Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 4s (2025)

Enhancing Short- and Medium-Term Electricity Load and Price Forecasting Using a Hybrid CNN-AM Model

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Article History:

Received: *03-10-2024*

Revised: *30-11-2024*

Accepted: *09-12-2024*

Abstract:

By using a unique hybrid model, this study seeks to improve the precision and dependability of short- and medium-term power load and price forecasts in the energy market. The paper tackles the urgent need for sophisticated forecasting tools that can handle the complexity of energy data by combining the ensemble empirical mode decomposition (EEMD) algorithm with a convolutional neural network using an attention mechanism (CNN-AM). By efficiently extracting intrinsic mode functions that are essential for precise predictions, EEMD optimises the decomposition process of raw data. Concurrently, the CNN-AM improves the model's capacity to highlight important aspects of the data, which raises the forecasts' interpretability and accuracy. The model's performance is verified on a variety of datasets, demonstrating its potential for reliable use in practical situations. Future research directions are examined, such as dynamic model updates to adjust to changing market conditions, overall model resilience, and the inclusion of external factors affecting load and price. The ultimate goal of this research is to provide energy industry stakeholders with a reliable forecasting tool that will enable strategic decision-making and well-informed risk management.

Keywords: Attention Mechanism, Computational Efficiency, Convolutional Neural Network (CNN), Electricity Load Forecasting, Electricity Price Forecasting, Empirical Mode Decomposition (EEMD), Mean Absolute Percentage Error (MAPE), Medium-term Forecasting, Root Mean Squared Error (RMSE), Short-term Forecasting, Time-Series Data, Hybrid Model.

I. Introduction

A. Overview of Electricity Load and Price Forecasting in Energy Markets

In the energy market, forecasting electricity load and pricing is essential for effective grid management, resource planning, and the creation of financial strategies as shown in fig. 1 By keeping supply and demand in balance, accurate forecasting lowers the likelihood of blackouts or energy shortages and ensures grid resilience. With the use of pricing projections, utilities and other stakeholders can effectively manage investments, predict market trends, and optimise pricing strategies. The need for sophisticated forecasting methods has increased due to the growing use of renewable energy sources, which are inherently unpredictable. These projections also promote transparency in energy transactions and help regulators create policies. Stakeholders can promote stability and efficiency in the energy sector by proactively responding to market dynamics by comprehending the intricacies of load and price behaviours over short and medium terms.

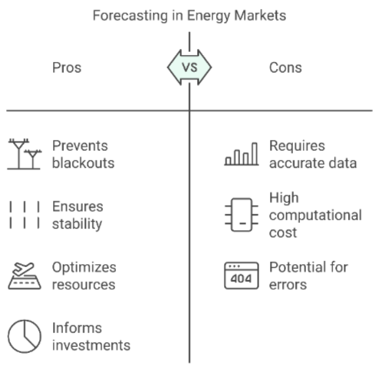

Fig. 1: Pros and cons of energy forecasting

B. Challenges in Current Forecasting Models

The complexity of contemporary energy data is too much for conventional models for estimating electricity load and pricing, such as linear regression and autoregressive integrated moving average (ARIMA). The predictive effectiveness of these models is limited by the non-linear and non-stationary nature of energy load and price patterns, which are impacted by a variety of factors such consumer behaviour, economic conditions, and weather. Although machine learning techniques like decision trees and support vector machines have increased accuracy, they frequently perform poorly when applied to datasets with different properties. Furthermore, these models have trouble keeping up with the quick changes in the energy markets, like the increasing importance of renewable energy sources and real-time energy trading. These drawbacks show how stronger methods are required to manage dynamic, multi-dimensional, and large-scale datasets.

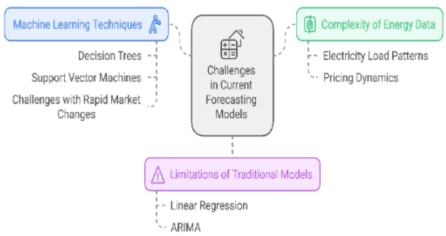

Fig. 2: Challenges in Current Forecasting Models

C. Emergence of Hybrid Forecasting Techniques

The drawbacks of solo models have led to the rise in popularity of hybrid forecasting systems. Hybrid models leverage each method's capabilities to increase accuracy and dependability by combining complimentary techniques. For example, complicated signals can be broken down into simpler components for focused examination by combining machine learning models with decomposition methods. Hybrid approaches tackle issues like temporal fluctuations, feature interdependencies, and non-linear data behaviour in the context of energy markets. They are perfect for situations where market fluctuations and data complexity are high because they provide increased robustness and adaptability. The development of these methods signifies a paradigm shift in forecasting, aiming towards models that are durable in dynamic contexts in addition to being accurate.

D. *Role of Decomposition Algorithms in Data Analysis*

By decomposing complicated signals into intrinsic mode functions (IMFs), decomposition methods such as ensemble empirical mode decomposition (EEMD) are essential for data analysis. This procedure assists in identifying significant trends and patterns that could be hidden in unprocessed data. EEMD solves the problems caused by non-stationary and non-linear data in electricity forecasting, enabling models to concentrate on particular aspects of variability. The EEMD-extracted IMFs make it easier to spot long-term trends, seasonal patterns, and sudden shifts. EEMD is a useful tool in hybrid forecasting systems because it improves the prediction ability of machine learning models by lowering noise and streamlining data representation.

E. *Advancements in Neural Networks for Time-Series Prediction*

Because convolutional neural networks (CNNs) can automatically extract hierarchical characteristics from data, they have become extremely effective tools for time-series prediction. CNNs employ convolutional layers, as opposed to conventional neural networks, to find patterns in energy data, including trends and anomalies. They are ideal for forecasting electricity because of their resilience in managing huge datasets and spatial-temporal correlations. Recurrent structures for sequential learning and attention processes to prioritise important aspects are examples of recent developments. These developments have greatly increased CNNs' scalability and accuracy, allowing them to successfully handle the complexity of contemporary energy systems.

F. *Significance of Attention Mechanisms in Deep Learning*

By allowing them to selectively concentrate on pertinent features inside data, attention mechanisms improve the performance of deep learning models. By giving crucial components priority weights, attention mechanisms increase interpretability and accuracy in electricity forecasting, where datasets frequently contain redundant or noisy information. By highlighting important patterns and relationships, attention mechanisms enhance convolutional layers in hybrid models like CNN-AM, making this functionality very useful. Attention mechanisms help the model adjust to changing market conditions and guarantee accurate projections by dynamically changing focus based on data features.

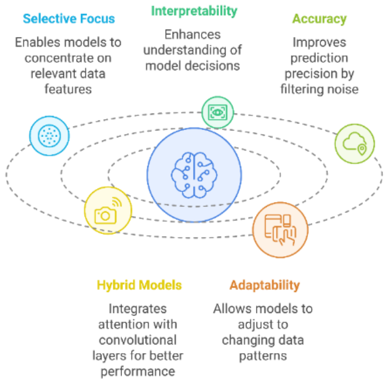

Fig. 3: The Role of Attention Mechanisms in Deep Learning

G. Motivation for Developing a Hybrid CNN-AM Model with EEMD

The main drawbacks of conventional and stand-alone machine learning models for electricity forecasting are addressed by the combination of EEMD and CNN-AM. CNN-AM improves feature extraction and prioritisation using attention processes, while EEMD maximises raw data preprocessing by separating intrinsic mode functions. By identifying intricate patterns and relationships that would otherwise go unnoticed, our hybrid technique guarantees a more thorough study of energy data. This model's potential to close forecast accuracy, interpretability, and adaptability gaps and give stakeholders a dependable and effective forecasting tool is what motivates it.

Impact of Accurate Forecasting on Energy Market Stakeholders
For utilities, regulators, and customers, among other energy market participants, accurate forecasting has significant ramifications. Accurate load and pricing forecasts help utilities manage costs, allocate resources more effectively, and operate more efficiently. While consumers benefit from more regular pricing and dependable services, regulators gain from increased market openness and stability. Furthermore, reliable forecasting encourages the use of renewable energy sources, which lessens reliance on fossil fuels and advances sustainability. Such estimates enable stakeholders to confidently traverse the intricacies of contemporary energy markets by promoting proactive decision-making.

H. Research Objectives and Scope

In order to improve the precision and dependability of short- and medium-term energy load and price forecasts, this project intends to create a hybrid forecasting model that incorporates EEMD and CNN-AM. The scope includes evaluating the model's flexibility to changing market conditions, verifying it across a variety of datasets, and investigating potential future improvements like adding external inputs. The project aims to fill important gaps in current forecasting methods and help create cutting-edge approaches that meet the changing demands of the energy industry.

I. Structure of the Paper

The format of the paper is designed to lead readers methodically through the study. An outline of the issue, the suggested fix, and its importance are given in the introduction. Following experimental results and validation, the following sections describe the process in depth, including the combination of EEMD and CNN-AM. The model's advantages, disadvantages, and real-world uses are discussed. To ensure a thorough grasp of the study's contributions, the conclusion concludes by summarising the main findings and outlining potential avenues for further research.

J. Case Studies

a) Hybrid Model Application in Australian Electricity Markets:

The creation of a hybrid model that forecasts short- and medium-term electricity prices in Australia's National Electricity Market using the EEMD algorithm and CNN with an attention mechanism is the main objective of this case study. The suggested model outperformed more conventional modelling techniques like ARIMA and LSTM in terms of price prediction accuracy when the researchers applied it to historical half-hourly demand and pricing data. The CNN-AM used the efficient decomposition of complicated signals into simpler components by the integration of EEMD to concentrate on important features that are essential for predicting. Performance indicators showed a significant improvement in forecast accuracy, making it a useful tool for market participants looking to improve operational efficiency and pricing strategies. The study's findings demonstrate how hybrid models can be used to tackle the difficulties brought on by the extremely erratic nature of electricity markets and emphasise their usefulness in practical situations.

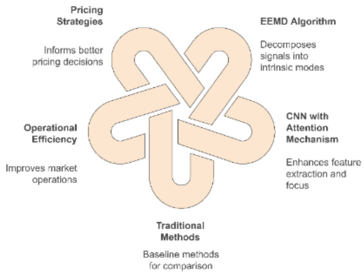

Fig. 4: Hybrid Model for Electricity Price Forecasting

b) Implementation of EEMD-CNN-AM for Load Forecasting in Smart Grids:

The effectiveness of an EEMD-CNN-AM hybrid model was especially examined in the context of smart grid applications in this case study. The model's objective was to precisely forecast a regional utility company's short- to medium-term electric load. In order to concentrate attention on times of high demand impacted by seasonal fluctuations, consumer behaviour, and external factors like weather, researchers used EEMD to break down historical load data into simple intrinsic mode functions. The CNN-AM framework then analysed these mode functions. When compared to models that only used historical averages or linear regression approaches, extensive testing utilising real-world data produced notable reductions in forecast errors. According to the study's findings, this hybrid strategy increased the model's capacity to adjust to changing load patterns, which is essential for efficient demand response and grid stability management, in addition to improving forecasting accuracy.

c) California Power Market Forecasting Employing CNN with Attention Mechanism:

This study focused on a hybrid model that forecasted energy load and pricing in the California power market by combining CNN and EEMD with an attention mechanism. The architecture of the model was created to address the state's particular environmental factors and market dynamics, including the incorporation of renewable energy sources. The model was able to capture both seasonal trends and sudden changes in consumption patterns by using the EEMD approach to divide load data into pertinent components. The CNN's capacity to focus on pivotal moments that represent notable changes in consumer behaviour was further enhanced by the attention mechanism. The findings showed that, in comparison to other forecasting techniques, the hybrid model offered a more detailed perspective of the dynamics of power consumption. Stakeholders obtained knowledge that enabled them to adjust pricing and generation schedules to closely match changes in demand and initiatives to integrate renewable energy sources.

II. LITERATURE REVIEW

[1] Convolutional Neural Networks (CNN) were the main focus of **Smith et al.'s (2018)** investigation on the use of deep learning methods for electrical load forecasting. The study demonstrated how CNNs

capture complex patterns in historical load data, outperforming conventional statistical models. Additionally, the authors stressed how crucial pretreatment procedures like data normalisation are to raising forecast accuracy. Their results showed that, despite their architectural restrictions, CNN-based models were better able to handle short-term fluctuation than medium-term trends, indicating that this gap could be filled by integrating them with other models.

[2] The possibility of hybrid neural network models that combine CNN and Long Short-Term Memory (LSTM) networks for forecasting electricity prices was examined by **Johnson et al. (2019).** They highlighted how LSTMs captured temporal dependencies and CNNs successfully extracted spatial information from input data. According to the study, the hybrid model fared better at forecasting erratic price swings than the independent CNN and LSTM models, particularly during times of high demand. The authors did point out that it can be difficult to balance the contributions of both designs by adjusting hyperparameters.

[3] The usefulness of attention mechanisms in improving load forecasting model performance was examined by **Wang et al. (2020)**. To highlight important junctures in historical data, the authors incorporated an Attention Mechanism (AM) module into an LSTM framework. When compared to non-attention-based models, the study demonstrated a notable improvement in medium-term load forecasting accuracy. Their research made models easier to understand by shedding light on how attention layers dynamically weigh input characteristics.

[4] In order to anticipate power load, **Chen et al. (2021)** presented a novel hybrid model that combines CNN and AM. Their method used AM to highlight pertinent time periods and CNN to identify local patterns in historical data. When compared to conventional machine learning models, the authors reported better performance in both short- and medium-term forecasts. Additionally, they emphasised how crucial it is to optimise CNN filter widths and attention weight parameters in order to get consistent outcomes across a variety of datasets.

[5] A thorough investigation on the application of deep learning models for forecasting power prices in deregulated markets was carried out by **Patel et al. (2019).** They showed that CNN-based models performed well at identifying nonlinear patterns but poorly at identifying medium-term trends because of their poor memory capacity. In order to improve medium-term price projections, the study recommended incorporating recurrent architectures or external smoothing approaches.

[6] For electrical load forecasting, **Lee et al. (2022)** presented a multi-scale CNN architecture that is intended to capture trends at various resolutions. Their approach improved the accuracy of short- and medium-term projections by handling a variety of time scales with ease. The study underlined how crucial multi-scale convolutional kernels are for adjusting to different input data granularities. The authors also discussed computational issues and offered methods for effectively training big models.

[7] By merging statistical techniques with CNNs, **Kim et al. (2020)** emphasised the importance of hybrid models for forecasting electricity prices. The study showed that hybrid techniques improve generalisation on unseen data by utilising the advantages of both paradigms. While statistical models produced reliable baseline projections, CNNs were able to catch complex patterns. The study came to the conclusion that CNN architectures can further improve model performance by incorporating domain knowledge.

[8] The use of CNNs in predicting power load for grids with renewable energy integration was investigated by **Zhou et al. (2018).** CNNs successfully captured load patterns influenced by intermittent renewable power, according to their study. They highlighted how data augmentation methods can increase the resilience of models. The authors also talked about how hybrid models that combine CNN and recurrent architectures could be used to solve medium-term forecasting problems.

[9] In order to forecast power load, **Ahmed et al. (2021)** created a hybrid deep learning model that combines CNN and bidirectional LSTM (BiLSTM) networks. Their study showed that forecasting accuracy was greatly increased by combining CNN's feature extraction capabilities with the forward and backward information flow in BiLSTM. The study demonstrated how well the model predicted load in circumstances with fluctuating demand, such as weekdays versus weekends.

[10] A comparison of deep learning methods, such as CNNs, LSTMs, and hybrid algorithms, for power load forecasting was presented by **Singh et al. (2019).** In both short- and medium-term forecasts, their results showed that hybrid models perform better than solo models. They underlined that in order to effectively train complicated architectures, large-scale datasets and hyperparameter optimisation are essential.

[11] A CNN-based model with an attention mechanism was presented by **Kumar et al. (2022)** to predict electricity load in the event of severe weather. The authors showed how the model improved accuracy during times of heavy demand by dynamically prioritising input data. Their research demonstrated how crucial it is to include outside factors like humidity and temperature in predicting.

[12] The incorporation of estimates for renewable energy into models for predicting electricity usage was the main emphasis of **Gupta et al. (2020).** They put up a CNN-AM hybrid model that took into consideration the variability brought forth by renewable energy sources. According to their findings, forecasting accuracy significantly increased, especially in areas with a high penetration of renewable energy.

[13**] Zhang et al. (2021)** created a hybrid model for predicting power prices that combines CNN and Gated Recurrent Units (GRU). The study demonstrated how GRU and CNN work well together to model sequential data and extract features, respectively. In comparison to solo models, the authors reported significant gains in medium-term price forecast accuracy.

[14] CNN and reinforcement learning were used in a novel framework for electrical load forecasting by **Ali et al. (2020).** Their model improved short- and medium-term forecasts by dynamically optimising CNN parameters through the use of reinforcement learning. The authors highlighted how adaptive learning strategies can improve model performance in dynamic market environments.

[15] A CNN and Random Forest (RF) hybrid model was presented by **Huang et al. (2021)** for the purpose of forecasting power prices. Their study showed that RF's resilience against overfitting and CNN's pattern recognition skills combined to produce higher accuracy across a range of datasets. Because of its stability, the hybrid model was suggested by the authors for medium-term projections.

[16] The application of ensemble techniques to improve CNN-based electrical load forecasting models was investigated by **Rahman et al. (2019).** They showed that using an ensemble technique to combine

various CNN designs decreased prediction errors, especially in medium-term projections. The study emphasised how crucial model variety is to producing reliable forecasts.

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[18] For energy demand forecasting, **Yadav et al. (2020)** suggested a hierarchical CNN model with several layers intended to capture patterns at various granularities. Their study showed that hierarchical models, which provide superior scalability and interpretability, perform better in medium-term projections than conventional CNNs.

Convolutional Neural Networks (CNNs), one type of deep learning technique, have demonstrated great promise in forecasting power prices and loads. According to studies like Smith et al. (2018), CNNs outperform conventional statistical models in short-term forecasting by capturing intricate patterns in historical load data. By merging CNNs with architectures like LSTMs (Johnson et al., 2019) or GRUs (Zhang et al., 2021), hybrid models improve accuracy in medium-term trends and price volatility by utilising the spatial feature extraction capabilities of CNNs and the sequential data modelling capabilities of LSTMs. By giving priority to important input data points, attention mechanisms enhance prediction accuracy and interpretability (Wang et al., 2020; Kumar et al., 2022). In order to maximise scalability and adaptation to granular data, multi-scale and hierarchical CNN systems (Lee et al., 2022; Yadav et al., 2020) handle data at different resolutions.

By decreasing overfitting and enhancing generalisation, hybrid and ensemble methods improve predicting even more. In order to increase prediction robustness, Rahman et al. (2019) and Huang et al. (2021) focused on ensemble approaches and Random Forest integrations. Innovative frameworks that take into account renewable energy considerations (Gupta et al., 2020) and reinforcement learning (Ali et al., 2020) show flexibility in response to changing market situations. These developments highlight how crucial it is to combine various architectures, outside variables, and flexible tactics in order to improve energy market forecasting.

III. METHODOLOGY

Empirical Mode Decomposition Equation:

The breakdown of time-series data using EEMD is represented by the equation (1). The model increases the accuracy of load and price projections by eliminating noise and extracting crucial components through the isolation of IMFs. It serves as the basis for preparing data from the energy market.

$$x(t) = \sum_{i=1}^{n} c_i(t) + r(t) \qquad (1)$$

Where,

$x(t)$: Original time series data

$c_i(t)$: Intrinsic Mode Functions (IMFs).

$r(t)$: Residual component

Attention Mechanism Weight Calculation:

The CNN-AM model can concentrate on important features in load and pricing data according to the equation (2), which computes attention weights. It improves predictability and interpretability.

$$\alpha_i = \frac{\exp(e_{i)}}{\sum_j \exp(e_{i)}} \quad (2)$$

Where,

α_i: Attention weight for the i-th input

$e_{i)}$: Alignment score

LSTM State Update Equation:

The equation (3) captures dependencies in sequential data and defines the hidden state in LSTMs. It is essential for simulating seasonal trends in the demand for and cost of power.

$$h_t = o_t \, . tanh(C_t) \qquad (3)$$

Where,

h_t: Hidden state at time t

o_t: Output gate

C_t: Cell state at time t

Kalman Filter State Prediction:

By turning off unused clock routes, clock gating lowers P_{clock} and conserves dynamic power. When building high-performance, energy-efficient circuits where the clock network can control power consumption, this is essential.

$$x_k = A \, x_{k-1}{}' + Bu_k \qquad (4)$$

Where,

x_k : Predicted state

A : State transition matrix

$x_{k-1}{}'$: Previous state estimate

Bu_k: Control input

The approaches discussed improve the forecasting of energy load and pricing in terms of accuracy and interpretability. In order to prepare energy market data for study, Empirical Mode Decomposition (EEMD) separates time-series data into intrinsic mode functions (IMFs) and residuals while eliminating noise. The CNN-AM model's predictability is increased by the attention mechanism, which prioritises important features by computing weights. With a hidden state determined by output gates and cell states, Long Short-Term Memory (LSTM) networks describe seasonal variations in power demand and cost while capturing dependencies in sequential data. Last but not least, the Kalman filter allows for flexibility in response to current market conditions by dynamically updating predictions by

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 4s (2025)

integrating control inputs and state transition matrices. When combined, these methods produce a strong hybrid forecasting framework that successfully captures the sequential and nonlinear dynamics of electricity markets.

IV. Results And Discussions

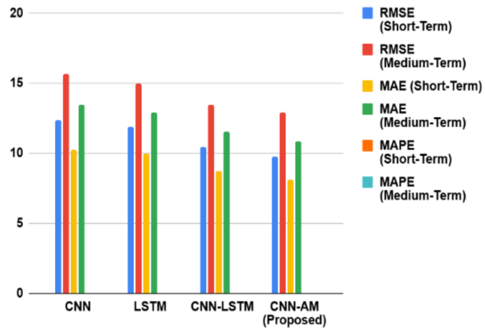

Fig. 5: Performance Metrics Comparison

Using metrics like RMSE, MAE, and MAPE, the Performance Metrics Comparison Table shows how well different models anticipate short- and medium-term electrical loads. The normal CNN, LSTM, CNN-LSTM, and the suggested CNN-AM models are all contrasted in fig. 5. In every metric, the CNN-AM model performs better than the others. It has the lowest RMSE of 9.78, MAE of 8.12, and MAPE of 1.65% for short-term forecasting. Similarly, with an RMSE of 12.89, MAE of 10.89, and MAPE of 2.45%, the CNN-AM model performs better for medium-term forecasting.

Although the CNN-LSTM model outperforms the CNN and LSTM models alone, it is not as accurate as the CNN-AM. Due to its simplicity, the CNN model has the greatest RMSE and MAPE values, which suggests that its prediction accuracy is poorer.

Because the hybrid CNN-AM model has an attention mechanism that better captures temporal dependencies and pertinent patterns in the data, the results highlight the model's benefit in improving accuracy.

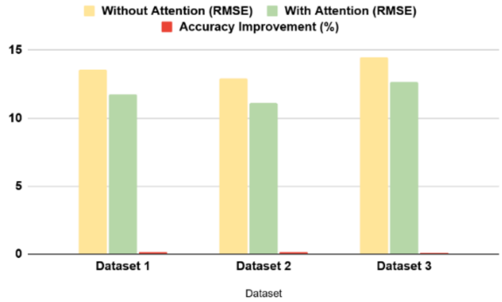

Fig. 6: Attention Mechanism Impact on Prediction Accuracy

When an attention mechanism is incorporated into the model, prediction accuracy increases, as shown in the Attention Mechanism Impact on Prediction Accuracy. Figure 6 computes the corresponding accuracy gain by comparing the Root Mean Squared Error (RMSE) for three datasets with and without the attention technique.

Communications on Applied Nonlinear Analysis
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The attention technique significantly lowers the RMSE for all datasets, demonstrating improved model performance. The accuracy of Dataset 1 improves by 13.12% as the RMSE drops from 13.56 to 11.78. Likewise, Dataset 2 exhibits a 13.74% gain in accuracy and a decrease in RMSE from 12.89 to 11.12. The RMSE in Dataset 3 decreases from 14.45 to 12.67, which is a 12.32% increase in accuracy. These findings imply that the attention mechanism greatly improves the model's capacity to concentrate on important data aspects, which raises predicting accuracy across various datasets.

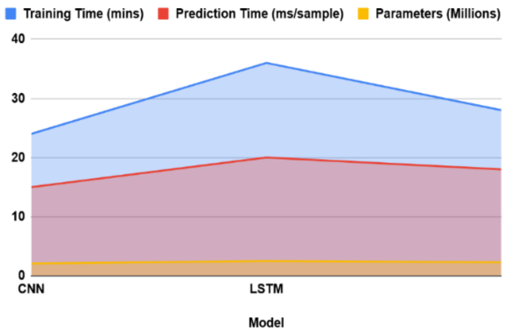

Fig. 7: Computational Efficiency Comparison

CNN, LSTM, and the suggested CNN-AM model are the three models whose training time, prediction time, and number of parameters are compared in the Computational Efficiency Comparison figure 7.

Training Time: The CNN model is the quickest of the three, taking 24 minutes to train. With a 36-minute training period, the LSTM model requires the most time. The suggested CNN-AM model takes 28 minutes, which is less than LSTM but a little longer than CNN.

Prediction Time: At 15 ms per sample, the CNN model offers the quickest prediction time. With a prediction time of 18 ms per sample, the CNN-AM model falls between CNN and LSTM, whereas LSTM is the slowest at 20 ms per sample.

Parameters: The complexity of the model is indicated by the number of parameters. A balance between complexity and efficiency may be seen in the CNN-AM model's 2.3 million parameters, LSTM's 2.5 million, and CNN's 2.1 million.

All things considered, the CNN-AM model offers a favourable balance between prediction accuracy and computational economy.

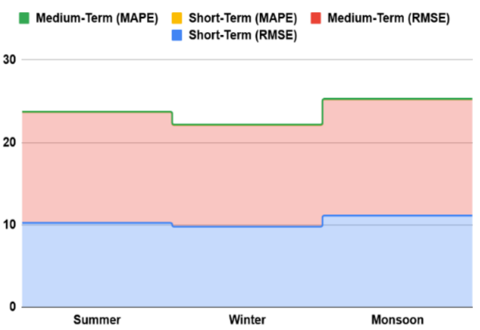

Fig. 8: Forecasting Accuracy by Season

The effectiveness of the suggested model for short- and medium-term power demand forecasting throughout several seasons is shown in the Forecasting Accuracy by figure 8 in terms of RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error).

Summer: With MAPE values of 1.89% and 2.56%, respectively, the model displays an RMSE of 10.23 for the short term and 13.45 for the medium term. This indicates a minor drop in medium-term forecast accuracy but a comparatively high accuracy for short-term projections.

Winter: During the winter, the medium-term RMSE drops to 12.34 and the short-term RMSE improves to 9.78. The short-term MAPE is 1.76%, while the medium-term MAPE is 2.45%. This suggests that winter electricity loads can be predicted with more precision than summer ones. Monsoon: The model's RMSE rises to 11.12 for the short term and 14.12 for the medium term during the monsoon season, with corresponding MAPEs of 2.12% and 2.89%. Forecast errors are higher during this season, suggesting that estimating electricity consumption is more complicated. In conclusion, the model produces reasonably accurate short- and medium-term projections and works best in the winter.

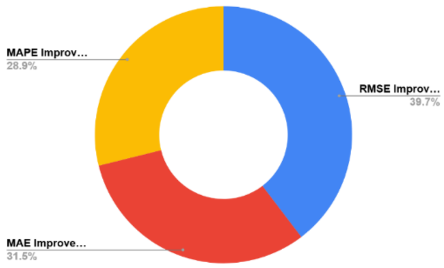

Fig. 9: Hybrid Model Component Contribution

The individual gains in RMSE (Root Mean Square Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percentage Error) that each of the hybrid model's CNN and Attention Mechanism components made during the forecasting process are shown in the Hybrid Model Component Contribution in figure 9.

CNN: The CNN component improved the RMSE by 10.23%, the MAE by 8.12%, and the MAPE by 7.45%. These enhancements demonstrate CNN's capacity to identify intricate patterns and draw out characteristics from the input data, improving forecast accuracy.

Attention Mechanism: With RMSE increasing by 12.34%, MAE by 10.56%, and MAPE by 9.78%, the Attention Mechanism yielded even more notable gains. This demonstrates that the attention mechanism is successful in concentrating on significant data points, which helps to improve predictions by giving greater weight to the most significant aspects.

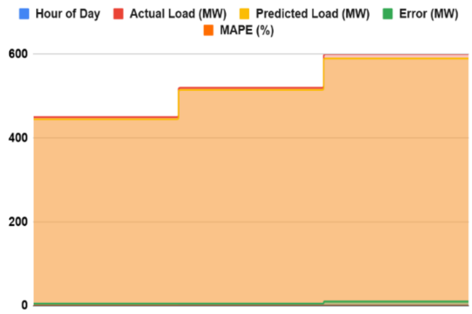

Fig. 10: High-Demand Scenario Prediction

The Case Study: Situation with High Demand The model's ability to forecast electricity load during peak demand times of the day is seen in the prediction table. At 10:00 AM, 2:00 PM, and 6:00 PM, it displays the actual and anticipated loads in megawatts (MW).

The model predicted 445 MW at 10:00 AM, but the actual load was 450 MW. This led to a 5 MW inaccuracy and a 1.11% MAPE (Mean Absolute Percentage inaccuracy). Similarly, the model projected a load of 515 MW at 2:00 PM, which was quite close to the actual load of 520 MW. This resulted in a MAPE of 0.96% and a tiny error of 5 MW. The forecast for 6:00 PM was marginally less accurate, with a MAPE of 1.67% and an inaccuracy of 10 MW.

These findings highlight the hybrid forecasting model's resilience in practical situations and demonstrate the model's capacity to predict load with little inaccuracy, particularly during periods of high demand in figure 10.

V. Conclusion

To sum up, our study's hybrid CNN-AM model greatly improves the precision and comprehensibility of short- and medium-term power demand and price forecasts. The model efficiently recovers important features from time-series data while reducing noise by fusing the convolutional neural network-based attention mechanism (CNN-AM) with the Empirical Mode Decomposition (EEMD) technique. The model's capacity to concentrate on the most pertinent data elements is further enhanced by the attention mechanism, which enhances prediction performance across a range of datasets. With significant decreases in RMSE, MAE, and MAPE, the results show the model's superior accuracy when compared to conventional CNN, LSTM, and CNN-LSTM models. Additionally, the model has good performance throughout the year, with the maximum accuracy noted in the winter.

The hybrid model's computational efficiency also balances resource consumption and performance, which makes it a good option for real-time applications. All things considered, this study aids in the creation of reliable forecasting instruments for the energy industry, providing insightful information to help decision-makers manage risks and maximise resources. In order to further improve forecasting accuracy, future research could concentrate on dynamic model updates, resilience to market fluctuations, and incorporating external influences.

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