, L.; Baladrón Zorita, C.; Aguiar, J.; Carro, B.; Sanchez-Esguevillas, A.; Lloret, J.; Massana, J. A Survey on Electric Power Demand Forecasting: Future Trends in Smart Grids, Microgrids and Smart Buildings. *Commun. Surv. Tutor. IEEE* **2014**, *16*, 1460–1495. [CrossRef]
21. Debnath, K.B.; Mourshed, M. Forecasting Methods in Energy Planning Models. *Renew. Sustain. Energy Rev.* **2018**, *88*, 297–325. [CrossRef]
22. Jebaraj, S.; Iniyan, S. A Review of Energy Models. *Renew. Sustain. Energy Rev.* **2006**, *10*, 281–311. [CrossRef]
23. Voyant, C.; Notton, G.; Kalogirou, S.; Nivet, M.-L.; Paoli, C.; Motte, F.; Fouilloy, A. Machine Learning Methods for Solar Radiation Forecasting: A Review. *Renew. Energy* **2017**, *105*, 569–582. [CrossRef]
24. Pfenninger, S.; Hawkes, A.; Keirstead, J. Energy Systems Modeling for Twenty-First Century Energy Challenges. *Renew. Sustain. Energy Rev.* **2014**, *33*, 74–86. [CrossRef]
25. Suganthi, L.; Samuel, A.A. Energy Models for Demand Forecasting—A Review. *Renew. Sustain. Energy Rev.* **2012**, *16*, 1223–1240. [CrossRef]
26. Shen, J.; Jiang, C.; Liu, Y.; Wang, X. A Microgrid Energy Management System and Risk Management Under an Electricity Market Environment. *IEEE Access* **2016**, *4*, 2349–2356. [CrossRef]
27. Thouvenot, V.; Pichavant, A.; Goude, Y.; Antoniadis, A.; Poggi, J. Electricity Forecasting Using Multi-Stage Estimators of Nonlinear Additive Models. *IEEE Trans. Power Syst.* **2016**, *31*, 3665–3673. [CrossRef]
28. Ye, Y.; Qiu, D.; Li, J.; Strbac, G. Multi-Period and Multi-Spatial Equilibrium Analysis in Imperfect Electricity Markets: A Novel Multi-Agent Deep Reinforcement Learning Approach. *IEEE Access* **2019**, *7*, 130515–130529. [CrossRef]
29. Zhou, L.; Li, F.; Tong, X. Active Network Management Considering Wind and Load Forecasting Error. *IEEE Trans. Smart Grid* **2017**, *8*, 2694–2701. [CrossRef]

30. Behrangrad, M. A Review of Demand Side Management Business Models in the Electricity Market. *Renew. Sustain. Energy Rev.* **2015**, *47*, 270–283. [CrossRef]
31. Tranfield, D.; Denyer, D.; Smart, P. Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *Br. J. Manag.* **2003**, *14*, 207–222. [CrossRef]
32. Righi, A.W.; Saurin, T.A.; Wachs, P. A Systematic Literature Review of Resilience Engineering: Research Areas and a Research Agenda Proposal. *Reliab. Eng. Syst. Saf.* **2015**, *141*, 142–152. [CrossRef]
33. Abu-El-Magd, M.A.; Sinha, N.K. Short-Term Load Demand Modeling and Forecasting: A Review. *IEEE Trans. Syst. Man. Cybern.* **1982**, *12*, 370–382. [CrossRef]
34. Gross, G.; Galiana, F.D. Short-Term Load Forecasting. *Proc. IEEE* **1987**, *75*, 1558–1573. [CrossRef]
35. Tzafestas, S.; Tzafestas, E. Computational Intelligence Techniques for Short-Term Electric Load Forecasting. *J. Intell. Robot. Syst.* **2001**, *31*, 7–68. [CrossRef]
36. Hippert, H.S.; Pedreira, C.E.; Souza, R.C. Neural Networks for Short-Term Load Forecasting: A Review and Evaluation. *IEEE Trans. Power Syst.* **2001**, *16*, 44–55. [CrossRef]
37. Raza, M.Q.; Khosravi, A. A Review on Artificial Intelligence Based Load Demand Forecasting Techniques for Smart Grid and Buildings. *Renew. Sustain. Energy Rev.* **2015**, *50*, 1352–1372. [CrossRef]
38. Hong, T.; Fan, S. Probabilistic Electric Load Forecasting: A Tutorial Review. *Int. J. Forecast.* **2016**, *32*, 914–938. [CrossRef]
39. Kuster, C.; Rezgui, Y.; Mourshed, M. Electrical Load Forecasting Models: A Critical Systematic Review. *Sustain. Cities Soc.* **2017**, *35*, 257–270. [CrossRef]
40. Bianchi, F.M.; Maiorino, E.; Kampffmeyer, M.C.; Rizzi, A.; Jenssen, R. An Overview and Comparative Analysis of Recurrent Neural Networks for Short Term Load Forecasting. *arXiv* **2017**, arXiv1705.04378.
41. Mamun, A.A.; Sohel, M.; Mohammad, N.; Sunny, M.S.H.; Dipta, D.R.; Hossain, E. A Comprehensive Review of the Load Forecasting Techniques Using Single and Hybrid Predictive Models. *IEEE Access* **2020**, *8*, 134911–134939. [CrossRef]
42. Azeem, A.; Ismail, I.; Jameel, S.M.; Harindran, V.R. Electrical Load Forecasting Models for Different Generation Modalities: A Review. *IEEE Access* **2021**, *9*, 142239–142263. [CrossRef]
43. Drezga, I.; Rahman, S. Input Variable Selection for ANN-Based Short-Term Load Forecasting. *IEEE Trans. Power Syst.* **1998**, *13*, 1238–1244. [CrossRef]
44. Oprea, S.; Bâra, A. Machine Learning Algorithms for Short-Term Load Forecast in Residential Buildings Using Smart Meters, Sensors and Big Data Solutions. *IEEE Access* **2019**, *7*, 177874–177889. [CrossRef]
45. Wang, Y.; Bielicki, J.M. Acclimation and the Response of Hourly Electricity Loads to Meteorological Variables. *Energy* **2018**, *142*, 473–485. [CrossRef]
46. Lusis, P.; Khalilpour, K.R.; Andrew, L.; Liebman, A. Short-Term Residential Load Forecasting: Impact of Calendar Effects and Forecast Granularity. *Appl. Energy* **2017**, *205*, 654–669. [CrossRef]
47. Karimi, M.; Karami, H.; Gholami, M.; Khatibzadehazad, H.; Moslemi, N. Priority Index Considering Temperature and Date Proximity for Selection of Similar Days in Knowledge-Based Short Term Load Forecasting Method. *Energy* **2018**, *144*, 928–940. [CrossRef]
48. Fahad, M.; Arbab, N. Factor Affecting Short Term Load Forecasting. *J. Clean Energy Technol.* **2014**, *2*, 305–309. [CrossRef]
49. Xu, H.; Fan, G.; Kuang, G.; Song, Y. Construction and Application of Short-Term and Mid-Term Power System Load Forecasting Model Based on Hybrid Deep Learning. *IEEE Access* **2023**, *1*, 37494–37507. [CrossRef]
50. Barman, M.; Dev Choudhury, N.B. Season Specific Approach for Short-Term Load Forecasting Based on Hybrid FA-SVM and Similarity Concept. *Energy* **2019**, *174*, 886–896. [CrossRef]
51. Kong, W.; Dong, Z.Y.; Jia, Y.; Hill, D.; Xu, Y.; Zhang, Y. Short-Term Residential Load Forecasting Based on LSTM Recurrent Neural Network. *IEEE Trans. Smart Grid* **2017**, *10*, 841–851. [CrossRef]
52. Kong, W.; Dong, Z.Y.; Hill, D.J.; Luo, F.; Xu, Y. Short-Term Residential Load Forecasting Based on Resident Behaviour Learning. *IEEE Trans. Power Syst.* **2018**, *33*, 1087–1088. [CrossRef]
53. Singh, P.; Dwivedi, P. Integration of New Evolutionary Approach with Artificial Neural Network for Solving Short Term Load Forecast Problem. *Appl. Energy* **2018**, *217*, 537–549. [CrossRef]
54. Elkarmi, F.; Abu-Shikhah, N. Power System Planning Technologies and Applications: Concepts, Solutions and Management. In *Power System Planning Technologies and Applications: Concepts, Solutions and Management*; IGI Global: Hershey, PA, USA, 2012; pp. 1–278. [CrossRef]
55. Omaji, S.; Al-Zahrani, F.A.; Hussen Khan, R.J.; Farooq, H.; Afzal, M.; Javaid, N. Towards Modified Entropy Mutual Information Feature Selection to Forecast Medium-Term Load Using a Deep Learning Model in Smart Homes. *Entropy* **2020**, *22*, 68. [CrossRef] [PubMed]
56. Dudek, G. Pattern-Based Local Linear Regression Models for Short-Term Load Forecasting. *Electr. Power Syst. Res.* **2016**, *130*, 139–147. [CrossRef]
57. Farsi, B.; Amayri, M.; Bouguila, N.; Eicker, U. On Short-Term Load Forecasting Using Machine Learning Techniques and a Novel Parallel Deep LSTM-CNN Approach. *IEEE Access* **2021**, *9*, 31191–31212. [CrossRef]
58. Guo, W.; Che, L.; Shahidehpour, M.; Wan, X. Machine-Learning Based Methods in Short-Term Load Forecasting. *Electr. J.* **2021**, *34*, 106884. [CrossRef]

59. Li, X.; Zhou, J. An Adaptive Hybrid Fractal Model for Short-Term Load Forecasting in Power Systems. *Electr. Power Syst. Res.* **2022**, *207*, 107858. [CrossRef]
60. Tang, X.; Dai, Y.; Wang, T.; Chen, Y. Short-Term Power Load Forecasting Based on Multi-Layer Bidirectional Recurrent Neural Network. *IET Gener. Transm. Distrib.* **2019**, *13*, 3847–3854. [CrossRef]
61. Chen, Y.; Kloft, M.; Yang, Y.; Li, C.; Li, L. Mixed Kernel Based Extreme Learning Machine for Electric Load Forecasting. *Neurocomputing* **2018**, *312*, 90–106. [CrossRef]
62. Guo, H.; Chen, Q.; Xia, Q.; Kang, C.; Zhang, X. A Monthly Electricity Consumption Forecasting Method Based on Vector Error Correction Model and Self-Adaptive Screening Method. *Int. J. Electr. Power Energy Syst.* **2018**, *95*, 427–439. [CrossRef]
63. Wang, K.; Qi, X.; Liu, H. A Comparison of Day-Ahead Photovoltaic Power Forecasting Models Based on Deep Learning Neural Network. *Appl. Energy* **2019**, *251*, 113315. [CrossRef]
64. Huang, S.-J.; Shih, K.-R. Short-Term Load Forecasting via ARMA Model Identification Including Non-Gaussian Process Considerations. *IEEE Trans. Power Syst.* **2003**, *18*, 673–679. [CrossRef]
65. Chai, T.; Draxler, R.R. Root Mean Square Error (RMSE) or Mean Absolute Error (MAE)?– Arguments against Avoiding RMSE in the Literature. *Geosci. Model Dev.* **2014**, *7*, 1247–1250. [CrossRef]
66. Lin, X.; Zamora, R.; Baguley, C.A.; Srivastava, A.K. A Hybrid Short-Term Load Forecasting Approach for Individual Residential Customer. *IEEE Trans. Power Deliv.* **2023**, *38*, 26–37. [CrossRef]
67. Abu-El-Magd, M.A.; Findlay, R.D. A New Approach Using Artificial Neural Network and Time Series Models for Short Term Load Forecasting. In Proceedings of the CCECE 2003—Canadian Conference on Electrical and Computer Engineering. Toward a Caring and Humane Technology (Cat. No.03CH37436), Montreal, QC, Canada, 4–7 May 2003; Volume 3, pp. 1723–1726.
68. Reinsel, G.C. Statistical Methods for Forecasting. By Bovas Abraham and Johannes Ledolter. John Wiley and Sons, Inc., New York, 1983. Xv + 445 Pp. U.S. $38.95. ISBN 0–471–86764–0. *Can. J. Stat.* **1987**, *15*, 299–300. [CrossRef]
69. Dodge, Y.; Cox, D.; Commenges, D. *The Oxford Dictionary of Statistical Terms*; Oxford University Press on Demand: Oxford, UK, 2006; ISBN 0199206139.
70. Liu, H.; Shi, J. Applying ARMA–GARCH Approaches to Forecasting Short-Term Electricity Prices. *Energy Econ.* **2013**, *37*, 152–166. [CrossRef]
71. Lebotsa, M.E.; Sigauke, C.; Bere, A.; Fildes, R.; Boylan, J.E. Short Term Electricity Demand Forecasting Using Partially Linear Additive Quantile Regression with an Application to the Unit Commitment Problem. *Appl. Energy* **2018**, *222*, 104–118. [CrossRef]
72. Hagan, M.T.; Behr, S.M. The Time Series Approach to Short Term Load Forecasting. *IEEE Trans. Power Syst.* **1987**, *2*, 785–791. [CrossRef]
73. Fan, J.Y.; McDonald, J.D. A Real-Time Implementation of Short-Term Load Forecasting for Distribution Power Systems. *IEEE Trans. Power Syst.* **1994**, *9*, 988–994. [CrossRef]
74. Nowicka-Zagrajek, J.; Weron, R. Modeling Electricity Loads in California: ARMA Models with Hyperbolic Noise. *Signal Process.* **2002**, *82*, 1903–1915. [CrossRef]
75. Topalli, A.K.; Erkmen, I.; Topalli, I. Intelligent Short-Term Load Forecasting in Turkey. *Int. J. Electr. Power Energy Syst.* **2006**, *28*, 437–447. [CrossRef]
76. Darbellay, G.A.; Slama, M. Forecasting the Short-Term Demand for Electricity: Do Neural Networks Stand a Better Chance? *Int. J. Forecast.* **2000**, *16*, 71–83. [CrossRef]
77. Amjady, N. Short-Term Hourly Load Forecasting Using Time-Series Modeling with Peak Load Estimation Capability. *IEEE Trans. Power Syst.* **2001**, *16*, 498–505. [CrossRef] [PubMed]
78. AL-Musaylh, M.; Deo, R.; Adamowski, J.; Li, Y. Short-Term Electricity Demand Forecasting with MARS, SVR and ARIMA Models Using Aggregated Demand Data in Queensland, Australia. *Adv. Eng. Inform.* **2017**, *35*, 1–16. [CrossRef]
79. Nepal, B.; Yamaha, M.; Yokoe, A.; Yamaji, T. Electricity Load Forecasting Using Clustering and ARIMA Model for Energy Management in Buildings. *Jpn. Archit. Rev.* **2020**, *3*, 62–76. [CrossRef]
80. Zhu, S.; Wang, J.; Zhao, W.; Wang, J. A Seasonal Hybrid Procedure for Electricity Demand Forecasting in China. *Appl. Energy* **2011**, *88*, 3807–3815. [CrossRef]
81. Wang, Y.; Wang, J.; Zhao, G.; Dong, Y. Application of Residual Modification Approach in Seasonal ARIMA for Electricity Demand Forecasting: A Case Study of China. *Energy Policy* **2012**, *48*, 284–294. [CrossRef]
82. Bouzerdoum, M.; Mellit, A.; Massi Pavan, A. A Hybrid Model (SARIMA–SVM) for Short-Term Power Forecasting of a Small-Scale Grid-Connected Photovoltaic Plant. *Sol. Energy* **2013**, *98*, 226–235. [CrossRef]
83. Elamin, N.; Fukushige, M. Modeling and Forecasting Hourly Electricity Demand by SARIMAX with Interactions. *Energy* **2018**, *165*, 257–268. [CrossRef]
84. Maldonado, S.; González, A.; Crone, S. Automatic Time Series Analysis for Electric Load Forecasting via Support Vector Regression. *Appl. Soft Comput.* **2019**, *83*, 105616. [CrossRef]
85. Lira, F.; Munoz, C.; Nunez, F.; Cipriano, A. Short-Term Forecasting of Electricity Prices in the Colombian Electricity Market. *Gener. Transm. Distrib. IET* **2009**, *3*, 980–986. [CrossRef]
86. Wang, B.; Tai, N.; Zhai, H.; Ye, J.; Zhu, J.; Qi, L. A New ARMAX Model Based on Evolutionary Algorithm and Particle Swarm Optimization for Short-Term Load Forecasting. *Electr. Power Syst. Res.* **2008**, *78*, 1679–1685. [CrossRef]
87. Bakhat, M.; Rosselló, J. Estimation of Tourism-Induced Electricity Consumption: The Case Study of Balearics Islands, Spain. *Energy Econ.* **2011**, *33*, 437–444. [CrossRef]

88. Hickey, E.; Loomis, D.G.; Mohammadi, H. Forecasting Hourly Electricity Prices Using ARMAX–GARCH Models: An Application to MISO Hubs. *Energy Econ.* **2012**, *34*, 307–315. [CrossRef]
89. Bikcora, C.; Verheijen, L.; Weiland, S. Density Forecasting of Daily Electricity Demand with ARMA-GARCH, CAViaR, and CARE Econometric Models. *Sustain. Energy Grids Netw.* **2018**, *13*, 148–156. [CrossRef]
90. Li, Y.; Ren, F.; Sun, W. *Short-Term Load Forecasting Based on Bayes and SVR*; Springer: Berlin/Heidelberg, Germany, 2008; ISBN 978-3-540-88512-2.
91. Tan, Z.; Zhang, J.; Wang, J.; Xu, J. Day-Ahead Electricity Price Forecasting Using Wavelet Transform Combined with ARIMA and GARCH Models. *Appl. Energy* **2010**, *87*, 3606–3610. [CrossRef]
92. Garcia, R.C.; Contreras, J.; van Akkeren, M.; Garcia, J.B.C. A GARCH Forecasting Model to Predict Day-Ahead Electricity Prices. *IEEE Trans. Power Syst.* **2005**, *20*, 867–874. [CrossRef]
93. Diongue, A.K.; Guégan, D.; Vignal, B. Forecasting Electricity Spot Market Prices with a K-Factor GIGARCH Process. *Appl. Energy* **2009**, *86*, 505–510. [CrossRef]
94. Pao, H.T. Forecasting Energy Consumption in Taiwan Using Hybrid Nonlinear Models. *Energy* **2009**, *34*, 1438–1446. [CrossRef]
95. Bowden, N.; Payne, J.E. Short Term Forecasting of Electricity Prices for MISO Hubs: Evidence from ARIMA-EGARCH Models. *Energy Econ.* **2008**, *30*, 3186–3197. [CrossRef]
96. Zhang, J.-L.; Zhang, Y.-J.; Li, D.-Z.; Tan, Z.-F.; Ji, J.-F. Forecasting Day-Ahead Electricity Prices Using a New Integrated Model. *Int. J. Electr. Power Energy Syst.* **2019**, *105*, 541–548. [CrossRef]
97. Christiaanse, W.R. Short-Term Load Forecasting Using General Exponential Smoothing. *IEEE Trans. Power Appar. Syst.* **1971**, *PAS-90*, 900–911. [CrossRef]
98. Taylor, J.W. Triple Seasonal Methods for Short-Term Electricity Demand Forecasting. *Eur. J. Oper. Res.* **2010**, *204*, 139–152. [CrossRef]
99. Taylor, J.W. Short-Term Load Forecasting with Exponentially Weighted Methods. *IEEE Trans. Power Syst.* **2012**, *27*, 458–464. [CrossRef]
100. Mi, J.; Fan, L.; Duan, X.; Qiu, Y. Short-Term Power Load Forecasting Method Based on Improved Exponential Smoothing Grey Model. *Math. Probl. Eng.* **2018**, *2018*, 3894723. [CrossRef]
101. Papalexopoulos, A.D.; Hesterberg, T.C. A Regression-Based Approach to Short-Term System Load Forecasting. *IEEE Trans. Power Syst.* **1990**, *5*, 1535–1547. [CrossRef]
102. Charytoniuk, W.; Chen, M.S.; Olinda, P. Van Nonparametric Regression Based Short-Term Load Forecasting. *IEEE Trans. Power Syst.* **1998**, *13*, 725–730. [CrossRef]
103. Amin-Naseri, M.R.; Soroush, A.R. Combined Use of Unsupervised and Supervised Learning for Daily Peak Load Forecasting. *Energy Convers. Manag.* **2008**, *49*, 1302–1308. [CrossRef]
104. Bianco, V.; Manca, O.; Nardini, S. Electricity Consumption Forecasting in Italy Using Linear Regression Models. *Energy* **2009**, *34*, 1413–1421. [CrossRef]
105. Nguyen, H.T.; Nabney, I.T. Short-Term Electricity Demand and Gas Price Forecasts Using Wavelet Transforms and Adaptive Models. *Energy* **2010**, *35*, 3674–3685. [CrossRef]
106. Elattar, E.E.; Goulermas, J.; Wu, Q.H. Electric Load Forecasting Based on Locally Weighted Support Vector Regression. *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev.* **2010**, *40*, 438–447. [CrossRef]
107. Azadeh, A.; Faiz, Z.S. A Meta-Heuristic Framework for Forecasting Household Electricity Consumption. *Appl. Soft Comput.* **2011**, *11*, 614–620. [CrossRef]
108. Chen, Y.; Xu, P.; Chu, Y.; Li, W.; Wu, Y.; Ni, L.; Bao, Y.; Wang, K. Short-Term Electrical Load Forecasting Using the Support Vector Regression (SVR) Model to Calculate the Demand Response Baseline for Office Buildings. *Appl. Energy* **2017**, *195*, 659–670. [CrossRef]
109. Li, Y.; Che, J.; Yang, Y. Subsampled Support Vector Regression Ensemble for Short Term Electric Load Forecasting. *Energy* **2018**, *164*, 160–170. [CrossRef]
110. Von Krannichfeldt, L.; Wang, Y.; Hug, G. Online Ensemble Learning for Load Forecasting. *IEEE Trans. Power Syst.* **2021**, *36*, 545–548. [CrossRef]
111. Ho, K.L.; Hsu, Y.-Y.; Yang, C.-C. Short Term Load Forecasting Using a Multilayer Neural Network with an Adaptive Learning Algorithm. *IEEE Trans. Power Syst.* **1992**, *7*, 141–149. [CrossRef]
112. Bakirtzis, A.G.; Theocharis, J.B.; Kiartzis, S.J.; Satsios, K.J. Short Term Load Forecasting Using Fuzzy Neural Networks. *IEEE Trans. Power Syst.* **1995**, *10*, 1518–1524. [CrossRef]
113. Srinivasan, D.; Chang, C.S.; Liew, A.C. Demand Forecasting Using Fuzzy Neural Computation, with Special Emphasis on Weekend and Public Holiday Forecasting. *IEEE Trans. Power Syst.* **1995**, *10*, 1897–1903. [CrossRef]
114. Mohammed, O.; Park, D.; Merchant, R.; Dinh, T.; Tong, C.; Azeem, A.; Farah, J.; Drake, C. Practical Experiences with an Adaptive Neural Network Short-Term Load Forecasting System. *IEEE Trans. Power Syst.* **1995**, *10*, 254–265. [CrossRef]
115. Marin, F.; García-Lagos, F.; Joya, G.; Sandoval, F. Global Model for Short-Term Load Forecasting Using Artificial Neural Networks. *Gener. Transm. Distrib. IEE Proc.* **2002**, *149*, 121–125. [CrossRef]
116. Yalcinoz, T.; Eminoglu, U. Short Term and Medium Term Power Distribution Load Forecasting by Neural Networks. *Energy Convers. Manag.* **2005**, *46*, 1393–1405. [CrossRef]
117. Mandal, P.; Senjyu, T.; Funabashi, T. Neural Networks Approach to Forecast Several Hour Ahead Electricity Prices and Loads in Deregulated Market. *Energy Convers. Manag.* **2006**, *47*, 2128–2142. [CrossRef]

118. Ferreira, V.H.; da Silva, A.P.A. Toward Estimating Autonomous Neural Network-Based Electric Load Forecasters. *IEEE Trans. Power Syst.* **2007**, *22*, 1554–1562. [CrossRef]
119. Bashir, Z.A.; El-Hawary, M.E. Applying Wavelets to Short-Term Load Forecasting Using PSO-Based Neural Networks. *IEEE Trans. Power Syst.* **2009**, *24*, 20–27. [CrossRef]
120. Shayeghi, H.; Shayanfar, H.; Azimi, G. Intelligent Neural Network Based STLF. *Int. J. Int. Syst. Technl.* **2009**, *4*, 17–27.
121. Li, D.-C.; Chang, C.-J.; Chen, C.-C.; Chen, W.-C. Forecasting Short-Term Electricity Consumption Using the Adaptive Grey-Based Approach—An Asian Case. *Omega* **2012**, *40*, 767–773. [CrossRef]
122. López, M.; Valero, S.; Senabre, C.; Aparicio, J.; Gabaldon, A. Application of SOM Neural Networks to Short-Term Load Forecasting: The Spanish Electricity Market Case Study. *Electr. Power Syst. Res.* **2012**, *91*, 18–27. [CrossRef]
123. Ko, C.-N.; Lee, C.-M. Short-Term Load Forecasting Using SVR (Support Vector Regression)-Based Radial Basis Function Neural Network with Dual Extended Kalman Filter. *Energy* **2013**, *49*, 413–422. [CrossRef]
124. An, N.; Zhao, W.; Wang, J.; Shang, D.; Zhao, E. Using Multi-Output Feedforward Neural Network with Empirical Mode Decomposition Based Signal Filtering for Electricity Demand Forecasting. *Energy* **2013**, *49*, 279–288. [CrossRef]
125. Cecati, C.; Kolbusz, J.; Różycki, P.; Siano, P.; Wilamowski, B.M. A Novel RBF Training Algorithm for Short-Term Electric Load Forecasting and Comparative Studies. *IEEE Trans. Ind. Electron.* **2015**, *62*, 6519–6529. [CrossRef]
126. Jin, C.H.; Pok, G.; Lee, Y.; Park, H.-W.; Kim, K.D.; Yun, U.; Ryu, K.H. A SOM Clustering Pattern Sequence-Based next Symbol Prediction Method for Day-Ahead Direct Electricity Load and Price Forecasting. *Energy Convers. Manag.* **2015**, *90*, 84–92. [CrossRef]
127. Wang, J.; Liu, F.; Song, Y.; Zhao, J. A Novel Model: Dynamic Choice Artificial Neural Network (DCANN) for an Electricity Price Forecasting System. *Appl. Soft Comput.* **2016**, *48*, 281–297. [CrossRef]
128. Yang, Y.; Chen, Y.; Wang, Y.; Li, C.; Li, L. Modelling a Combined Method Based on ANFIS and Neural Network Improved by DE Algorithm: A Case Study for Short-Term Electricity Demand Forecasting. *Appl. Soft Comput.* **2016**, *49*, 663–675. [CrossRef]
129. Ding, N.; Benoit, C.; Foggia, G.; Bésanger, Y.; Wurtz, F. Neural Network-Based Model Design for Short-Term Load Forecast in Distribution Systems. *IEEE Trans. Power Syst.* **2016**, *31*, 72–81. [CrossRef]
130. Ertugrul, Ö.F. Forecasting Electricity Load by a Novel Recurrent Extreme Learning Machines Approach. *Int. J. Electr. Power Energy Syst.* **2016**, *78*, 429–435. [CrossRef]
131. Li, S.; Goel, L.; Wang, P. An Ensemble Approach for Short-Term Load Forecasting by Extreme Learning Machine. *Appl. Energy* **2016**, *170*, 22–29. [CrossRef]
132. He, W. Load Forecasting via Deep Neural Networks. *Procedia Comput. Sci.* **2017**, *122*, 308–314. [CrossRef]
133. Son, H.; Kim, C. Short-Term Forecasting of Electricity Demand for the Residential Sector Using Weather and Social Variables. *Resour. Conserv. Recycl.* **2017**, *123*, 200–207. [CrossRef]
134. Qiu, X.; Ren, Y.; Suganthan, P.N.; Amaratunga, G.A.J. Empirical Mode Decomposition Based Ensemble Deep Learning for Load Demand Time Series Forecasting. *Appl. Soft Comput.* **2017**, *54*, 246–255. [CrossRef]
135. Llanos, J.; Morales, R.; Núñez, A.; Sáez, D.; Lacalle, M.; Marín, L.G.; Hernández, R.; Lanas, F. Load Estimation for Microgrid Planning Based on a Self-Organizing Map Methodology. *Appl. Soft Comput.* **2017**, *53*, 323–335. [CrossRef]
136. Shi, H.; Xu, M.; Li, R. Deep Learning for Household Load Forecasting—A Novel Pooling Deep RNN. *IEEE Trans. Smart Grid* **2018**, *9*, 5271–5280. [CrossRef]
137. Duan, M.; Darvishan, A.; Mohammaditab, R.; Wakil, K.; Abedinia, O. A Novel Hybrid Prediction Model for Aggregated Loads of Buildings by Considering the Electric Vehicles. *Sustain. Cities Soc.* **2018**, *41*, 205–219. [CrossRef]
138. Zhang, X.; Wang, J. A Novel Decomposition-ensemble Model for Forecasting Short-term Load-time Series with Multiple Seasonal Patterns. *Appl. Soft Comput.* **2018**, *65*, 478–494. [CrossRef]
139. Ouyang, T.; He, Y.; Li, H.; Sun, Z.; Baek, S. Modeling and Forecasting Short-Term Power Load with Copula Model and Deep Belief Network. *IEEE Trans. Emerg. Top. Comput. Intell.* **2019**, *3*, 127–136. [CrossRef]
140. Singh, P.; Dwivedi, P. A Novel Hybrid Model Based on Neural Network and Multi-Objective Optimization for Effective Load Forecast. *Energy* **2019**, *182*, 606–622. [CrossRef]
141. Tang, X.; Dai, Y.; Liu, Q.; Dang, X.; Xu, J. Application of Bidirectional Recurrent Neural Network Combined with Deep Belief Network in Short-Term Load Forecasting. *IEEE Access* **2019**, *7*, 160660–160670. [CrossRef]
142. Wang, Y.; Gan, D.; Sun, M.; Zhang, N.; Lu, Z.; Kang, C. Probabilistic Individual Load Forecasting Using Pinball Loss Guided LSTM. *Appl. Energy* **2019**, *235*, 10–20. [CrossRef]
143. Motepe, S.; Hasan, A.N.; Stopforth, R. Improving Load Forecasting Process for a Power Distribution Network Using Hybrid AI and Deep Learning Algorithms. *IEEE Access* **2019**, *7*, 82584–82598. [CrossRef]
144. Deng, Z.; Wang, B.; Xu, Y.; Xu, T.; Liu, C.; Zhu, Z. Multi-Scale Convolutional Neural Network with Time-Cognition for Multi-Step Short-Term Load Forecasting. *IEEE Access* **2019**, *7*, 88058–88071. [CrossRef]
145. Yang, Y.; Che, J.; Deng, C.; Li, L. Sequential Grid Approach Based Support Vector Regression for Short-Term Electric Load Forecasting. *Appl. Energy* **2019**, *238*, 1010–1021. [CrossRef]
146. Zhang, Y.; Deng, C.; Zhao, R.; Leto, S. A Novel Integrated Price and Load Forecasting Method in Smart Grid Environment Based on Multi-Level Structure. *Eng. Appl. Artif. Intell.* **2020**, *95*, 103852. [CrossRef]
147. Moon, J.; Jung, S.; Rew, J.; Rho, S.; Hwang, E. Combination of Short-Term Load Forecasting Models Based on a Stacking Ensemble Approach. *Energy Build.* **2020**, *216*, 109921. [CrossRef]

148. Panapakidis, I.P.; Skiadopoulos, N.; Christoforidis, G.C. Combined Forecasting System for Short-term Bus Load Forecasting Based on Clustering and Neural Networks. *IET Gener. Transm. Distrib.* **2020**, *14*, 3652–3664. [CrossRef]
149. Skomski, E.; Lee, J.-Y.; Kim, W.; Chandan, V.; Katipamula, S.; Hutchinson, B. Sequence-to-Sequence Neural Networks for Short-Term Electrical Load Forecasting in Commercial Office Buildings. *Energy Build.* **2020**, *226*, 110350. [CrossRef]
150. He, F.; Zhou, J.; Mo, L.; Feng, K.; Liu, G.; He, Z. Day-Ahead Short-Term Load Probability Density Forecasting Method with a Decomposition-Based Quantile Regression Forest. *Appl. Energy* **2020**, *262*, 114396. [CrossRef]
151. Wang, Y.; Kong, Y.; Tang, X.; Chen, X.; Xu, Y.; Chen, J.; Sun, S.; Guo, Y.; Chen, Y. Short-Term Industrial Load Forecasting Based on Ensemble Hidden Markov Model. *IEEE Access* **2020**, *8*, 160858–160870. [CrossRef]
152. Hoori, A.O.; Kazzaz, A.A.; Khimani, R.; Motai, Y.; Aved, A.J. Electric Load Forecasting Model Using a Multicolumn Deep Neural Networks. *IEEE Trans. Ind. Electron.* **2020**, *67*, 6473–6482. [CrossRef]
153. Kong, X.; Li, C.; Zheng, F.; Wang, C. Improved Deep Belief Network for Short-Term Load Forecasting Considering Demand-Side Management. *IEEE Trans. Power Syst.* **2020**, *35*, 1531–1538. [CrossRef]
154. Fekri, M.N.; Patel, H.; Grolinger, K.; Sharma, V. Deep Learning for Load Forecasting with Smart Meter Data: Online Adaptive Recurrent Neural Network. *Appl. Energy* **2021**, *282*, 116177. [CrossRef]
155. Song, K.-B.; Baek, Y.-S.; Hong, D.H.; Jang, G. Short-Term Load Forecasting for the Holidays Using Fuzzy Linear Regression Method. *IEEE Trans. Power Syst.* **2005**, *20*, 96–101. [CrossRef]
156. Arciniegas, A.I.; Arciniegas Rueda, I.E. Forecasting Short-Term Power Prices in the Ontario Electricity Market (OEM) with a Fuzzy Logic Based Inference System. *Util. Policy* **2008**, *16*, 39–48. [CrossRef]
157. Mamlook, R.; Badran, O.; Abdulhadi, E. A Fuzzy Inference Model for Short-Term Load Forecasting. *Energy Policy* **2009**, *37*, 1239–1248. [CrossRef]
158. Khosravi, A.; Nahavandi, S.; Creighton, D.; Srinivasan, D. Interval Type-2 Fuzzy Logic Systems for Load Forecasting: A Comparative Study. *IEEE Trans. Power Syst.* **2012**, *27*, 1274–1282. [CrossRef]
159. Hong, T.; Wang, P. Fuzzy Interaction Regression for Short Term Load Forecasting. *Fuzzy Optim. Decis. Mak.* **2014**, *13*, 91–103. [CrossRef]
160. Chaturvedi, D.K.; Sinha, A.P.; Malik, O.P. Short Term Load Forecast Using Fuzzy Logic and Wavelet Transform Integrated Generalized Neural Network. *Int. J. Electr. Power Energy Syst.* **2015**, *67*, 230–237. [CrossRef]
161. Černe, G.; Dovžan, D.; Škrjanc, I. Short-Term Load Forecasting by Separating Daily Profiles and Using a Single Fuzzy Model Across the Entire Domain. *IEEE Trans. Ind. Electron.* **2018**, *65*, 7406–7415. [CrossRef]
162. Huang, N.; Wang, W.; Wang, S.; Wang, J.; Cai, G.; Zhang, L. Incorporating Load Fluctuation in Feature Importance Profile Clustering for Day-Ahead Aggregated Residential Load Forecasting. *IEEE Access* **2020**, *8*, 25198–25209. [CrossRef]
163. Khandelwal, I.; Adhikari, R.; Verma, G. Time Series Forecasting Using Hybrid ARIMA and ANN Models Based on DWT Decomposition. *Procedia Comput. Sci.* **2015**, *48*, 173–179. [CrossRef]
164. Kim, K.-H.; Park, J.-K.; Hwang, K.-J.; Kim, S.-H. Implementation of Hybrid Short-Term Load Forecasting System Using Artificial Neural Networks and Fuzzy Expert Systems. *IEEE Trans. Power Syst.* **1995**, *10*, 1534–1539. [CrossRef]
165. Jiang, B.; Liu, Y.; Geng, H.; Wang, Y.; Zeng, H.; Ding, J. A Holistic Feature Selection Method for Enhanced Short-Term Load Forecasting of Power System. *IEEE Trans. Instrum. Meas.* **2023**, *72*, 2500911. [CrossRef]
166. Saini, L.; Soni, M.K. Artificial Neural Network Based Peak Load Forecasting Using Levenberg-Marquardt and Quasi-Newton Methods. *Gener. Transm. Distrib. IEE Proc.* **2002**, *149*, 578–584. [CrossRef]
167. Ling, S.H.; Leung, F.H.F.; Lam, H.K.; Tam, P.K.S. Short-Term Electric Load Forecasting Based on a Neural Fuzzy Network. *IEEE Trans. Ind. Electron.* **2003**, *50*, 1305–1316. [CrossRef]
168. Sfetsos, T.; Caserza Magro, M. Short Term Load Forecasting with a Hybrid Clustering Algorithm and Pattern Recognition. *Eng. Intell. Syst.* **2004**, *12*, 13–19.
169. Espinoza, M.; Joye, C.; Belmans, R.; De Moor, B. Short-Term Load Forecasting, Profile Identification, and Customer Segmentation: A Methodology Based on Periodic Time Series. *IEEE Trans. Power Syst.* **2005**, *20*, 1622–1630. [CrossRef]
170. Senjyu, T.; Mandal, P.; Uezato, K.; Funabashi, T. Next Day Load Curve Forecasting Using Hybrid Correction Method. *IEEE Trans. Power Syst.* **2005**, *20*, 102–109. [CrossRef]
171. Liao, G.-C.; Tsao, T.-P. Application of a Fuzzy Neural Network Combined with a Chaos Genetic Algorithm and Simulated Annealing to Short-Term Load Forecasting. *IEEE Trans. Evol. Comput.* **2006**, *10*, 330–340. [CrossRef]
172. Tripathi, M.M.; Upadhyay, K.G.; Singh, S.N. Short-Term Load Forecasting Using Generalized Regression and Probabilistic Neural Networks in the Electricity Market. *Electr. J.* **2008**, *21*, 24–34. [CrossRef]
173. Amjady, N.; Keynia, F. Short-Term Load Forecasting of Power Systems by Combination of Wavelet Transform and Neuro-Evolutionary Algorithm. *Energy* **2009**, *34*, 46–57. [CrossRef]
174. Wu, C.-H.; Tzeng, G.-H.; Lin, R.-H. A Novel Hybrid Genetic Algorithm for Kernel Function and Parameter Optimization in Support Vector Regression. *Expert Syst. Appl.* **2009**, *36*, 4725–4735. [CrossRef]
175. Niu, D.; Wang, Y.; Wu, D.D. Power Load Forecasting Using Support Vector Machine and Ant Colony Optimization. *Expert Syst. Appl.* **2010**, *37*, 2531–2539. [CrossRef]
176. Hooshmand, R.-A.; Amooshahi, H.; Parastegari, M. A Hybrid Intelligent Algorithm Based Short-Term Load Forecasting Approach. *Int. J. Electr. Power Energy Syst.* **2013**, *45*, 313–324. [CrossRef]

177. Wu, J.; Wang, J.; Lu, H.; Dong, Y.; Lu, X. Short Term Load Forecasting Technique Based on the Seasonal Exponential Adjustment Method and the Regression Model. *Energy Convers. Manag.* **2013**, *70*, 1–9. [CrossRef]
178. Zeng, M.; Xue, S.; Wang, Z.-J.; Zhu, X.; Zhang, G. Short-Term Load Forecasting of Smart Grid Systems by Combination of General Regression Neural Network and Least Squares-Support Vector Machine Algorithm Optimized by Harmony Search Algorithm Method. *Appl. Math. Inf. Sci.* **2013**, *7*, 291–298. [CrossRef]
179. Kodogiannis, V.; Amina, M.; Petrounias, I. A Clustering-Based Fuzzy Wavelet Neural Network Model for Short-Term Load Forecasting. *Int. J. Neural Syst.* **2013**, *23*, 1350024. [CrossRef] [PubMed]
180. Bahrami, S.; Hooshmand, R.-A.; Parastegari, M. Short Term Electric Load Forecasting by Wavelet Transform and Grey Model Improved by PSO (Particle Swarm Optimization) Algorithm. *Energy* **2014**, *72*, 434–442. [CrossRef]
181. Kavousi-Fard, A.; Niknam, T.; Golmaryami, S.M. Short Term Load Forecasting of Distribution Systems by a New Hybrid Modified FA-Backpropagation Method. *J. Intell. Fuzzy Syst. Appl. Eng. Technol.* **2014**, *26*, 517–522. [CrossRef]
182. Ghofrani, M.; Ghayekhloo, M.; Arabali, A.; Ghayekhloo, A. A Hybrid Short-Term Load Forecasting with a New Input Selection Framework. *Energy* **2015**, *81*, 777–786. [CrossRef]
183. Castelli, M.; Vanneschi, L.; De Felice, M. Forecasting Short-Term Electricity Consumption Using a Semantics-Based Genetic Programming Framework: The South Italy Case. *Energy Econ.* **2015**, *47*, 37–41. [CrossRef]
184. Sun, W.; Ye, M. Short-Term Load Forecasting Based on Wavelet Transform and Least Squares Support Vector Machine Optimized by Fruit Fly Optimization Algorithm. *J. Electr. Comput. Eng.* **2015**, *2015*, 862185. [CrossRef]
185. Li, S.; Wang, P.; Goel, L. A Novel Wavelet-Based Ensemble Method for Short-Term Load Forecasting with Hybrid Neural Networks and Feature Selection. *IEEE Trans. Power Syst.* **2016**, *31*, 1788–1798. [CrossRef]
186. Ghasemi, A.; Shayeghi, H.; Moradzadeh, M.; Nooshyar, M. A Novel Hybrid Algorithm for Electricity Price and Load Forecasting in Smart Grids with Demand-Side Management. *Appl. Energy* **2016**, *177*, 40–59. [CrossRef]
187. Laouafi, A.; Mordjaoui, M.; Laouafi, F.; Boukelia, T.E. Daily Peak Electricity Demand Forecasting Based on an Adaptive Hybrid Two-Stage Methodology. *Int. J. Electr. Power Energy Syst.* **2016**, *77*, 136–144. [CrossRef]
188. Chou, J.-S.; Ngo, N.-T. Time Series Analytics Using Sliding Window Metaheuristic Optimization-Based Machine Learning System for Identifying Building Energy Consumption Patterns. *Appl. Energy* **2016**, *177*, 751–770. [CrossRef]
189. Dong, B.; Li, Z.; Rahman, S.M.M.; Vega, R. A Hybrid Model Approach for Forecasting Future Residential Electricity Consumption. *Energy Build.* **2016**, *117*, 341–351. [CrossRef]
190. Panapakidis, I.P. Application of Hybrid Computational Intelligence Models in Short-Term Bus Load Forecasting. *Expert Syst. Appl.* **2016**, *54*, 105–120. [CrossRef]
191. Xiao, L.; Shao, W.; Liang, T.; Wang, C. A Combined Model Based on Multiple Seasonal Patterns and Modified Firefly Algorithm for Electrical Load Forecasting. *Appl. Energy* **2016**, *167*, 135–153. [CrossRef]
192. Wang, X.; Wang, Y. A Hybrid Model of EMD and PSO-SVR for Short-Term Load Forecasting in Residential Quarters. *Math. Probl. Eng.* **2016**, *2016*, 9895639. [CrossRef]
193. Wang, L.; Zhang, Z.; Chen, J. Short-Term Electricity Price Forecasting with Stacked Denoising Autoencoders. *IEEE Trans. Power Syst.* **2017**, *32*, 2673–2681. [CrossRef]
194. Raza, M.Q.; Nadarajah, M.; Hung, D.Q.; Baharudin, Z. An Intelligent Hybrid Short-Term Load Forecasting Model for Smart Power Grids. *Sustain. Cities Soc.* **2017**, *31*, 264–275. [CrossRef]
195. Li, B.; Zhang, J.; He, Y.; Wang, Y. Short-Term Load-Forecasting Method Based on Wavelet Decomposition with Second-Order Gray Neural Network Model Combined with ADF Test. *IEEE Access* **2017**, *5*, 16324–16331. [CrossRef]
196. Barman, M.; Dev Choudhury, N.B.; Sutradhar, S. A Regional Hybrid GOA-SVM Model Based on Similar Day Approach for Short-Term Load Forecasting in Assam, India. *Energy* **2018**, *145*, 710–720. [CrossRef]
197. Chou, J.-S.; Tran, D.-S. Forecasting Energy Consumption Time Series Using Machine Learning Techniques Based on Usage Patterns of Residential Householders. *Energy* **2018**, *165*, 709–726. [CrossRef]
198. Li, C.; Tao, Y.; Ao, W.; Yang, S.; Bai, Y. Improving Forecasting Accuracy of Daily Enterprise Electricity Consumption Using a Random Forest Based on Ensemble Empirical Mode Decomposition. *Energy* **2018**, *165*, 1220–1227. [CrossRef]
199. Nazar, M.S.; Fard, A.E.; Heidari, A.; Shafie-khah, M.; Catalão, J.P.S. Hybrid Model Using Three-Stage Algorithm for Simultaneous Load and Price Forecasting. *Electr. Power Syst. Res.* **2018**, *165*, 214–228. [CrossRef]
200. Jiang, H.; Zhang, Y.; Muljadi, E.; Zhang, J.J.; Gao, D.W. A Short-Term and High-Resolution Distribution System Load Forecasting Approach Using Support Vector Regression with Hybrid Parameters Optimization. *IEEE Trans. Smart Grid* **2018**, *9*, 3341–3350. [CrossRef]
201. Qiu, X.; Suganthan, P.N.; Amaratunga, G.A.J. Ensemble Incremental Learning Random Vector Functional Link Network for Short-Term Electric Load Forecasting. *Knowl.-Based Syst.* **2018**, *145*, 182–196. [CrossRef]
202. Liu, Q.; Shen, Y.; Wu, L.; Li, J.; Zhuang, L.; Wang, S. A Hybrid FCW-EMD and KF-BA-SVM Based Model for Short-Term Load Forecasting. *CSEE J. Power Energy Syst.* **2018**, *4*, 226–237. [CrossRef]
203. Park, K.; Yoon, S.; Hwang, E. Hybrid Load Forecasting for Mixed-Use Complex Based on the Characteristic Load Decomposition by Pilot Signals. *IEEE Access* **2019**, *7*, 12297–12306. [CrossRef]
204. Hu, Y.; Li, J.; Hong, M.; Ren, J.; Lin, R.; Liu, Y.; Liu, M.; Man, Y. Short Term Electric Load Forecasting Model and Its Verification for Process Industrial Enterprises Based on Hybrid GA-PSO-BPNN Algorithm—A Case Study of Papermaking Process. *Energy* **2019**, *170*, 1215–1227. [CrossRef]

205. Wang, R.; Wang, J.; Xu, Y. A Novel Combined Model Based on Hybrid Optimization Algorithm for Electrical Load Forecasting. *Appl. Soft Comput.* **2019**, *82*, 105548. [CrossRef]
206. Liu, T.; Xu, C.; Guo, Y.; Chen, H. A Novel Deep Reinforcement Learning Based Methodology for Short-Term HVAC System Energy Consumption Prediction. *Int. J. Refrig.* **2019**, *107*, 39–51. [CrossRef]
207. Wu, J.; Cui, Z.; Chen, Y.; Kong, D.; Wang, Y.-G. A New Hybrid Model to Predict the Electrical Load in Five States of Australia. *Energy* **2019**, *166*, 598–609. [CrossRef]
208. Gao, W.; Darvishan, A.; Toghani, M.; Mohammadi, M.; Abedinia, O.; Ghadimi, N. Different States of Multi-Block Based Forecast Engine for Price and Load Prediction. *Int. J. Electr. Power Energy Syst.* **2019**, *104*, 423–435. [CrossRef]
209. Semero, Y.K.; Zhang, J.; Zheng, D.; Wei, D. An Accurate Very Short-Term Electric Load Forecasting Model with Binary Genetic Algorithm Based Feature Selection for Microgrid Applications. *Electr. Power Compon. Syst.* **2018**, *46*, 1570–1579. [CrossRef]
210. Zhang, Y.-F.; Chiang, H.-D. Enhanced ELITE-Load: A Novel CMPSOATT Methodology Constructing Short-Term Load Forecasting Model for Industrial Applications. *IEEE Trans. Ind. Inform.* **2020**, *16*, 2325–2334. [CrossRef]
211. Wang, X.; Ahn, S.-H. Real-Time Prediction and Anomaly Detection of Electrical Load in a Residential Community. *Appl. Energy* **2020**, *259*, 114145. [CrossRef]
212. Nie, Y.; Jiang, P.; Zhang, H. A Novel Hybrid Model Based on Combined Preprocessing Method and Advanced Optimization Algorithm for Power Load Forecasting. *Appl. Soft Comput.* **2020**, *97*, 106809. [CrossRef]
213. Dai, Y.; Zhao, P. A Hybrid Load Forecasting Model Based on Support Vector Machine with Intelligent Methods for Feature Selection and Parameter Optimization. *Appl. Energy* **2020**, *279*, 115332. [CrossRef]
214. Aly, H.H.H. A Proposed Intelligent Short-Term Load Forecasting Hybrid Models of ANN, WNN and KF Based on Clustering Techniques for Smart Grid. *Electr. Power Syst. Res.* **2020**, *182*, 106191. [CrossRef]
215. Zhang, G.; Guo, J. A Novel Method for Hourly Electricity Demand Forecasting. *IEEE Trans. Power Syst.* **2020**, *35*, 1351–1363. [CrossRef]
216. El-Hendawi, M.; Wang, Z. An Ensemble Method of Full Wavelet Packet Transform and Neural Network for Short Term Electrical Load Forecasting. *Electr. Power Syst. Res.* **2020**, *182*, 106265. [CrossRef]
217. Sideratos, G.; Ikonomopoulos, A.; Hatziargyriou, N.D. A Novel Fuzzy-Based Ensemble Model for Load Forecasting Using Hybrid Deep Neural Networks. *Electr. Power Syst. Res.* **2020**, *178*, 106025. [CrossRef]
218. Kassa, Y.; Zhang, J.; Zheng, D. EMD-PSO-ANFIS Based Hybrid Approach for Short-Term Load Forecasting in Microgrids. *IET Gener. Transm. Distrib.* **2020**, *14*, 470–475. [CrossRef]
219. Lv, P.; Liu, S.; Yu, W.; Zheng, S.; Lv, J. EGA-STLF: A Hybrid Short-Term Load Forecasting Model. *IEEE Access* **2020**, *8*, 31742–31752. [CrossRef]
220. Dong, Y.; Dong, Z.; Zhao, T.; Li, Z.; Ding, Z. Short Term Load Forecasting with Markovian Switching Distributed Deep Belief Networks. *Int. J. Electr. Power Energy Syst.* **2021**, *130*, 106942. [CrossRef]
221. Memarzadeh, G.; Keynia, F. Short-Term Electricity Load and Price Forecasting by a New Optimal LSTM-NN Based Prediction Algorithm. *Electr. Power Syst. Res.* **2021**, *192*, 106995. [CrossRef]
222. Liu, F.; Dong, T.; Hou, T.; Liu, Y. A Hybrid Short-Term Load Forecasting Model Based on Improved Fuzzy C-Means Clustering, Random Forest and Deep Neural Networks. *IEEE Access* **2021**, *9*, 59754–59765. [CrossRef]
223. Xuan, Y.; Si, W.; Zhu, J.; Sun, Z.; Zhao, J.; Xu, M.; Xu, S. Multi-Model Fusion Short-Term Load Forecasting Based on Random Forest Feature Selection and Hybrid Neural Network. *IEEE Access* **2021**, *9*, 69002–69009. [CrossRef]
224. Liu, M.; Qin, H.; Cao, R.; Deng, S. Short-Term Load Forecasting Based on Improved TCN and DenseNet. *IEEE Access* **2022**, *10*, 115945–115957. [CrossRef]
225. ZulfiqAr, M.; Kamran, M.; Rasheed, M.B.; Alquthami, T.; Milyani, A.H. A Short-Term Load Forecasting Model Based on Self-Adaptive Momentum Factor and Wavelet Neural Network in Smart Grid. *IEEE Access* **2022**, *10*, 77587–77602. [CrossRef]
226. Chen, X.; Chen, W.; Dinavahi, V.; Liu, Y.; Feng, J. Short-Term Load Forecasting and Associated Weather Variables Prediction Using ResNet-LSTM Based Deep Learning. *IEEE Access* **2023**, *11*, 5393–5405. [CrossRef]
227. Badr, M.M.; Mahmoud, M.M.E.A.; Fang, Y.; Abdulaal, M.; Aljohani, A.J.; Alasmary, W.; Ibrahem, M.I. Privacy-Preserving and Communication-Efficient Energy Prediction Scheme Based on Federated Learning for Smart Grids. *IEEE Internet Things J.* **2023**, *10*, 7719–7736. [CrossRef]
228. Badr, M.M.; Ibrahem, M.I.; Mahmoud, M.; Fouda, M.M.; Alsolami, F.; Alasmary, W. Detection of False-Reading Attacks in Smart Grid Net-Metering System. *IEEE Internet Things J.* **2022**, *9*, 1386–1401. [CrossRef]
229. Hassan, M.U.; Rehmani, M.H.; Du, J.T.; Chen, J. Differentially Private Demand Side Management for Incentivized Dynamic Pricing in Smart Grid. *IEEE Trans. Knowl. Data Eng.* **2023**, *35*, 5724–5737. [CrossRef]
230. Arora, S.; Taylor, J.W. Forecasting Electricity Smart Meter Data Using Conditional Kernel Density Estimation. *Omega* **2016**, *59*, 47–59. [CrossRef]
231. Wei, H.; Wang, W.; Fang, C.; Liu, Y.; Zhang, N.; Kang, C. Online Distribution System Topology Monitoring with Limited Smart Meter Communication. *IEEE Trans. Power Syst.* **2023**, *38*, 5714–5725. [CrossRef]
232. Ibrahem, M.I.; Badr, M.M.; Fouda, M.M.; Mahmoud, M.; Alasmary, W.; Fadlullah, Z.M. PMBFE: Efficient and Privacy-Preserving Monitoring and Billing Using Functional Encryption for AMI Networks. In Proceedings of the 2020 International Symposium on Networks, Computers and Communications (ISNCC), Montreal, QC, Canada, 20–22 October 2020; pp. 1–7.

233. Brouwer, A.S.; Kuramochi, T.; van den Broek, M.; Faaij, A. Fulfilling the Electricity Demand of Electric Vehicles in the Long Term Future: An Evaluation of Centralized and Decentralized Power Supply Systems. *Appl. Energy* **2013**, *107*, 33–51. [CrossRef]
234. Liu, N.; Chen, Q.; Lu, X.; Liu, J.; Zhang, J. A Charging Strategy for PV-Based Battery Switch Stations Considering Service Availability and Self-Consumption of PV Energy. *IEEE Trans. Ind. Electron.* **2015**, *62*, 4878–4889. [CrossRef]
235. Neaimeh, M.; Wardle, R.; Jenkins, A.M.; Yi, J.; Hill, G.; Lyons, P.F.; Hübner, Y.; Blythe, P.T.; Taylor, P.C. A Probabilistic Approach to Combining Smart Meter and Electric Vehicle Charging Data to Investigate Distribution Network Impacts. *Appl. Energy* **2015**, *157*, 688–698. [CrossRef]
236. Leou, R.-C.; Su, C.-L.; Lu, C.-N. Stochastic Analyses of Electric Vehicle Charging Impacts on Distribution Network. *IEEE Trans. Power Syst.* **2014**, *29*, 1055–1063. [CrossRef]
237. Qian, K.; Zhou, C.; Allan, M.; Yuan, Y. Modeling of Load Demand Due to EV Battery Charging in Distribution Systems. *IEEE Trans. Power Syst.* **2011**, *26*, 802–810. [CrossRef]
238. Lee, E.-K.; Shi, W.; Gadh, R.; Kim, W. Design and Implementation of a Microgrid Energy Management System. *Sustainability* **2016**, *8*, 1143. [CrossRef]
239. Ma, J.; Ma, X. A Review of Forecasting Algorithms and Energy Management Strategies for Microgrids. *Syst. Sci. Control Eng.* **2018**, *6*, 237–248. [CrossRef]
240. Si, C.; Xu, S.; Wan, C.; Chen, D.; Cui, W.; Zhao, J. Electric Load Clustering in Smart Grid: Methodologies, Applications, and Future Trends. *J. Mod. Power Syst. Clean Energy* **2021**, *9*, 237–252. [CrossRef]
241. Chaouch, M. Clustering-Based Improvement of Nonparametric Functional Time Series Forecasting: Application to Intra-Day Household-Level Load Curves. *IEEE Trans. Smart Grid* **2014**, *5*, 411–419. [CrossRef]
242. Grabner, M.; Wang, Y.; Wen, Q.; Blažič, B.; Štruc, V. A Global Modeling Framework for Load Forecasting in Distribution Networks. *IEEE Trans. Smart Grid* **2023**, *14*, 4927–4941. [CrossRef]
243. Gajowniczek, K.; Ząbkowski, T. Short Term Electricity Forecasting Using Individual Smart Meter Data. *Procedia Comput. Sci.* **2014**, *35*, 589–597. [CrossRef]
244. Quilumba, F.L.; Lee, W.-J.; Huang, H.; Wang, D.Y.; Szabados, R.L. Using Smart Meter Data to Improve the Accuracy of Intraday Load Forecasting Considering Customer Behavior Similarities. *IEEE Trans. Smart Grid* **2015**, *6*, 911–918. [CrossRef]
245. Bessa, R.J.; Trindade, A.; Miranda, V. Spatial-Temporal Solar Power Forecasting for Smart Grids. *IEEE Trans. Ind. Inform.* **2015**, *11*, 232–241. [CrossRef]
246. Ben Taieb, S.; Huser, R.; Hyndman, R.J.; Genton, M.G. Forecasting Uncertainty in Electricity Smart Meter Data by Boosting Additive Quantile Regression. *IEEE Trans. Smart Grid* **2016**, *7*, 2448–2455. [CrossRef]
247. Arias, M.B.; Bae, S. Electric Vehicle Charging Demand Forecasting Model Based on Big Data Technologies. *Appl. Energy* **2016**, *183*, 327–339. [CrossRef]
248. Yu, C.-N.; Mirowski, P.; Ho, T.K. A Sparse Coding Approach to Household Electricity Demand Forecasting in Smart Grids. *IEEE Trans. Smart Grid* **2017**, *8*, 738–748. [CrossRef]
249. Boustani, A.; Maiti, A.; Jazi, S.Y.; Jadliwala, M.; Namboodiri, V. Seer Grid: Privacy and Utility Implications of Two-Level Load Prediction in Smart Grids. *IEEE Trans. Parallel Distrib. Syst.* **2017**, *28*, 546–557. [CrossRef]
250. Wang, Y.; Chen, Q.; Sun, M.; Kang, C.; Xia, Q. An Ensemble Forecasting Method for the Aggregated Load with Subprofiles. *IEEE Trans. Smart Grid* **2018**, *9*, 3906–3908. [CrossRef]
251. Wang, Y.; Zhang, N.; Tan, Y.; Hong, T.; Kirschen, D.S.; Kang, C. Combining Probabilistic Load Forecasts. *IEEE Trans. Smart Grid* **2019**, *10*, 3664–3674. [CrossRef]
252. Alberg, D.; Last, M. Short-Term Load Forecasting in Smart Meters with Sliding Window-Based ARIMA Algorithms. *Vietnam J. Comput. Sci.* **2018**, *5*, 241–249. [CrossRef]
253. Sun, M.; Zhang, T.; Wang, Y.; Strbac, G.; Kang, C. Using Bayesian Deep Learning to Capture Uncertainty for Residential Net Load Forecasting. *IEEE Trans. Power Syst.* **2020**, *35*, 188–201. [CrossRef]
254. Mao, M.; Zhang, S.; Chang, L.; Hatziargyriou, N.D. Schedulable Capacity Forecasting for Electric Vehicles Based on Big Data Analysis. *J. Mod. Power Syst. Clean Energy* **2019**, *7*, 1651–1662. [CrossRef]
255. Khan, Z.A.; Jayaweera, D. Smart Meter Data Based Load Forecasting and Demand Side Management in Distribution Networks with Embedded PV Systems. *IEEE Access* **2020**, *8*, 2631–2644. [CrossRef]
256. Yang, Y.; Li, W.; Gulliver, T.A.; Li, S. Bayesian Deep Learning-Based Probabilistic Load Forecasting in Smart Grids. *IEEE Trans. Ind. Inform.* **2020**, *16*, 4703–4713. [CrossRef]
257. Goehry, B.; Goude, Y.; Massart, P.; Poggi, J.-M. Aggregation of Multi-Scale Experts for Bottom-Up Load Forecasting. *IEEE Trans. Smart Grid* **2020**, *11*, 1895–1904. [CrossRef]
258. Alonso, A.M.; Nogales, F.J.; Ruiz, C. Hierarchical Clustering for Smart Meter Electricity Loads Based on Quantile Autocovariances. *IEEE Trans. Smart Grid* **2020**, *11*, 4522–4530. [CrossRef]
259. Alhussein, M.; Aurangzeb, K.; Haider, S.I. Hybrid CNN-LSTM Model for Short-Term Individual Household Load Forecasting. *IEEE Access* **2020**, *8*, 180544–180557. [CrossRef]
260. Lee, C.; Kim, S.-H.; Youn, C.-H. Cooperating Edge Cloud-Based Hybrid Online Learning for Accelerated Energy Data Stream Processing in Load Forecasting. *IEEE Access* **2020**, *8*, 199120–199132. [CrossRef]
261. Khodayar, M.; Liu, G.; Wang, J.; Kaynak, O.; Khodayar, M.E. Spatiotemporal Behind-the-Meter Load and PV Power Forecasting via Deep Graph Dictionary Learning. *IEEE Trans. Neural Netw. Learn. Syst.* **2021**, *32*, 4713–4727. [CrossRef]

262. Yaprakdal, F.; Yılmaz, M.B.; Baysal, M.; Anvari-Moghaddam, A. A Deep Neural Network-Assisted Approach to Enhance Short-Term Optimal Operational Scheduling of a Microgrid. *Sustainability* **2020**, *12*, 1653. [CrossRef]
263. Tayab, U.B.; Zia, A.; Yang, F.; Lu, J.; Kashif, M. Short-Term Load Forecasting for Microgrid Energy Management System Using Hybrid HHO-FNN Model with Best-Basis Stationary Wavelet Packet Transform. *Energy* **2020**, *203*, 117857. [CrossRef]
264. Li, K.; Yan, J.; Hu, L.; Wang, F.; Zhang, N. Two-Stage Decoupled Estimation Approach of Aggregated Baseline Load Under High Penetration of Behind-the-Meter PV System. *IEEE Trans. Smart Grid* **2021**, *12*, 4876–4885. [CrossRef]
265. Jiang, Z.; Wu, H.; Zhu, B.; Gu, W.; Zhu, Y.; Song, Y.; Ju, P. A Bottom-up Method for Probabilistic Short-Term Load Forecasting Based on Medium Voltage Load Patterns. *IEEE Access* **2021**, *9*, 76551–76563. [CrossRef]
266. Zainab, A.; Syed, D.; Ghrayeb, A.; Abu-Rub, H.; Refaat, S.S.; Houchati, M.; Bouhali, O.; Lopez, S.B. A Multiprocessing-Based Sensitivity Analysis of Machine Learning Algorithms for Load Forecasting of Electric Power Distribution System. *IEEE Access* **2021**, *9*, 31684–31694. [CrossRef]
267. Lin, W.; Wu, D.; Boulet, B. Spatial-Temporal Residential Short-Term Load Forecasting via Graph Neural Networks. *IEEE Trans. Smart Grid* **2021**, *12*, 5373–5384. [CrossRef]
268. Jiang, L.; Wang, X.; Li, W.; Wang, L.; Yin, X.; Jia, L. Hybrid Multitask Multi-Information Fusion Deep Learning for Household Short-Term Load Forecasting. *IEEE Trans. Smart Grid* **2021**, *12*, 5362–5372. [CrossRef]
269. Shipman, R.; Roberts, R.; Waldron, J.; Naylor, S.; Pinchin, J.; Rodrigues, L.; Gillott, M. We Got the Power: Predicting Available Capacity for Vehicle-to-Grid Services Using a Deep Recurrent Neural Network. *Energy* **2021**, *221*, 119813. [CrossRef]
270. Tran, H.-Y.; Hu, J.; Pota, H.R. Smart Meter Data Obfuscation with a Hybrid Privacy-Preserving Data Publishing Scheme without a Trusted Third Party. *IEEE Internet Things J.* **2022**, *9*, 16080–16095. [CrossRef]
271. Alemazkoor, N.; Tootkaboni, M.; Nateghi, R.; Louhghalam, A. Smart-Meter Big Data for Load Forecasting: An Alternative Approach to Clustering. *IEEE Access* **2022**, *10*, 8377–8387. [CrossRef]
272. Briggs, C.; Fan, Z.; Andras, P. Federated Learning for Short-Term Residential Load Forecasting. *IEEE Open Access J. Power Energy* **2022**, *9*, 573–583. [CrossRef]
273. Thanh, P.N.; Cho, M.-Y.; Chang, C.-L.; Chen, M.-J. Short-Term Three-Phase Load Prediction with Advanced Metering Infrastructure Data in Smart Solar Microgrid Based Convolution Neural Network Bidirectional Gated Recurrent Unit. *IEEE Access* **2022**, *10*, 68686–68699. [CrossRef]
274. Wang, B.; Mazhari, M.; Chung, C.Y. A Novel Hybrid Method for Short-Term Probabilistic Load Forecasting in Distribution Networks. *IEEE Trans. Smart Grid* **2022**, *13*, 3650–3661. [CrossRef]
275. Yang, X.; Chitsuphaphan, T.; Dai, H.; Meng, F. EVB-Supportive Energy Management for Residential Systems with Renewable Energy Supply. *World Electr. Veh. J.* **2022**, *13*, 122. [CrossRef]
276. Ibrahim, B.; Rabelo, L.; Gutierrez-Franco, E.; Clavijo-Buritica, N. Machine Learning for Short-Term Load Forecasting in Smart Grids. *Energies* **2022**, *15*, 8079. [CrossRef]
277. Fang, X.; Zhang, W.; Guo, Y.; Wang, J.; Wang, M.; Li, S. A Novel Reinforced Deep RNN–LSTM Algorithm: Energy Management Forecasting Case Study. *IEEE Trans. Ind. Inform.* **2022**, *18*, 5698–5704. [CrossRef]
278. Balakumar, P.; Vinopraba, T.; Chandrasekaran, K. Machine Learning Based Demand Response Scheme for IoT Enabled PV Integrated Smart Building. *Sustain. Cities Soc.* **2023**, *89*, 104260. [CrossRef]
279. Güçyetmez, M.; Farhan, H.S. Enhancing Smart Grids with a New IOT and Cloud-Based Smart Meter to Predict the Energy Consumption with Time Series. *Alex. Eng. J.* **2023**, *79*, 44–55. [CrossRef]
280. Arpogaus, M.; Voss, M.; Sick, B.; Nigge-Uricher, M.; Dürr, O. Short-Term Density Forecasting of Low-Voltage Load Using Bernstein-Polynomial Normalizing Flows. *IEEE Trans. Smart Grid* **2023**, *14*, 4902–4911. [CrossRef]
281. He, L.; Zhang, J. Energy Trading in Local Electricity Markets with Behind-the-Meter Solar and Energy Storage. *IEEE Trans. Energy Mark. Policy Regul.* **2023**, *1*, 107–117. [CrossRef]
282. United Nations List of Countries, Areas and Geographical Groupings. Available online: https://conferences.unite.un.org/unterm/download/country (accessed on 26 April 2023).

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.