INTERNATIONAL JOURNAL OF LATEST TECHNOLOGY IN ENGINEERING, MANAGEMENT & APPLIED SCIENCE (IJLTEMAS)

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIII, Issue IX, September 2024

Enhancing Electricity Demand Forecasting Accuracy Through Hybrid Models and Deep Learning Techniques: A Systematic Literature Review

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DOI: https://doi.org/10.51583/IJLTEMAS.2024.130908

Received: 16 July 2024; Accepted: 29 July 2024; Published: 05 October 2024

Abstract: This reviewed literature on electricity forecasting covers its history, terminology, and techniques. A systematic review of existing studies highlighted key findings and future research opportunities. Conventional statistical techniques and MLA can predict electricity demand over time with various techniques and forecasting windows tailored to data and problem specifics. Most studies focused on STLF, often without testing techniques on MTLF and LTLF. The key findings include: Many studies (26%) used conventional statistical methods like ARIMA, ARIMAX, and SARIMAX for electricity forecasting, often without benchmarking algorithms. Various factors, such as time, weather, electricity price, population, and economy, influence ELF. Weather parameters were the most commonly used predictors, though performance varied across studies. A global increase in electricity demand has driven numerous studies, though less research has been done in low- and middle-income countries. Deep neural networks like LSTM have been underutilised in electricity forecasting. LSTM's ability to store memory and address the vanishing gradient problem makes it promising for future research, particularly in hybrid models combining CNN and LSTM for forecasting peak load demand based on economic and environmental factors.

I. Introduction

The review provides a concise overview of electricity load forecasting (ELF). It covers the fundamental concepts, various types of load forecasting, and the factors that influence electricity demand forecasting. Additionally, it reviews relevant machine learning algorithms and related studies, concluding with a chapter summary. Electricity Demand - Global electricity consumption has surged more rapidly than overall energy usage in recent years. From 1980 to 2013, annual global electricity consumption rose from 7,300 TWh to 22,100 TWh. In the 21st century, the growth rate of electricity consumption has averaged 3.4% per year, outpacing the 2.2% annual increase in overall energy consumption (Liu, 2015). According to the IEA's Electricity Market Report, global electricity demand, which declined by about 1% in 2020 due to the Covid-19 pandemic, was expected to grow by nearly 5% in 2021 and 4% in 2022, driven by economic recovery. Developing regions in Asia and Central and South America have seen particularly rapid increases in electricity consumption.

In Ghana, the history of the power industry dates back to the colonial era, when energy was primarily supplied by isolated diesel generators owned by industries, municipalities, and institutions like hospitals and schools (Kumi, 2017). Despite significant increases in installed generation capacity from 1,730 MW in 2006 to 3,795 MW in 2016, Ghana has faced persistent energy supply issues, resulting in an average daily economic loss of US $2.1 million. During this period, peak power consumption grew by 50%, from 1,393 MW to 2,087 MW. The National Electrification Scheme (NES), launched in 1990, has significantly increased electricity access, which rose from 15-20% in 1990 to 82.5% in 2016. However, Ghana may miss its goal of universal access by 2020 by 5% unless the electrification rate increases.

Ghana's Electricity Demand and Supply Nexus - From 2006 to 2016, Ghana's peak electricity demand grew by 49.8%, from 1,393 MW to 2,087 MW, averaging an annual increase of 4.29% (Energy Commission of Ghana, 2016a; VRA, 2015; Energy Commission of Ghana, 2017, cited by Kumi, 2017). Over the same period, generation capacity more than doubled, with an average annual increase of 8.60%, rising from 1,730 MW to 3,759 MW. Despite this, power shortages have persisted due to various challenges.

Ghana's gross electricity consumption fluctuated from 9,059 GWh in 2006 to 7,413 GWh in 2007 before increasing by an average of 10.8% annually until 2014. This trend reversed with an 11.3% decline from 2014 to 2015, followed by a 15.3% rise in 2016 (Energy Commission of Ghana, 2016a; Energy Commission of Ghana, 2017, cited by Kumi, 2017).

Accurate power forecasting is crucial for effective energy resource planning and management, as it directly impacts a country's economic activities (Hadjout et al., 2021).

Brief History of Electricity Load Forecasting (ELF): ELF involves predicting future load requirements to make informed system expansion decisions. The concept dates back to 1965 (Heinemann and Nordmian, cited by Yang et al., 2019) and has since evolved, yielding increasingly accurate results. ELF underpins system expansion and tariff decisions.

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Basic Concept of ELF: An electricity demand forecast model typically involves setting a learning objective, collecting and partitioning data into training and testing sets, selecting a suitable machine learning algorithm (MLA), and evaluating the model's performance using metrics such as RMSE, MAPE, and correlation coefficient. The predicted output is compared to the desired output to assess the model's accuracy.

Factors Influencing ELF: Several factors influence system load behavior, necessitating a thorough understanding for accurate forecasting. These factors include:

Weather: Parameters like temperature, humidity, and wind speed affect electrical appliance usage.

Time and Day: Load variations depend on the time of day, holidays, weekdays/weekends, and seasons.

Economic: Factors like industrialization, load management policies, and electricity pricing significantly impact load trends.

Random Disturbance: Unexpected events, such as industrial shutdowns or special events like football matches, cause load variations.

Customer Category: Load factors vary for residential, commercial, and industrial customers, influenced by production levels, population growth, and other demographic factors.

These factors are detailed in studies by Charytoniuk et al. (1998), Hassan et al. (2014), Mengying et al. (2019), Ruzic et al. (2003), and Zivanovic (2002)

Table 1: Common Evaluation Metrics for Electric Load Demand Forecasters

Abbreviation	**Evaluation Metric**	**Definition**
RMSE	Root Mean Squared Error	
MAE	Mean Absolute Error	
MAPE	Mean Absolute Percentage Error	
NS	Nash-Sutcliffe Coefficient Radius	
RPD	Relative Percentage Difference	
AUC	Area Under the Curve	
NMSE	Normalised Mean Squared Error	
MSPE	Mean Squared Prediction Error	
RMSEP	Root Mean Square Prediction Error	
MBE	Mean Bias Error	
R	Correlation Coefficient	
	Accuracy	
	Precision	PRE=TP/(TP+FP)
	Recall	REC=TP/(TP+FN)
MedAE	Median Absolute Error	MedAE(y,ŷ)=median(

Types of ELF: Electricity demand forecasting (ELF) can be categorized by the techniques used or the forecasting duration. This section elaborates on these categories in detail.

ELF Types Based on Forecasting Intervals (Lead Time) {ELF can be divided into very short-term, short-term, medium-term, and long-term forecasts based on the forecasting intervals, also known as lead time. Table 2.2 summarizes the types of load forecasting and their applications, as detailed in works by Kuster et al. (2017), Nti et al. (2019), and Nti et al. (2020).

Table 2: Summary of Load Forecasting Types

Nature of Forecast	**Lead Time**	**Application**
Very short-term	Seconds to minutes	Generation, distribution schedules, and contingency analysis for system security

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Short-term	Half an hour to a few hours	Distribution of spinning reserve, operational planning, unit commitment, maintenance schedule
Medium-term	A few days to weeks	Seasonal peak planning (winter, summer)
Long-term	Months to years	Generation growth planning

Problems in Short-Term Load Forecasting (STLF): There are several issues encountered in STLF, which are discussed below:

1. **Input-Output Relationship**: Most STLF methods use an artificial neural network (ANN) structure to model the input-output relationship. However, designing this network requires detailed prior knowledge. Incorrect network design can lead to poor predictions. Identifying significant input variables is also challenging. Too many or too few variables can reduce accuracy. Clustering and mode recognition tools can improve results by better representing system properties, though they still require prior knowledge for effective clustering.
2. **Expert Experience:** Experienced personnel in power grids and load dispatch centers often outperform computer forecasts. Thus, expert systems and fuzzy inference systems are used, but this requires transforming expert knowledge into a rule database.
3. **Anomalous Days:** Predicting unusual load days, such as holidays or extreme weather days, is difficult due to their differing load behavior. Using historical data from the past five years can help, but load growth may still cause dissimilarities.
4. **Weather Data:** Weather significantly impacts forecasting accuracy. Despite advances in weather forecasting, inaccuracies remain. Detailed weather data is often unavailable, which can lead to errors in load forecasting.
5. **Training Problems:** ANN-based load forecasting involves training and predicting with two data sets: training and testing data. Overfitting can occur if the model performs well on training data but poorly on new data. Proper training methods are needed to avoid this.
6. **Reliability:** Economic development often outpaces power investment, leading to energy shortages. Demand-side management can disrupt natural load curves, complicating forecasting. Ensuring reliable data and removing noise is essential for accurate forecasts.

Requirements of STLF: A sound STLF system should meet the following requirements (Dewari & Bhandari, 2015):

1. **Accuracy:** The primary requirement for STLF is accuracy, as it underpins economic dispatch, system reliability, and electricity market trading.
2. **Speed:** The STLF program should utilize the latest historical and weather data to increase accuracy and reduce computation time. Programs with long training times should be replaced with faster techniques that maintain accuracy.
3. **Detection of Bad Data:** Modern STLF systems should automatically detect and eliminate erroneous data, reducing the burden on operators.
4. **User-Friendliness:** The load forecasting interface should be intuitive, allowing users to easily define forecasts and view results both numerically and graphically.
5. **Automatic Forecasting:** To reduce the risk of inaccurate forecasts, STLF systems should automatically generate final results based on past performance, without requiring operator intervention.

ELF Based on Techniques: ELF techniques can be broadly classified into three categories: correlation, extrapolation, and a combination of both (Eeeguide.com, 2014; Nti et al., 2019).

- Correlation Techniques: These relate system load to various economic and demographic factors, helping forecasters understand the relationship between load growth and measurable factors.
- Extrapolation Techniques: These include time-series or conventional methods that fit trend curves to historical data. The forecast is obtained by evaluating the trend curve function at the desired future point.

No single forecasting method is universally applicable. ELF techniques are categorized into data-driven (AI) techniques and engineering techniques, though there is no consensus on which is superior.

Machine Learning Algorithms: Machine learning (ML), a subset of artificial intelligence (AI), provides methods for solving complex problems (Stanisavljevic & Spitzer, 2016). ML enables software and machines to learn from experience without explicit programming. According to literature (Nti et al., 2019; Simeone, 2018; Stanisavljevic & Spitzer, 2016), ML algorithms can be categorized into:

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- Supervised Learning (SL): The algorithm learns from labeled data (training data) to build a model that predicts outcomes for new data.
- Unsupervised Learning (UL): The algorithm learns from unlabeled data to identify patterns and build models.
- Semi-Supervised Learning (SSL): Combines aspects of supervised and unsupervised learning.
- Reinforcement Learning (RL): The algorithm interacts with an environment to achieve a goal, learning from actions without a teacher.

Examples of ML algorithms include General Regression Neural Network (GRNN), Support Vector Machine (SVM), Artificial Neural Networks (ANN), and many others (Nti et al., 2021). Figure 2.2 illustrates ML algorithm classifications and examples.

A Systematic Review of Related Works:

This section provides a systematic review of studies on ELF. According to Keele (2007), a systematic literature review (SLR) aims to identify, assess, and discuss relevant works to answer research questions. An SLR must be comprehensive and unbiased to be scientifically valuable.

Kamilaris and Prenafeta-Boldú (2018) stated that SLR helps develop essential insights and identify potential research gaps. This study adopts a 3-stage SLR process (Ardabili et al., 2020; Mosavi et al., 2019; Sharma et al., 2020)

1. **Pre-Operational (Review Planning):**
2. **Operational (Conducting the Review):**
3. **Post-Operational (Review Findings):**

The aim is to answer questions such as: What factors influence ELF? What ML algorithms are used for electricity demand forecasting? What are the strengths and weaknesses of these algorithms? What timeframes and evaluation metrics are used in ELF?

Table 3: Articles Inclusion Criteria (IC)

Criteria	Definition
IC 1	Articles focused on electricity forecasting
IC 2	Articles written in English
IC 3	Articles published from 2014 onwards
IC 4	Review articles on topics other than ELF

Table 4: Articles Exclusion Criteria (EC)

Criteria	Definition
EC 1	Articles not focused on electricity forecasting
EC 2	Articles not written in English
EC 3	Articles published before 2014
EC 4	Review articles specifically on ELF

Table 5: Quality Assessment Criteria

Criteria	Definition
QAC 1	Are the objectives of the article clearly defined?
QAC 2	Are the methods and tools effectively used?
QAC 3	Are the study outcomes clearly and comprehensively explained?
QAC 4	Is there a logical connection between the study's introduction, outcomes, and conclusions?
QAC 5	Is the article a complete and cohesive work?

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II. Review Outcome

This section outlines the results of the SLR, highlighting key findings and gaps in the literature that justify the significance of this study.

Year-wise and Publisher-wise Distribution of Articles

Recently, electricity demand forecasting has gained significant attention in both academia and industry. Table 6 illustrates the yearly distribution of articles, showing a growing interest in electricity load forecasting over the years.

Table 6: Year-wise Distribution of Articles

Year	No. of Articles	%
2014	7	19%
2015	3	8%
2016	5	14%
2017	6	16%
2018	7	19%
2019	6	16%
2020	3	8%

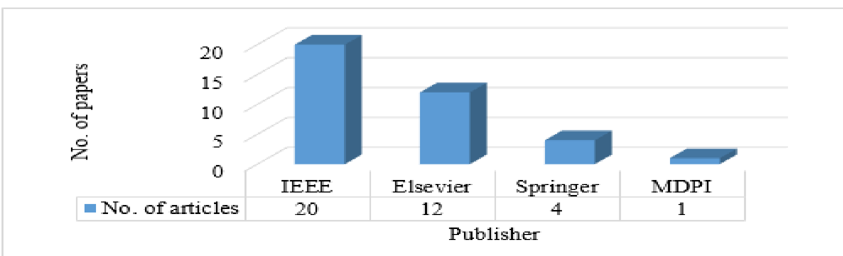

Figure 1

Figure 1 shows the distribution of articles by publisher, indicating that publishers like IEEE, Elsevier, and Springer recognize the importance of studies in this field. IEEE had the highest number of publications, likely due to its focus on engineering works.

Analysis Based on Used Forecaster: presents the most commonly used forecasting techniques in electricity demand literature. Seasonal ARIMA and ANN are the most popular classical methods for electricity load forecasting. The ARIMA model is favored for its ability to handle seasonal components in LTLF, where variations are less frequent. ANN and SVM are prominent computational intelligence techniques effective in modeling the non-linearity and complex relationships in electricity demand influenced by economic and environmental factors. However, existing AI-based models mainly address VSTLF challenges, while traditional statistical methods are static and rely on historical data (Bedi & Toshniwal, 2019).

Combining multiple forecasting techniques into hybrid models is believed to enhance accuracy. Hybrid models integrate various ML algorithms to leverage their strengths. Studies like Ganguly et al. (2020), Haq & Ni (2019), Jarndal & Hamdan (2017), Rusli et al. (2019), and Yildiz et al. (2017) demonstrate that hybrid techniques outperform individual models in electricity forecasting.

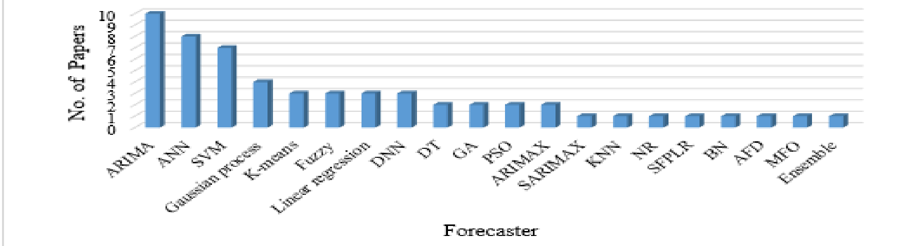

Figure 2

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Figure 2: Most Used Forecasters in Electricity Demand Forecasting: Deep neural networks, such as ANN (including BPNN and CNN), have been less frequently used. Only a few studies have applied DBN (Dedinec et al., 2016; Haq & Ni, 2019) and LSTM (Bedi & Toshniwal, 2019). PCA is widely used for dimensionality reduction (Aneiros et al., 2016; De Felice et al., 2015; Yildiz et al., 2017), while ensemble learning techniques, believed to be superior to single learners, have also been adopted (de Oliveira & Cyrino Oliveira, 2018; Divina et al., 2018; Pannakkong et al., 2018).

Despite the popularity of ARIMA and ANN, Pereira et al. (2015) found that the Fuzzy Inference System (FIS) performed better than SARIMAX. Fu et al. (2015) reported that SVM outperformed ARIMAX, DT, and ANN. Conversely, Azad et al. (2018) found that ANN optimized by the sine-cosine algorithm and GH outperformed SVM. These mixed findings suggest that the choice of forecasting method depends on factors like data characteristics, task type (regression or classification), and forecasting period.

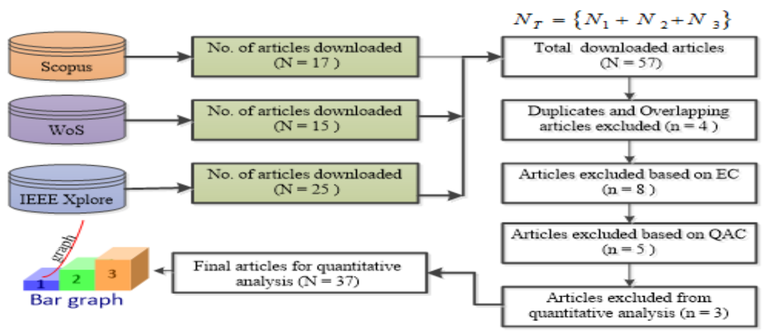

Figure 3

Figure 3 highlights the evaluation metrics commonly used to validate forecasting performance in literature, with MAPE, RMSE, and MAE being the most frequently used due to their suitability for regression analysis.

Figure 2.9: Commonly Used Evaluation Metrics

III. Summary of Analyzed Articles

Table 2.9 summarizes the analyzed articles. A significant proportion (56%) used correction techniques, 41% used extrapolation techniques, and 3% combined both. The forecasting windows showed 55% used STLF, 18% VSTLF, 16% LTLF, and 11% MTLF.

Of the 37 articles, 82% aimed to forecast future electricity demand using regression analysis, with few studies (5%) adopting classification techniques, and 13% using clustering methods. The origin of the analyzed articles showed 15% from Australia, 12% from India, and 7% each from Thailand, China, and Italy.

Figure 2.7 summarizes the most common predictors for electricity demand. Various factors like time, day, temperature, weather, and economic conditions influence ELF. Weather parameters, especially temperature, were the most frequently used predictors for STLF, MTLF, and LTLF. Studies often used historical load demand and weather variables (temperature, humidity, precipitation, and solar gain) as predictors. Economic variables and historical load demand were also commonly used, reflecting the interconnected nature of electricity consumption with human activities, population, and economic status.

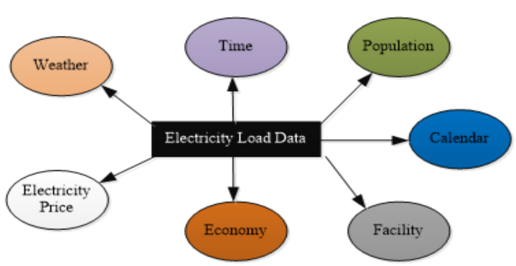

Figure 4 Different Factors Influencing ELF

MATLAB is the most commonly used platform for electricity forecasting due to its numerous built-in functions.

The significance of diverse forecasting methodologies and their applications has been highlighted by this systematic assessment of the literature, which delves into the changing landscape of energy demand forecasting. Many machine learning techniques,

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including ANN and SVM, as well as conventional statistical techniques like ARIMA, have been applied extensively and demonstrated significant forecasting performance. However, these traditional approaches are unable to completely address the continuous issues posed by the complexity and non-linearity of electricity consumption patterns.

According to the assessment, there is a growing interest in hybrid models, which mix several algorithms to take use of each one's unique characteristics and increase predicting accuracy. Research employing hybrid methodologies has shown to perform better than single-method approaches, indicating a promising avenue for further investigation. The article also emphasizes the unrealized promise of deep learning methods, especially LSTM networks, which provide sophisticated capabilities in processing sequential data and addressing problems such as the vanishing gradient problem.

The examined research identify crucial predictors like meteorological characteristics, economic indicators, and historical load data, which are important elements determining electricity demand. The emphasis on obtaining accurate and trustworthy forecasts is reflected in the widespread use of regression analysis and error metrics like MAPE, RMSE, and MAE for performance validation.

The research identifies shortcomings in the application of contemporary forecasting approaches despite notable developments, particularly in low- and middle-income nations. This emphasizes how more study is required to create reliable models that can be applied in a variety of geographic and economic circumstances.

Conclusion, there is a great deal of potential for improving the precision and dependability of electricity demand projections through the incorporation of deep learning methods and hybrid models. Subsequent investigations have to center on delving into these sophisticated techniques, refining their implementation throughout various projection periods, and attending to the particular requirements of marginalized areas. By doing this, the industry can get one step closer to creating all-inclusive solutions that facilitate effective global energy planning and management.

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