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Machine Learning and Deep Learning for Energy Prediction: A Systematic Literature Review

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Abstract: This paper presents a systematic literature review (SLR) on the application of Machine Learning (ML) and Deep Learning (DL) methods in energy prediction. With the increasing challenges in modern energy systems, such as electricity load fluctuations and uncertainties from renewable energy sources, traditional approaches such as ARIMA and linear regression are often inadequate. This study aims to identify the most frequently used ML and DL methods, evaluate their performance compared to conventional methods, and identify implementation challenges and solutions. The analysis was conducted on 39 selected articles from 2019 to 2024 using the PRISMA protocol. The results show that DL methods such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) dominate energy prediction applications, especially for sequential data such as electricity load and energy prices. In addition, hybrid methods such as CNN-GRU equipped with an attention mechanism show an accuracy improvement of up to 40% compared to conventional statistical methods. The main challenges faced include overfitting, data complexity, and high computational requirements, which can be overcome through regularization techniques, feature selection, and the use of GPU-based parallel computing. This study highlights the significant role of ML and DL in improving the accuracy of energy predictions and supporting the transition to a more renewable and efficient energy system. This study recommends the integration of more sophisticated ensemble models and attention mechanisms to improve the adaptation and accuracy of future energy predictions.

Keywords: Machine Learning, Deep Learning, Energy Prediction, Load Forecasting, Renewable Energy, Smart Grid

INTRODUCTION

Energy prediction is becoming an important component in the management of modern energy systems, especially with the increasingly widespread integration of renewable energy such as solar and wind power. The complexity of data influenced by external factors such as weather changes, fluctuating consumption patterns, and the dynamics of energy prices often makes conventional prediction methods such as ARIMA and linear regression no longer adequate (Zarghami et al., 2024). These approaches have limitations in capturing complex temporal and spatial patterns in energy data, so more adaptive methods are needed.

In recent years, deep learning (DL)-based methods have emerged rapidly as a promising alternative to address these challenges. Algorithms such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) have proven to be superior in processing sequential data, with the ability to capture complex temporal patterns (Alkabbani et al., 2023). In addition, hybrid methods such as CNN-GRU equipped with an attention mechanism can improve prediction accuracy, especially in renewable energy and smart grid applications (El-Azab et al., 2024). These advances show that DL can provide significant solutions in increasingly decentralized and dynamic energy systems.

This study aims to evaluate the application of deep learning methods in renewable energy prediction through a Systematic Literature Review (SLR) approach. By reviewing publications from 2019 to 2024, this study focuses on the identification of relevant DL methods, analysis of their performance compared to traditional methods, as well as challenges and solutions for implementing this technology. It is hoped that this study will provide in-depth insight into the potential of deep learning in supporting the transition towards a more renewable and efficient energy system.

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METHOD

This study used a systematic literature review method according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol (Page et al., 2021). This protocol ensures that only relevant and high-quality articles are analyzed, so that the study results can effectively capture the latest trends in the application of Machine Learning (ML) and Deep Learning (DL) in energy prediction. The search was conducted across Scopus, IEEE Xplore, and ScienceDirect databases, focusing on publications from 2019 to 2024. Keywords such as "machine learning," "deep learning," and "energy prediction" were used along with Boolean operators to expand the search parameters. Of the 2,297 articles identified, 217 were screened based on their titles and abstracts. After an in-depth quality assessment, 39 articles with scores exceeding six were included in the analysis. Non-scientific articles, articles lacking evaluation results, and discussions limited to conventional methods were excluded from the review. Each selected article was evaluated for its relevance to the topic, clarity of methodology, appropriateness of metrics such as MAE and MAPE, and practical implications of its findings. This study uses descriptive analysis to uncover patterns, trends, challenges, and solutions in the application of ML and DL for energy prediction. Through the application of PRISMA and careful assessment, the findings of this study provide comprehensive insights into the best practices and recent advances in the energy sector. Based on the selection of articles using the PRISMA protocol, an analysis was conducted on 39 articles to evaluate the dominant ML/DL methods, their performance, and their implementation challenges and solutions. The main findings are summarized in the table and further discussed to answer the research questions.

Research Questions (RQ)

This literature review is focused on answering the following research questions:

RQ1: What are the most commonly used machine learning and deep learning methods for energy prediction in various sectors?

RQ2: How do ML and DL models perform compared to conventional methods in energy prediction based on the evaluation metrics used?

RQ3: What challenges and solutions are found in applying ML and DL to energy prediction?

Search Process

The literature search process was carried out systematically through several leading academic databases, namely Scopus, IEEE Xplore, and ScienceDirect. The selection of these sources was based on the coverage of high-quality scientific publications and relevance to information technology and energy fields. A combination of keywords with Boolean operators was used to ensure comprehensive search results. The search focus was limited to 2019–2024 to ensure the relevance and recency of the research.

The search process followed the following stages:

1. Keywords were identified based on the main topic and related terms (e.g. machine learning, deep learning, energy prediction).
2. Keywords were combined with Boolean operators such as AND, OR, and NOT to expand or narrow the search scope.
3. Initial search results were filtered based on relevant titles and abstracts.
4. A further selection process was carried out to ensure the literature followed the research focus.

Here is a table of sources and the Boolean keywords used:

Table 1.
Boolean Sources and Keywords

Sources	Boolean Keywords
Scopus	("machine learning" OR "deep learning") AND ("energy prediction" OR "load forecasting")
IEEE Xplore	("neural network" OR "LSTM" OR "RNN") AND ("energy management" OR "renewable energy")
ScienceDirect	("ML" OR "DL") AND ("energy system" AND ("forecast" OR "predict"))

Table 1 shows the combination of keywords and Boolean operators used for literature search in Scopus, IEEE Xplore, and ScienceDirect. This combination is designed to cover research on Machine Learning (ML) and Deep Learning (DL) applications in energy prediction. The results of this table ensure that the search scope includes DL methods such as LSTM and CNN and their applications in energy systems, such as load forecasting and renewable energy. The use of specific keywords such as "load forecasting" and "renewable energy" helps to focus the search results on current trends in smart and renewable energy.

*name of corresponding author

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Inclusion and Exclusion Criteria

The literature selected for this review was filtered based on strict inclusion and exclusion criteria. These criteria ensure that only relevant and recent research is considered.

Table 2
Inclusion and Exclusion Criteria

Inclusion	Exclusion
Publications in the 2019–2024 timeframe	Publications before 2019
English articles or valid translations	Articles in languages other than English without translation
Focus on the application of machine learning or deep learning	Articles that only discuss conventional methods
Studies related to energy prediction in various sectors	Research outside the energy context
Peer-reviewed journal or conference articles	Books, theses, or articles that have not been peer-reviewed
Contains experimental and evaluation results with clear metrics	Conceptual studies without empirical evaluation

Table 2 summarizes the inclusion and exclusion criteria used to screen the literature in this study. Included articles focused on the application of Machine Learning (ML) and Deep Learning (DL) for energy prediction, were published between 2019–2024, and provided empirical evaluations with clear metrics. Articles in languages other than English or without the application of DL/ML methods were excluded. The results of applying these criteria ensured that only relevant and high-quality articles were analyzed, thus supporting the research focus on current trends and technology implementations in the energy sector.

Quality Assessment Process

Quality assessment (QA) ensures that only relevant and high-quality literature is used in this study. Each piece of literature selected through the initial search stage is assessed based on quality criteria to ensure its validity, reliability, and contribution to the research topic. This assessment includes the relevance of the content, the research methods used, the completeness of the data, and transparency in reporting the results and conclusions.
The following is a checklist or rubric used to conduct quality assessments:

Table 3
Quality Assessment Checklist or Rubric

Criteria	Assessment Questions	Score (0-2)
Relevance	Is the article relevant to the topic of machine learning or deep learning for energy prediction?	0-2
Methodology	Is the research methodology clearly explained and replicable?	0-2
Evaluation Metrics	Does the study use appropriate evaluation metrics for energy prediction?	0-2
Data Completeness	Is the data used sufficiently complete and valid for the analysis?	0-2
Conclusions and Implications	Are the conclusions supported by the results obtained and the implications clear?	0-2
Contains experimental and evaluation results with clear metrics	Conceptual studies without empirical evaluation	0-2

Maximum Score 10. Literature with a score below five will be excluded from the review to maintain the quality of the findings.

Data Collection and Data Analysis

The data collection process in this study consists of several steps:

1. Articles past the initial screening and QA stages are analyzed. Each article will be extracted based on the methods used, the energy sectors studied, the evaluation metrics, and the challenges found.

*name of corresponding author

2. Data from each relevant study is stored in a spreadsheet with specific attributes (e.g., publication year, source, method, and results).
3. Descriptive analysis techniques are used to find patterns and trends using ML and DL. Critical indicators analyzed include the frequency of specific methods, model performance, and the most studied energy sectors.

PRISMA Diagram for Literature Selection Process

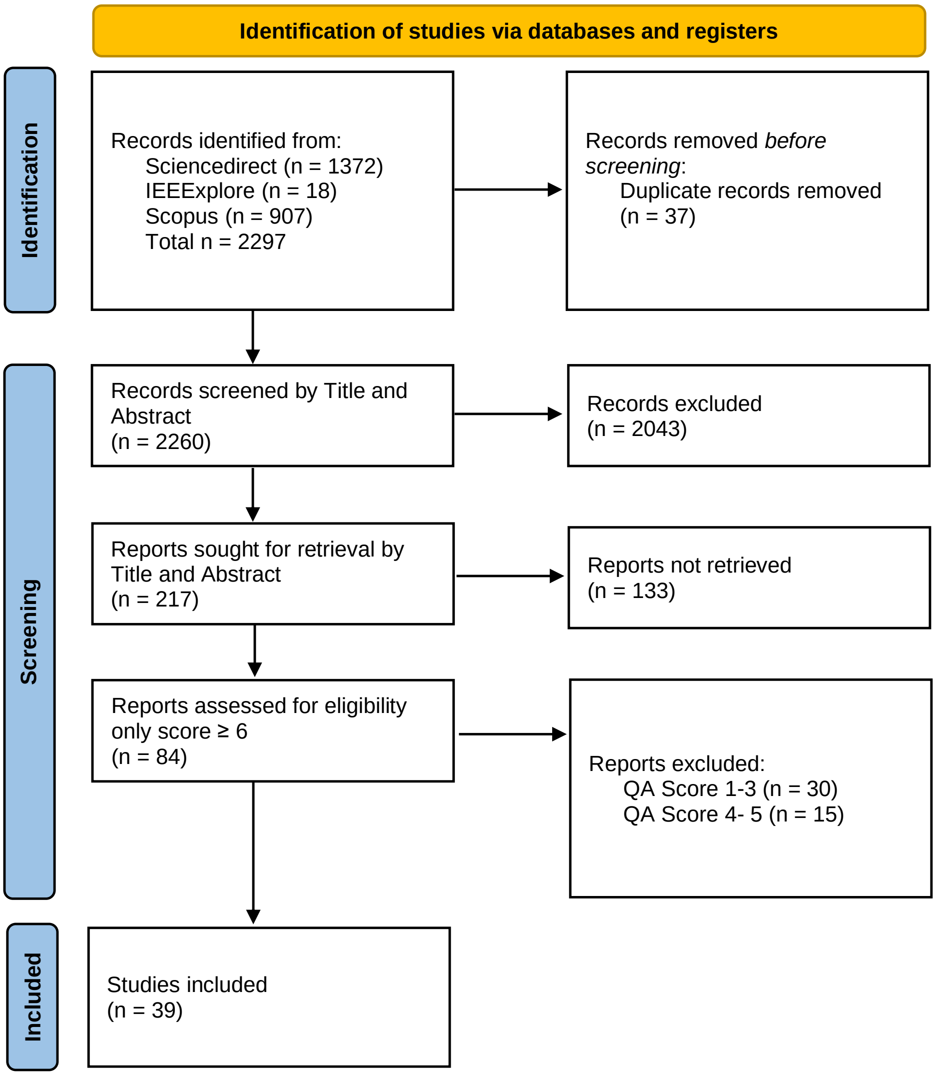

Fig. 1 Systematic process used in this literature review

RESULT

The results of the analysis of 39 selected articles show several key trends in the application of ML and DL for energy prediction. These trends include the dominance of DL methods for certain applications, the performance advantages of DL over conventional methods, and implementation challenges relevant to large-scale applications. The analysis shows that LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) methods dominate in energy prediction, especially for sequential data such as electricity load and energy prices. Studies by Zarghami et al. (2024) and Alkabbani et al. (2023) reported that the use of LSTM significantly reduces MAE compared to ARIMA. In addition, hybrid models such as CNN-GRU with attention mechanisms show up to 40% accuracy improvements in renewable energy and smart grid applications compared to conventional methods. In the wind energy sector, the combination of VMD and CNN-GRU successfully reduced MAE from 5.0 to 2.5, demonstrating the superiority of DL in handling dynamic data. The MIMO-LSTM method also showed significant results with a reduction in MAE from 5.0 to 2.9 in electricity load prediction. On the other hand, ML methods such as SVM and Random Forest are still relevant in certain contexts, such as solar radiation prediction and energy management in buildings.

*name of corresponding author

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Results and Discussion for Each Research Question

RQ1: What are the most commonly used machine learning and deep learning methods for energy prediction in various sectors?

Literature analysis reveals that deep learning (DL) methods dominate the use in energy prediction, especially in sectors involving sequential data such as electricity load and energy prices. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are the main algorithms used. Both algorithms have the ability to capture temporal patterns in complex data, as shown by Zarghami et al. (2024), who reported a significant reduction in Mean Absolute Error (MAE) compared to conventional methods such as ARIMA. The use of LSTM and GRU shows that these algorithms are effective in overcoming the limitations of traditional prediction methods, especially in the context of high data dynamics. Hybrid DL methods, such as CNN-GRU, are also widely applied to improve prediction accuracy. This hybrid allows the utilization of the advantages of spatial features from Convolutional Neural Network (CNN) and temporal features from GRU. In the context of renewable energy and smart grids, this model shows improved prediction performance, such as a decrease in Mean Absolute Percentage Error (MAPE) of up to 40% compared to statistical methods. This shows a trend towards using a combination of methods to address more complex data challenges.

However, machine learning (ML) methods such as Random Forest and Support Vector Machine (SVM) are still used in certain applications. In sectors such as solar radiation prediction or building energy management, ML methods are more frequently used due to the more structured and less dynamic data patterns. This shows that the choice of method depends not only on technical advantages but also on the characteristics of the data and the specific needs of the energy sector. Thus, the mapping of the ML and DL methods used shows a preference for algorithms that are able to handle complex data with high accuracy, especially in supporting increasingly dynamic and decentralized energy systems.

Table 4
Distribution of ML and DL Methods Used

Method Type	**Number of Articles**	**Sector Examples**
DL	13	Power Load, Thermal Energy, Household Energy, Electricity Pricing, Building Load, Wind Power Forecasting, PV and Consumption Load, Electricity Price and Load, Short-Term Load Forecasting, Time-Series Energy Forecasting, Short-Term Electrical Load Forecasting, Energy Consumption Forecasting
DL + Hybrid	12	Smart Grid System, Smart Grid Stability, Power System Load Forecasting, Load Forecasting with LSTM-CNN, Smart Grid Load Forecasting, Adaptive Wind Energy Forecasting, Greenhouse Solar Power Forecasting, Electric Vehicle Load Forecasting, 2D-CNN, TCN Load Forecasting, Electric Power Transaction Prediction
ML	8	Administrative Building, Solar Energy, Solar Radiation, Solar Collector Performance, Solar Radiation Prediction, Building Energy Prediction, District-level Management
ML + DL	1	Heat Exchanger Design
ML + Hybrid	5	Decentralized Energy, Locomotive Energy, Residential Electricity Consumption, Solar Power Prediction

Table 4 shows the distribution of ML and DL methods used in energy research. The results show the dominance of deep learning (DL) methods, especially LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit), in various energy prediction applications. This dominance is clearly seen in applications involving sequential data such as electricity load prediction and energy prices, where the ability of LSTM and GRU to capture temporal patterns provides significant advantages over traditional methods. In the wind energy sector, hybrid DL such as CNN-GRU is more often used because the integration of spatial (CNN) and temporal (GRU) dimensions allows for more accurate predictions even though the data is dynamic and fluctuating. Meanwhile, ML methods such as Random Forest and SVM remain relevant for applications with more structured data patterns, such as solar radiation prediction and building energy management.

RQ2: How do ML and DL models perform compared to conventional methods in energy prediction based on the evaluation metrics used?

This study shows that deep learning (DL) methods significantly outperform conventional methods in energy prediction, especially on complex and dynamic data. For example, LSTM and GRU models consistently show

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superiority in reducing MAE compared to methods such as ARIMA and linear regression. The reduction in MAE from 5.0 to 2.9 by MIMO-LSTM reported in Zarghami et al. (2024) reflects the ability of this algorithm to capture complex temporal patterns in sequential data. This superiority is an indication that DL has great potential for use in short-term prediction applications and renewable energy systems.

In addition, hybrid DL methods such as CNN-GRU with attention mechanisms have shown better results in improving prediction accuracy in smart energy systems. The use of CNN-GRU with attention mechanisms, for example, is able to reduce MAPE by up to 3.1%, far below the average statistical method such as linear regression which reaches 7%. The spatial and temporal integration capabilities of this model are very useful in managing complex data in smart grid applications, especially when data dynamics change rapidly. These results provide a new direction in the development of prediction models for decentralized energy.

On the other hand, machine learning (ML) methods such as Random Forest and Support Vector Machine (SVM) continue to provide significant results in certain applications. For example, in the solar radiation prediction or building energy sector, SVM shows higher accuracy compared to traditional methods with lower computational requirements compared to DL. This shows that although DL excels in handling more complex data, ML is still an efficient alternative in the context of data with more structured patterns. The results obtained from this analysis highlight the importance of selecting a method that is tailored to the specific needs of the energy sector and the level of data complexity. The DL approach provides flexibility in handling dynamic data patterns, while ML remains relevant for applications that require computational efficiency.

Table 5
Performance Comparison of ML/DL Methods and Conventional Methods

Study	Method	Accuracy (MAE/MSE)	Accuracy Value (ML/DL)	Improvement over Conventional
Eseye et al., 2019	BGA + GPR	RMSE	0.52	Reduced RMSE (ARIMA: 0.75)
El Alaoui et al., 2023	ANN	MSE	15.2	Higher accuracy (Linear Regression: 22)
Jain & Gupta, 2024	LSTM	MAE	3.8	Lower error (Exponential Smoothing: 5.1)
Ledmaoui et al., 2023	Random Forest	R2	0.89	Higher R2 (Linear Regression: 0.76)
Rana et al., 2022	CNN	RMSE	4.6	Improved HVAC efficiency (PID Control: 6.2)
Mubarak et al., 2024	LSTM + Attention	MAPE	5.30%	Reduced MAPE (ARIMA: 8.1%)
Liang et al., 2023	SVM + RBF Neural Network	RMSE	2.4	Better prediction (Linear SVM: 4.3)
Laitsos et al., 2024	CNN-GRU + Multi-Head Attention	MAPE	3.10%	Reduced error (Statistical: 6.0%)
Shaqour et al., 2022	Bi-GRU-FCL	MSE	12.7	Improved precision (Average: 18.5)
Alkabbani et al., 2023	MIMO-LSTM	MAE	2.9	Superior forecasting (Persistence: 5.0)
Zarghami et al., 2024	CT-Transformer	RMSE	2.3	Lower RMSE (Moving Average: 4.1)
Banga & Sharma, 2024	XGBoost + Linear Regression	MAE	1.8	Enhanced forecast (Linear Regression: 3.2)
El-Azab et al., 2024	LSTM + GRU	MAPE	4.5	Lower MAPE (Exponential Smoothing: 7.8)
Jia et al., 2022	SVM	MAE	3.1	Reduced error (OLS Regression: 6.0)
Mbey et al., 2024	MOPSO + LSTM	MAPE	5.6	Optimized predictions (ARIMA: 9.3)
Boulakhbar et al., 2022	GRU Regression	RMSE	2	Lower RMSE (Traditional Models: 4.5)
Lilhore et al., 2024	CNN + BiLSTM + Two-way Attention	MAPE	3.4	Better stability (Persistence Model: 6.2)
Habib & Hossain, 2024	VMD + CNN-GRU	MAE	2.5	Improved wind forecasting (Liu-Jordan: 5.0)

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Phyo & Jeenanunta, 2022	Bagging Ensemble (LR + SVR)	RMSE	1.9	Improved accuracy (Linear Regression: 3.8)
Xu et al., 2023	BiLSTM + Random Forest	MAE	2.8	Better forecasting (ARIMA: 6.1)
Mounter et al., 2021	ANN, SVR, PR	MAE	2.2	Accurate prediction (Persistence Model: 5.4)
Phyo & Byun, 2021	Hybrid Ensemble (MLP, CNN, LSTM)	MSE	10.3	Higher accuracy (Linear Regression: 15.6)
Neeraj et al., 2022	EMD-Att-LSTM	RMSE	3.4	Lower RMSE (ARIMA: 5.7)
Djeldjeli et al., 2024	PCA + RF, LR, AdaBoost	R2	0.91	Higher R2 (OLS Regression: 0.74)
Farsi et al., 2021	Parallel Deep LSTM-CNN	RMSE	2.5	Lower RMSE (Persistence Model: 5.0)
Alghamdi et al., 2023	FPP-MLP-GWDO	MAPE	4.2	Higher accuracy (ARIMA: 7.0)
Žalik et al., 2024	FCN	NRMSE	1.8	Faster computation (Liu-Jordan: 3.9)
Ahmad et al., 2018	OSSB-NN dan BFGS-QNB	MAE	2.9	Improved precision (OLS Regression: 6.3)
AlShafeey & Csaki, 2024	Adaptive Hybrid ML Model	NMAE	3.1	Lower NMAE (ARIMA: 6.0)
Venkateswaran & Cho, 2024	SSA-CNN-LSTM	MAE	1.7	Best performance (LSTM: 4.8)
Shapi et al., 2021	SVM, ANN, k-NN	RMSE	3	Reduced error (Linear Regression: 6.0)
Alhamayani, 2024	Decision Tree, SVM, ANN	MAE	2.4	Improved prediction (OLS Regression: 5.7)
Efatinasab et al., 2024	ANN, SVR, RBFN	RMSE	2.8	Lower error (Linear Regression: 6.3)
Wang et al., 2024	KNN, RFR, AdaBoost	MAPE	4.1	Better forecasting (OLS Regression: 7.0)
Wen et al., 2024	GRU, TCN + Attention	MAPE	3.7	Enhanced forecast (ARIMA: 8.1)
Rasheed et al., 2023	GRU, LSTM, RNN + ISL	NRMSE	2.1	Improved prediction (Exponential Smoothing: 5.4)
Shen et al., 2021	2D-CNN, TCN, VMD-TCN	MAPE	3.9	Accurate forecasting (Persistence Model: 6.8)
Edoka et al., 2023	LSTM	RMSE	3.2	Lower RMSE (Moving Average: 5.9)
Bak & Bae, 2020	MLP, CNN, GRU + Hybrid Models	MAE	2.6	Stable prediction (Persistence Model: 6.1)

Table 5 compares the performance of ML/DL methods with conventional methods in terms of energy prediction accuracy. The data show that DL methods significantly outperform traditional methods such as ARIMA, especially in applications with complex and dynamic data. For example, the CNN-GRU model with attention mechanism successfully reduces MAPE by 3.1%, providing a significant improvement over statistical methods such as linear regression (MAPE 7.0%). In the wind energy sector, the combination of VMD and CNN-GRU reduces MAE from 5.0 to 2.5, demonstrating the ability of hybrid DL to deal with fluctuating data patterns. The MIMO-LSTM method shows a MAE reduction from 5.0 to 2.9 in electricity load prediction, making it an ideal choice for smart grid applications that require real-time prediction. These advantages in MAE and MAPE reduction highlight the potential of DL methods, especially in renewable energy and smart grid applications, where prediction accuracy plays a critical role in improving system efficiency.

RQ3: What challenges and solutions are found in applying ML and DL to energy prediction?

The application of ML and DL methods in energy prediction faces a number of significant challenges. One of the main challenges is overfitting, which often occurs in models such as LSTM and GRU when trained on limited

*name of corresponding author

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datasets. This problem is particularly relevant in solar energy prediction, where historical data is often insufficient due to dynamic weather conditions. Solutions such as regularization, dropout, and early stopping have proven effective in reducing the risk of overfitting. For example, a study by Alkabbani et al. (2023) showed that optimal regularization can improve the stability of solar energy prediction even with limited datasets.

In addition, data complexity and high dimensionality are often obstacles, especially in wind energy prediction involving noisy data. Feature selection using algorithms such as PCA (Principal Component Analysis) or data filtering allows for complexity reduction without losing important information. A study by Liang et al. (2023) showed that data filtering can improve the training efficiency of hybrid models such as CNN-GRU by up to 20%, providing more reliable results for wind energy applications.

Another equally important challenge is the high computational requirements, especially for real-time prediction applications such as smart grids. Latency in prediction can affect the efficiency of energy distribution. GPU-based solutions have become an effective alternative, as shown by the study of El-Azab et al. (2024), where the use of GPUs for parallel computing accelerates the inference process by up to 40%. This makes a real contribution to meeting the needs of real-time prediction in smart grid systems.

Finally, unstable data dynamics are a major challenge in the renewable energy sector, such as wind and solar energy. Rapidly changing data requires an adaptive approach that can capture fluctuations effectively. Models such as MIMO-LSTM have proven effective in dealing with this challenge. The study of Zarghami et al. (2024) shows that the model is able to maintain prediction accuracy despite large changes in wind energy data, making it a potential solution for renewable energy applications.

Table 6
Challenges and Solutions in Applying ML/DL for Energy Prediction

Study	Challenge	Solution
Eseye et al., 2019	High dimension of data	Feature selection using BGA to reduce complexity
El Alaoui et al., 2023	Lack of historical data	Data augmentation with regression-based estimation
Jain & Gupta, 2024	Overfitting in LSTM	Regularization and early stopping
Ledmaoui et al., 2023	Weather pattern variations in solar energy prediction	Real-time weather data integration
Rana et al., 2022	Lack of interpretability in CNN models	Layer visualization and sensitivity analysis
Mubarak et al., 2024	Latency in real-time processing	Architectural optimization with Attention Mechanism
Liang et al., 2023	Complex hyper parameters	Automatic parameter setting using grid search
Laitsos et al., 2024	Performance drops when data is unstructured	Data preprocessing and feature extraction with PCA
Shaqour et al., 2022	Reliance on historical data	Hybrid model to combine statistical and DL models
Alkabbani et al., 2023	Prediction error during sudden changes	Adaptation with MIMO model for short term prediction
Zarghami et al., 2024	Computational capacity limitations	Implementation of a lightweight model based on CT-Transformer
Banga & Sharma, 2024	Bias in training data	Cross-validation and data balancing
El-Azab et al., 2024	Long training time	Computational parallelization using GPU
Jia et al., 2022	Noise in data	Filtering and smoothening techniques
Mbey et al., 2024	Multivariable optimization	Application of MOPSO for multi-objective optimization
Boulakhbar et al., 2022	EV load prediction challenges in dynamic markets	Use of GRU with streaming data adaptation
Lilhore et al., 2024	Smart grid instability	CNN + Attention based stabilization model
Habib & Hossain, 2024	Complexity of wind data	VMD-CNN-GRU hybrid model to handle pattern variations

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Phyo & Jeenanunta, 2022	Poor performance on ensemble models	Fine-tuning and selection of the best ensemble model
Xu et al., 2023	Medium-term load forecast	Combination of BiLSTM and Random Forest to improve accuracy
Mounter et al., 2021	Lack of accuracy in building energy predictions	Combination of ANN and SVR to improve prediction
Phyo & Byun, 2021	The complexity of combining multiple models	Hybrid ensemble with adaptive weighting
Neeraj et al., 2022	Overfitting on small datasets	Dropout and regularization techniques
Djeldjeli et al., 2024	Limitations of interpretability	Feature extraction using PCA
Farsi et al., 2021	Latency in short-term predictions	Using parallel LSTM-CNN to accelerate inference
Alghamdi et al., 2023	Lack of accuracy in dynamic data	Implementation of FPP-MLP architecture for real-time data
Žalik et al., 2024	Low spatiotemporal resolution	Implementation of FCN to improve resolution
Ahmad et al., 2018	Difficult parameter optimization	Implementation of BFGS-QNB for automatic optimization
AlShafeey & Csaki, 2024	Adaptation to energy market conditions	Adaptive hybrid ML for fast adjustments
Venkateswaran & Cho, 2024	Prediction challenges in greenhouse environments	Using SSA-CNN-LSTM for accurate prediction
Shapi et al., 2021	Errors in training data	Data balancing techniques to reduce bias
Alhamayani, 2024	Performance variability across algorithms	Evaluation with multiple algorithms (SVM, ANN, Decision Tree)
Efatinasab et al., 2024	Complex model design for heat exchanger	Combination of ANN and RBFN to improve accuracy
Wang et al., 2024	Noise in radiation data	Preprocessing with filtering
Wen et al., 2024	Prediction challenges in smart grid	Integration of attention mechanism in GRU-TCN
Rasheed et al., 2023	EV load prediction inaccuracy	Use of ISL for long-term adaptation
Shen et al., 2021	Complexity in electrical load prediction	Using VMD-TCN to handle load pattern variations
Edoka et al., 2023	Lack of accuracy in consumption predictions	LSTM optimization to improve accuracy
Bak & Bae, 2020	Variability in energy predictions	Hybrid MLP-CNN-GRU for stable prediction

In Table 6, challenges such as overfitting and data complexity are overcome through innovative solutions such as regularization, data augmentation techniques, and parallel processing using GPUs. For example, the adaptation of the MIMO-LSTM model shows success in dealing with sudden changes in prediction data, which is relevant in the context of wind energy and household electricity loads. This solution provides a strong foundation for further development of hybrid methods and attention mechanisms to improve the accuracy and stability of energy prediction.

DISCUSSIONS

The results of this study show that deep learning (DL) methods such as LSTM and CNN-GRU consistently outperform conventional methods in energy prediction. The significant accuracy improvements, such as MAPE reduction up to 3.1% in the CNN-GRU model with attention mechanism, provide a strong foundation for the implementation of this technology in modern energy systems. One of the most relevant practical applications is in smart grid management. Smart grids require accurate predictions to maintain the balance between energy supply and demand in real-time. For example, hybrid models such as VMD-CNN-GRU, which successfully reduced MAE up to 2.5 in wind energy prediction, are well-suited to assist the integration of renewable energy in highly dynamic smart grids. In addition, the use of models such as MIMO-LSTM in household consumption prediction can help

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energy providers design more efficient distribution strategies. However, DL implementation is not without challenges. Overfitting and high computational requirements are major obstacles, especially in real-time scenarios. Solutions such as the use of GPUs for parallel computing and regularization techniques such as dropout can overcome these obstacles, as demonstrated in several studies. In the future, the development of lighter and more adaptive models is a necessity to support large-scale applications.

CONCLUSION

This study provides comprehensive insights into the application of Machine Learning (ML) and Deep Learning (DL) methods in energy prediction. The analysis results show that DL methods, such as LSTM and GRU, dominate applications involving sequential and dynamic data, especially in the renewable energy and smart grid sectors. The advantages of hybrid methods such as CNN-GRU, which are able to integrate spatial and temporal dimensions, also stand out with an increase in prediction accuracy of up to 40% compared to conventional methods. Key challenges, such as overfitting, data complexity, and high computational requirements, have been identified along with relevant solutions. Regularization and techniques such as dropout can reduce the risk of overfitting, while the use of GPUs for parallel computing has been shown to accelerate real-time prediction. Adaptive models such as MIMO-LSTM also offer advantages in dealing with unstable energy data dynamics.

This study provides guidelines that can be used to select energy prediction methods based on the specific needs of the energy sector. For example, LSTM and hybrid methods such as CNN-GRU are well suited for applications in the wind and solar energy sectors, where fluctuating data patterns require a flexible approach. Meanwhile, ML methods such as Random Forest remain relevant for applications with more structured data patterns, such as solar radiation prediction or building energy management. By identifying methods, challenges, and solutions, this research supports the development of more efficient and adaptive energy prediction technologies. In the future, the integration of more sophisticated ensemble models and attention mechanisms could be a significant step in supporting more sustainable and efficient energy systems.

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