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Deep Learning Applied to Univariate Electricity Consumption Time Series: A Systematic Literature Review

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Abstract

This article presents a Systematic Literature Review (SLR) of studies applying Deep Learning (DL) models to forecast Electricity Consumption (EC) using univariate time series. After screening 2,800 articles through well-defined inclusion and exclusion criteria, 62 studies were selected for analysis. These studies were systematically organized to highlight DL architectures, performance metrics, preprocessing practices, and key methodological choices. The review uniquely focuses on univariate contexts—an underexplored but relevant scenario for energy forecasting, especially where data availability is limited. The paper identifies dominant trends, methodological gaps, and emerging challenges, offering a critical foundation for future research in the field.

Keywords

Systematic Literature Review, Deep Learning, Univariate Time Series, Electricity Consumption Prediction, Energy Forecasting

1. Introduction

Electricity is fundamental to modern societies and economies. Its importance continues to grow as electricity-based technologies, such as electric vehicles, electric public transportation, industrial automation and robotics, become increasingly popular. According to the International Energy Agency (IEA), global electricity demand increased by 4.3% in 2024 and will continue to grow at a rate of close to 4% per year until 2027. Furthermore, power generation is the largest source of carbon dioxide (CO_2) emissions worldwide, with electricity and heat generation accounting for approximately 40% of global energy-related CO_2 emissions [1]. Consequently, modern energy systems require a continuous supply to guarantee safe and affordable access to electricity while reducing global CO_2 emissions, which is one of the main challenges for governments and researchers. In the field of energy planning, accurate load forecasts are essential for infrastructure development and long-term investment decisions and, from an environmental perspective, play a crucial role in reducing carbon footprints and promoting sustainability. Thus, an accurate prediction of electricity consumption (EC) with minimal error is imperative. To this end, researchers and experts strive to develop the most efficient and advanced methods for load forecasting [2].

One of the approaches used for load forecasting is data-driven models. The recent advancements in smart grid technology and the Internet of Things (IoT) have significantly increased the volume of data related to EC. This newfound accessibility has sparked researchers' interest in utilizing various data-driven models to forecast energy usage [3]. These models leverage historical and real-time data, i.e. Time Series (TS), to predict future energy demand. In recent years, Deep Learning (DL) models have emerged among these techniques due to their improved capabilities in handling these large datasets [4], as well as processing to learn various levels of abstraction, facilitating feature extraction from TS, being now commonly deployed for its analysis [5].

A TS is a sequence of data points x(t), where t represents time, and x reflects a variable that changes over time, such as temperature or electricity consumption [6]. TS are used to model and forecast EC patterns [7], enabling accurate predictions with Deep Neural Networks (DNNs) such as Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BLSTM).

DL offers clear advantages for TS analysis over traditional methods, which often struggle with complex, non-linear patterns in large datasets like electricity consumption TS. DL models can automatically extract features using techniques such as convolution and attention, reducing the need for manual engineering and enabling accurate predictions from large volumes of data. This capability makes them particularly promising for addressing the growing complexity associated with big data management, a challenge that has become especially relevant in recent years [4]. Furthermore, DL models, when compared to traditional (“shallow”) neural networks, can retain and store more information in their neurons, allowing generalization to patterns not explicitly present in the training data [4]. However, a drawback of DL methods is that they are often challenging to train and involve a substantial number of hyperparameters [4]. In [8] the authors consider computational complexity as a drawback of DL as well.

Recent advances in the field of DL have made DNNs a powerful tool for TS forecasting. The evolution of DNN architectures stands out, with models such as LSTM [9], Gated Recurrent Units (GRU) [10] and Transformer [10] which are especially suitable for temporal prediction tasks, as they can capture both short- and long-term dependencies in energy usage data, handling complex and non-linear relationships more effectively than traditional methods [11],[12]. The models developed for such tasks are described in many contexts, such as in residential environments [13],[14], in special environments such as schools and factories [15],[16], in buildings [17], [18], [19], [20], among others.

Although multivariate time series models are increasingly explored in energy forecasting, many real-world applications—especially in developing regions, small-scale buildings, or emerging IoT-based monitoring systems—still rely heavily on univariate energy consumption data. These contexts often lack access to comprehensive datasets that include weather, occupancy, or external variables, either due to limited infrastructure or privacy restrictions. Therefore, evaluating the effectiveness of deep learning architectures under univariate settings remains a critical and underexplored challenge. Focusing on univariate time series not only enhances the applicability of the findings to data-scarce environments but also enables the assessment of model performance in more constrained, yet operationally common, scenarios in the energy domain.

This systematic literature review provides a novel and comprehensive synthesis of recent advancements in applying DL techniques to univariate energy consumption (EC) time series forecasting. While multivariate models dominate the literature, this review focuses exclusively on univariate approaches, which remain highly relevant in data-scarce or cost-constrained environments. By mapping the prevalence, performance, and limitations of 62 studies published between 2019 and 2025, this review identifies critical methodological trends, such as the dominance of LSTM-based architectures, the underutilization of statistical validation, and the limited adoption of automated hyperparameter optimization techniques. The analysis contributes to the field by highlighting current research gaps—particularly the lack of comparative benchmarks between univariate and multivariate forecasting models—and by offering a clear roadmap for future experimental studies and applied implementations in real-world energy systems.

The remainder of this article is structured as follows: Section 2 details the methodology, including the research questions, search string, inclusion and exclusion criteria, and a quantitative summary of the selected studies. Section 3 presents a descriptive analysis and graphical representations. Section 4 discusses the main findings, addresses the research questions, outlines future challenges, and concludes the review.

2. Research Methodology

ML and DL techniques are increasingly explored for forecasting EC using time series, aiming to optimize usage and reduce costs sustainably [7]. This article presents a Systematic Literature Review (SLR) to assess the current research landscape, identify knowledge gaps, and propose directions for future studies.
Following Kitchenham's guidelines [21], a SLR should be conducted based on a predefined search strategy. Based on the proposals of the Kitchenham [21] and Alazemi et al. [22] and with the necessary adaptations to conduct this SLR, the applied methodology includes the following steps: (i) specifying the Research Questions (RQs) and search string; (ii) inclusion/exclusion criteria; (iii) literature search results; (iv) descriptive analysis; (v) review findings and (vi) future challenges.

2.1. Specifying the research questions and search string

The aim of this systematic review was to investigate DL architecture models for predicting EC. The following research questions were formulated:

RQ1 - What are the most used DL architecture to predict energy consumption (EC) using univariate time series data?

RQ2 - What performance metrics are used to evaluate deep learning models in EC prediction tasks, and how do they influence the interpretation of results?

RQ3 - What data preprocessing and feature engineering techniques are commonly applied in DL models for univariate time series energy prediction?

RQ4 – Are statistical tests performed to support conclusions?

RQ5 - What are the main challenges and limitations reported in studies using deep learning for univariate time series energy consumption prediction?

The initial search string used was: ("EC Prediction") AND ("deep learning" or "LSTM" OR "BLSTM" OR "CNN-LSTM" OR "GRU" OR "Reservoir" OR "Transfer Learning" OR "autoencoder"). The acronym "EC" (Electricity Consumption) was initially used in the search strategy. However, as it retrieved studies unrelated to the energy domain. To improve precision and relevance, the full term "Electricity Consumption" was incorporated into the search.

2.2. Inclusion/exclusion criteria

Studies were included if they (i) focused on the application of DL techniques to electricity consumption (EC) forecasting; (ii) used univariate time series data; (iii) were based on EC as the primary data source; (iv) were published in peer-reviewed journals; and (v) were published between 2019 and 2025.

Studies were excluded if they (i) used multivariate time series with external variables (e.g., weather, occupancy, or building features); (ii) focused on demand forecasting instead of electricity consumption; (iii) targeted specific appliances or energy sources (e.g., solar, wind); (iv) addressed related topics without applying DL to EC forecasting (e.g., energy management, IoT security); (v) were review articles, conference papers, or academic theses.

2.3. Results of the systematic search

Figure 1 shows the overview of the bibliographic research. Based on the research questions, the search string was defined to locate the studies to be analyzed in the Google Scholar, Science Direct, and Springer databases. With the aim of considering current trends on the subject, as well as its future horizons, only articles published between 2019 and 2025 were included. 2000 files were found in Google Scholar, 631 in the Science Direct database, and 169 in Springer, totalling 2800 files, to which the first filter was applied. The titles of the articles were analyzed to determine if they addressed EC TS forecasting using DL. Articles that did not meet these criteria were removed from the pool of articles, resulting in the exclusion of 1973 articles, and then 827 articles were analyzed using the second filter. The second filter was based on the inclusion and exclusion criteria (see item 2.2), requiring reading of the abstracts and conclusions and, sometimes, the full text. At this stage, 540 articles were excluded. Finally, 287 articles were read in full to assess, once again, whether all inclusion and exclusion criteria were met. As a result of this stage, 225 articles were excluded, with the main reasons for exclusion being the use of external data such as weather information, the objective of the work being the prediction of demand rather than consumption, and some studies focusing on predicting consumption for a specific piece of equipment or context.

The final SLR included 62 studies. The following information was extracted: title, publication date, deep learning architecture, use of IoT, preprocessing, metaheuristics, comparison with machine learning, performance metrics, and statistical tests.

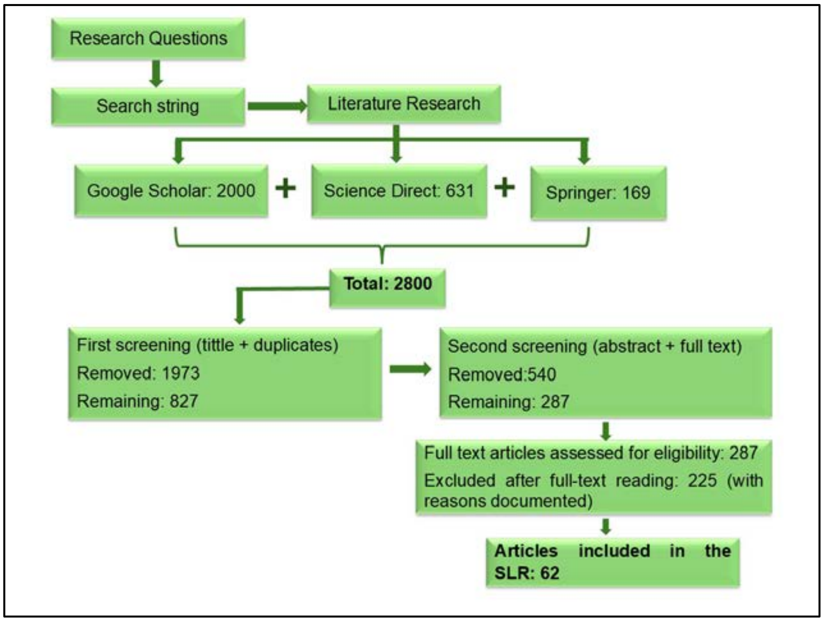

Figure 1. Overview of the bibliographic research

3. Descriptive analysis

Figures 2 (a, b, c and d) shows the first part of the descriptive analysis of the articles assessed in the review. As Figure 2a shows, the investigation of DL methods for univariate TS has increased over the years. In 2022 and 2024, the number of published articles (12 and 15, respectively) approximately doubled compared to earlier years (6 articles in 2019, 6 in 2020, and 5 in 2021). According to Figure 2b, 67.74% of the studies employed two or more DL architectures, while 32.26% used only one architecture, often for comparison with conventional machine learning (ML) models or to assess the impact of different Optimization Metaheuristics (OMHs) during training. Figure 2c indicates that only 19.67% of the articles used IoT-generated datasets, while 80.33% relied on conventional datasets. Notably, publicly available IoT datasets were not classified as datasets "obtained from IoT systems" in this review. Figure 2d shows that 32.26% of the articles used a single time series, while 67.74% analyzed multiple univariate TS.

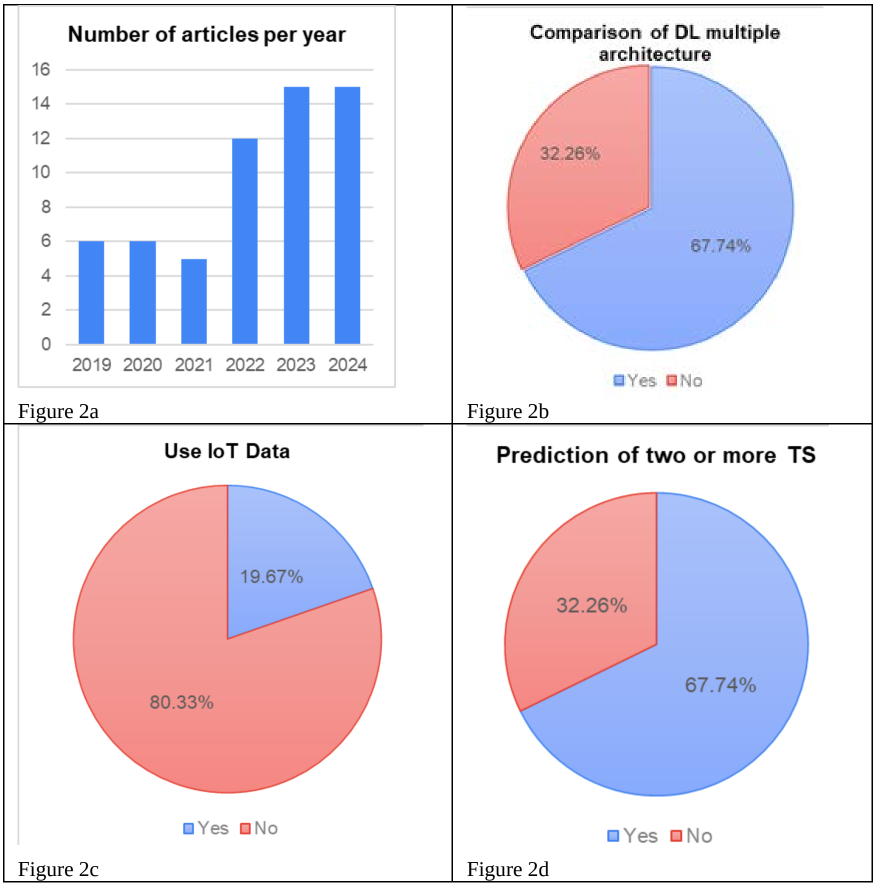

Figure 2. Descriptive analysis of the articles assessed: (a) Number of articles per year since 2019; (b) Comparison between multiple DL architectures; (c) Usage of IoT data; (d) Prediction of multiple univariate TS data

Figures 3 (a, b, c and d) continue the descriptive analysis with other significant trends. As depicted in Figure 3a, 29.03% of the studies integrated OMHs with DL architectures. However, only 3.23% used Time Series Cross-Validation (TSCV) (Figure 3b). Figure 3c reveals that 62.90% of the reviewed articles conducted comparative analysis between DL and traditional ML models. Finally, Figure 3d highlights a critical gap: only 9.68% of the articles applied statistical tests to support their conclusions. This lack of statistical validation may undermine the robustness of performance comparisons and conclusions drawn in many studies.

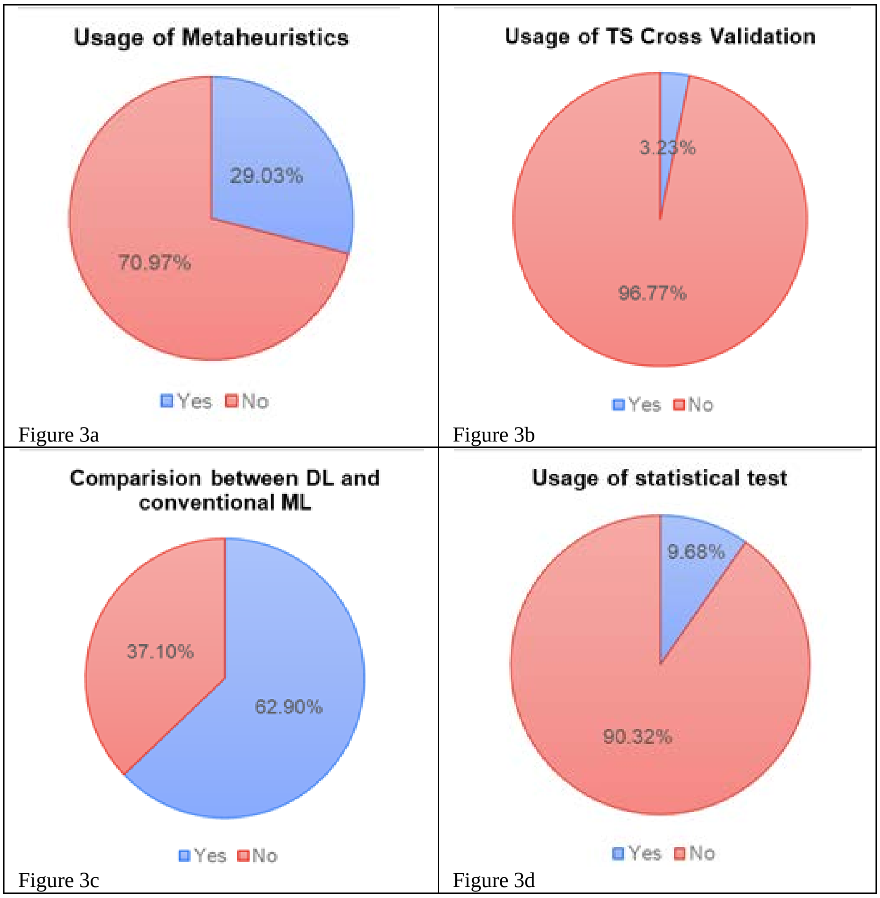

Figure 3. Descriptive analysis of the articles assessed (continued): (a) Usage of OMH; (b) Usage of TSCV; (c) Comparison between DL and conventional ML; (d) Usage of statistical tests

Figure 4 shows the number of occurrences of the most relevant DL architectures in the present review. Table 1 shows the architectures with their main references, as well as the articles reviewed that used them. Other DL architectures were also used such as gated-FCN [23]. Nested LSTM and Stacked LSTM were considered as LSTM variants.

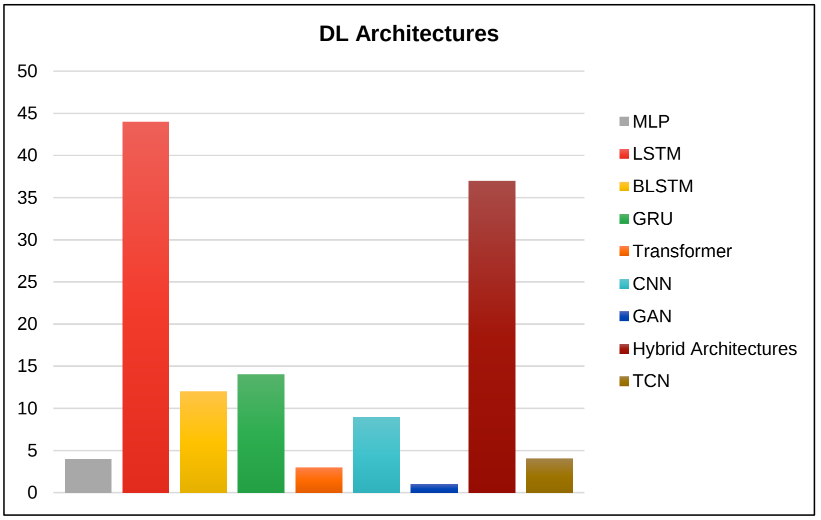

Figure 4. Occurrences of the most relevant DL architectures found in the review

Table 1. Occurrence of the most relevant DL architectures in the present review

DL Architecture	Number of Occurrences	Articles in the present review
Deep MLP	4	[25], [58], [14], [64]
LSTM [65]	44	[47], [57], [33], [66], [24], [25], [34], [35], [18], [36], [58], [26], [67], [60], [68], [14], [45], [29], [53], [52] [15], [16], [27], [28], [48], [69], [59], [70], [71], [72], [7], [61], [44][73], [49], [74], [40], [75], [64], [63], [62], [51], [76], [77]
BLSTM [78]	12	[47], [25], [27], [48], [7], [73], [49], [30], [50] [40], [32], [51]
GRU [10]	14	[33], [25], [34], [35], [19], [36], [68], [14], [15], [17], [44], [49], [63],[43]
Transformer [79]	3	[15], [63], [76]
CNN [80]	9	[13], [52], [16], [28], [48], [17], [73], [40], [42]
GAN [81]	1	[20]
TCN [82]	4	[34], [36], [15], [69]
Hybrid Architecture	37	[33], [24], [25], [34],[35], [18], [19], [36], [83], [26], [37], [38], [68],[39], [14], [45], [29], [16], [27], [28], [48], [17], [59], [17], [23], [72], [44], [46], [30], [31], [40], [32], [63], [41], [42], [43], [76]

Here are some patterns observed in the papers:

(i) LSTM architecture, in addition to being the most widely used, was also employed in hybrid architectures, often combined with CNN, GRU, BLSTM, Prophet. Most studies adjusted LSTM hyperparameters manually through trial-and-error, although a few implemented optimization metaheuristics such as Genetic Algorithms, PSO, or CVOA. Several studies also explored LSTM variants, including BLSTM, Enhanced LSTM (ILSTM), Stacked LSTM, and hybrid models incorporating Kalman filters or wavelet transforms.

(ii) Hybrid deep learning architectures have been used to improve energy consumption prediction by combining spatial feature extractors (e.g., CNN, signal decomposition) with temporal sequence models (e.g., LSTM, GRU, BLSTM). Several studies have employed decomposition techniques, such as VMD, EEMD, or wavelet transforms, to reduce noise and clarify patterns prior to training [18],[24],[25],[26],[27],[28],[29],[30],[31],[32]. These hybrid models often target long-term, multi-stage prediction tasks, outperforming traditional standalone models [33][34],[35],[36],[37],[38],[39],[29],[40],[41],[42]. In several cases, hyperparameter tuning has been optimized using metaheuristics such as PSO, GA, and IDBO [18],[24],[26],[38],[28],[30],[32],[43].These models have been applied to residential, industrial, and smart grid datasets, confirming their versatility and effectiveness [14],[17],[16],[35],[27],[23],[44],[45],[46],[31],[42].

(iii) Bidirectional LSTM (BLSTM) have been frequently applied in multi-step or hourly forecasting tasks, particularly in residential, public building, and smart grid contexts [47], [25], [48], [49], [50], [40]In many cases, BLSTM has been integrated into hybrid architectures, commonly paired with CNN or decomposition techniques such as wavelet transform or VMD, enhancing feature extraction and sequence learning [25],[27],[30],[32],[51]. Overall, BLSTM-based models have consistently demonstrated competitive or superior performance compared to unidirectional LSTM, particularly in scenarios that require the recognition of symmetric or bidirectional patterns in energy data.

(iv) GRU has been applied as a standalone model or in hybrid architectures, often combined with CNN, LSTM or feedforward layers to balance computational efficiency with sequence modelling capability, as in [19]. Designed as a simplified alternative to LSTM, GRU reduces model complexity by using fewer gates, making it suitable for scenarios with limited computational resources or smaller datasets. Despite its superior computational efficiency (fewer parameters), GRU did not outperform LSTM in most cases, especially on tasks that unlock long-term memory or more accurate predictions [15],[33]. Also, in [33] and [49] LSTM outperformed GRU on datasets with more complex temporal structures. In other cases, GRU has been effectively integrated into hybrid frameworks (e.g., CNN-GRU in [17] GRU+FF in [19]) to improve performance in specific scenarios.

(v) CNN has been used primarily in hybrid architectures, most paired with LSTM, GRU, or BLSTM, typically serving as a feature extractor. Some models incorporate optimization strategies, attention mechanisms, or pooling techniques to improve CNN performance. Despite their success, CNN effectiveness has sometimes been limited by their inability to capture long-range temporal dependencies without additional recurrent or transformer-based layers, as the authors present in in [13],[16],[28],[41] and [52].

Although the main objective of this review is to analyze the application of DNNs in univariate energy consumption forecasting, our analysis included comparative studies with conventional Machine Learning (ML) models, such as Support Vector Regression (SVR), Random Forest (RF), ARIMA or XGBoost (XGB). These classical methods were not part of the inclusion criteria, but were recorded during data extraction, as identified in Table 2 and quantified in Figure 5.

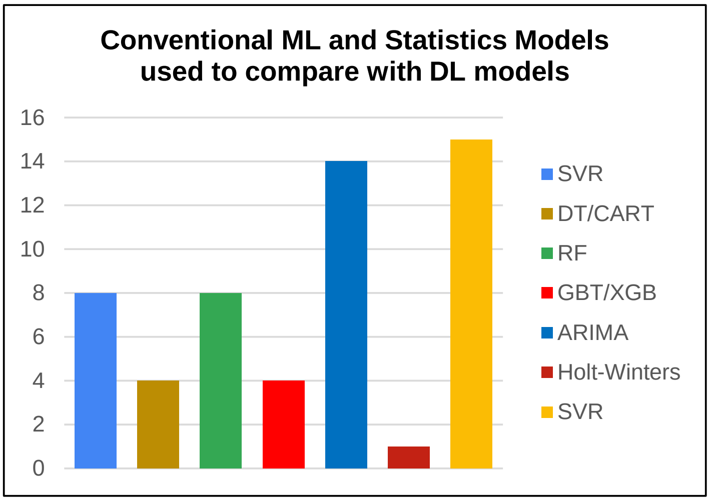

Figure 5. Occurrences of the most relevant conventional ML architectures and statistical models found in the review that were used to compare with DL models

Table 2. List of articles with the occurrences of the most relevant conventional ML architectures and statistical models found in the review that were used to compare with DL models

ML Model	Number of Occurrences	Articles in the present review
ANN	8	[13], [24], [25], [20], [26], [70], [71], [30]
Decision Tree/Classification and Regression Trees (DT/CART) [84]	4	[25], [59],[51]
Random Forest [85]	8	[25], [18], [58], [59], [61], [73], [50], [51]
GBT [86][87] XGB [88]	4	[71], 50], [73], [46]
ARIMA [89]	14	[24], [26], [37], [68], [16], [27], [28], [48], [23] [75], [32], [41], [62], [77]
Holt-Winters [90]	1	[27]
Support Vector Regression [91] [92]	15	[13], [26], [39], [24], [25], [18], [58], [20], [14], [29], [27], [70], [71],[72], [73], [51]

The most relevant OMHs and their occurrence are shown in Table 3 and other OMHs such as FFOA [59], Coronavirus Optimization Algorithm (CVOA) [53], Gravitational Search Algorithm (GSA) [54], Flower Pollination Algorithm (FPA)[55], and Cat Swarm Optimization (CSO) [56] were also used in the articles reviewed.

Table 3. Occurrence of the most relevant OMHs in the articles reviewed

OMH	Number of Occurrences	Articles in the present review
Genetic Algorithm (GA) [93]	3	[47], [26], [60]
Particle Swarm Optimization (PSO) [94]	4	[18], [58], [26], [38]
Grey Wolf Optimization (GWO)[95]	1	[38]
Differential Evolution (DE) [96]	1	[60]
Bayesian Optimization (BO) [97]	2	[36], [44]

Figure 6 shows the number of occurrences of the most relevant metrics found in the present review.

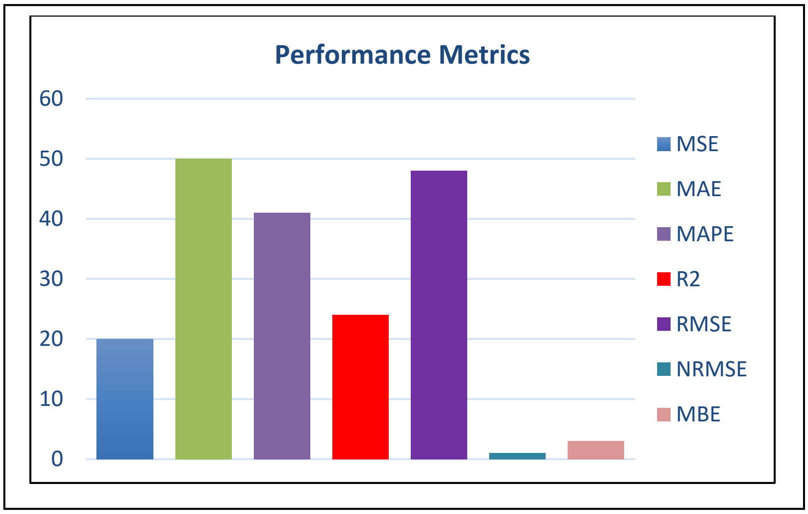

Figure 6. Occurrences of the most relevant performance metrics found in the review

4. Review finding, discussion, and future challenges

In this section, we present the directions found for the initial questions, as outlined in section 2.1, and we highlight some important points identified in the analysis of the 62 works in this review.

4.1. Answers to the Research Questions

RQ1 - What are the most used DL architecture to predict energy consumption (EC) using univariate time series data? The most used DL architectures among the analyzed works are LSTM, Hybrid Architectures, GRU, CNN, BLSTM, CNN, MLP, TCN, Transformer and GAN (considering from the highest to the lowest number of occurrences - see Figure 4). Patterns observed in the use of the most cited architectures were described in section 3.

RQ2 - What performance metrics are used to evaluate deep learning models in EC prediction tasks, and how do they influence the interpretation of results? The most adopted performance metrics in the reviewed studies are RMSE, MAE, MAPE, and R^2. As shown in Section 3 (see figure 6), RMSE is the predominant choice, often accompanied by MAE and MAPE in a complementary fashion. However, few studies justify their choice of metric based on the nature of the dataset or the prediction objective. RMSE and MAE are widely used due to their interpretability and ease of comparison across studies, yet they differ in sensitivity to outliers—RMSE penalizes large deviations more heavily. Despite this, many articles do not explore this distinction, and metric selection appears to follow conventions rather than methodological reasoning. Moreover, the exclusive use of point-based error metrics, without statistical tests or confidence intervals, limits the robustness of comparisons between models. Only a small portion of the studies complement their evaluations with statistical significance tests or uncertainty analysis. This suggests a methodological gap and highlights the need for standardized benchmarking practices in DL-based EC forecasting. Future studies should be encouraged to combine multiple metrics and adopt statistical validation techniques to ensure more reliable model comparisons.

RQ3 - What data preprocessing and feature engineering techniques are commonly applied in DL models for univariate time series energy prediction? Normalization, especially Min-Max scaling, is the most used technique, followed by frequent use of downsampling methods, such as those in [19],[47],[57],[33],[58]. Some studies applied data reshaping methods [20],[26],[52], such as windowing or sequence framing. Correlation techniques were less frequent, and the use of artificial data generation appears in some works such as [20] and [59]. These preprocessing strategies enhance model performance and ensure result reliability across different EC prediction scenarios.

RQ4 - Are the research results supported by statistical tests? It was observed that there is little use of statistical tests in the reviewed works [33],[60],[16],[7],[61],[62] Despite requiring repeated runs, statistical tests in time series forecasting are generally not computationally expensive and are essential to confirm whether performance differences are significant or due to random variation. They also support model generalization, providing a more robust basis for comparing models.

RQ5 - What are the main challenges and limitations reported in studies using deep learning for univariate time series energy consumption prediction?

(i) Limited performance in long-term forecasting: Many DL models showed reduced accuracy when applied to long-term prediction tasks. This is often due to their inability to capture cross-period variations or seasonal dependencies, which are critical in extended forecasting windows [41].

(ii) (ii) Vanishing/Exploding Gradient Issues in Recurrent Networks: Despite the popularity of RNNs and LSTMs, several studies have reported difficulties in capturing long-range dependencies due to gradient instability. These negative impacts affect model training and prediction robustness [63].

(iii) High computational cost of advanced architectures: While architectures such as Transformers have shown excellent predictive capabilities, their application is often constrained by the computational demands required for training and inference. This limitation hinders their use in embedded systems, IoT devices, and resource-constrained environments [41].

(iv) Lack of statistical validation: Only a small fraction of the reviewed studies (9.68%) applied statistical tests to support the significance of their results. This omission compromises the reliability of model comparisons and may lead to misleading conclusions based solely on performance metrics.

(v) Manual hyperparameter tuning: In most studies, hyperparameter optimization was performed manually through trial and error, which may not lead to optimal settings and often lacks reproducibility. Few studies have employed metaheuristics or AutoML frameworks to automate this process.

(vi) Limited use of real-world IoT data: Although smart metering and IoT devices are increasingly available, only 19.67% of the studies used real IoT-collected datasets. This raises concerns about the generalizability of findings when models are trained on publicly available or simulated datasets that do not reflect practical noise or system behavior.

(vii) Narrow focus on univariate inputs: While this SLR deliberately targeted univariate approaches, several studies acknowledged that excluding external variables (e.g., weather, occupancy, pricing) may reduce the predictive accuracy in real-world applications.

4.2. Critical observations emerging from the review

The in-depth analysis of the 62 reviewed studies reveals broader patterns that complement the answers to the research questions and suggest directions for future research.

(i) Implementation lag and adoption gap: A clear delay was observed between the theoretical development of DL architectures in Computer Science and their application in EC forecasting. For instance, although LSTM was proposed in 1997, it is still predominant, while more recent architectures like TCN (2018) are less adopted. This gap suggests a slow integration of innovative models into real-world energy systems, possibly due to barriers in computational resources or domain adaptation.

(ii) Underutilization of automated optimization: Despite the increasing complexity of DL models, only a minority of studies applied metaheuristics or AutoML tools for hyperparameter tuning. Manual trial-and-error remains the norm, which hampers reproducibility and performance scalability.

AutoML tools, though promising, were cited in just a few papers, indicating a missed opportunity for model efficiency and robustness.

(iii) Limited realism in datasets: Only 19.67% of the works used datasets collected directly from IoT systems. This lack of real-world data reduces the ecological validity of many models, as they may not reflect the variability, noise, and constraints typical of operational energy systems.

(iv) Lack of comparative analyses between univariate and multivariate TS: Although this review focused on univariate TS by design, the absence of studies comparing the predictive power and trade-offs between univariate and multivariate approaches represents a significant research gap. Such comparisons would clarify when the added complexity of multivariate models is justified.

These observations indicate the need for a stronger methodological framework that integrates real-world validation, statistical robustness, and automated model optimization to enhance the relevance and applicability of DL-based forecasting models.

4.3. Future challenges

Despite the growing maturity of DL approaches in electricity consumption (EC) forecasting, several challenges remain open and require further research. Based on the findings of this review, four key directions for future investigation are identified. The table 4 summarizes key limitations identified in the reviewed studies, their justifications, and possible directions for future investigations:

Table 4. Future research challenges in electricity consumption forecasting using DL

Future Challenge	Justification	Research Directions
Comparative Evaluation: Univariate vs. Multivariate TS	Univariate models dominate due to simplicity and data availability, but multivariate models may enhance accuracy.	Design controlled experiments comparing univariate and multivariate models; evaluate trade-offs in accuracy and complexity.
Robustness and Generalization Across Datasets	Performance on isolated datasets may not generalize; robust validation across diverse datasets is needed.	Adopt cross-dataset evaluations, use statistical testing, and develop benchmarking protocols for reproducibility.
Transfer Learning and Model Scalability	Training from scratch is resource-intensive; transfer learning can improve efficiency and adaptability.	Investigate pretrained models, assess transferability across domains; evaluate DL scalability for broad deployment.
Ethical and Privacy Considerations	IoT-based EC forecasting involves sensitive data, requiring ethical safeguards and privacy-preserving techniques.	Implement federated learning and differential privacy; define governance frameworks and ensure algorithmic transparency.

5. Conclusions

This systematic literature review synthesized and analyzed 62 peer-reviewed articles that applied DL models to electricity consumption (EC) forecasting using univariate time series. The review provided a comprehensive overview of the most employed architectures—such as LSTM, GRU, CNN, BLSTM, and Transformer—alongside the evaluation metrics, preprocessing strategies, and experimental practices adopted in recent years.

The findings highlight a growing interest in leveraging DL for univariate EC forecasting, despite limitations in model generalization, the underuse of statistical testing, and inconsistent approaches to hyperparameter tuning. The choice of univariate time series, although more constrained, revealed to be a viable strategy in data-limited or cost-sensitive contexts.

By mapping current practices and gaps, this review supports future research directions, including comparative studies between univariate and multivariate time series, enhanced benchmarking protocols, and the adoption of advanced techniques such as AutoML and transfer learning. The article contributes both a methodological reference for replication and a critical baseline for further advancement in this increasingly relevant field.

Conflicts of Interest

The authors declare that there are no personal, professional, or financial relationships that could be construed as potential conflicts of interest regarding the content of this manuscript.

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