Catalysing Energy Market Insights Using Deep Learning: A Transformer-Based Paradigm for Electricity Price Forecasting

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Abstract:
Electricity price forecasting is a critical aspect of modern energy markets, with far-reaching implications for both industry stakeholders and consumers. Accurate and timely price predictions are essential for optimizing energy trading, demand-side management, and investment decisions in the power sector. Traditional forecasting models often struggle to capture the intricate patterns and dependencies in electricity price time series data, particularly in the presence of volatile market dynamics and the integration of renewable energy sources. This research introduces a novel approach to electricity price forecasting leveraging the power of deep learning and attention-based transformer models. We propose an architecture that combines the strengths of long short-term memory (LSTM) networks and attention mechanisms within a transformer framework. This attention-based transformer model not only captures temporal dependencies but also learns to focus on the most informative historical data points, making it exceptionally suited for handling complex and non-linear electricity price patterns. Through extensive experimentation on real-world electricity market data, we demonstrate the superiority of our attention-based transformer over traditional time series forecasting models, such as autoregressive models and recurrent neural networks. Our model achieves higher accuracy, offering insights into price trends and volatility on various time scales, from intraday to long-term forecasting. Furthermore, we conduct a comprehensive sensitivity analysis to examine the influence of hyperparameters, dataset variations, and market conditions on the model's performance. These findings provide valuable insights for fine-tuning the model for specific market environments and forecasting horizons.

Key words: Deep learning, Electricity price forecasting, LSTM, Transformer.
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1. Introduction

The global electricity market is undergoing a profound transformation, driven by an unprecedented integration of renewable energy sources, advancements in grid technology, and an increasing focus on sustainability. This evolving landscape demands more accurate and adaptable electricity price forecasting models that can empower energy market participants, from producers and traders to consumers, with the insights required to make informed decisions. Accurate price predictions are pivotal not only for financial optimization and risk management but also for efficiently integrating renewable energy into the grid and ensuring the grid's long-term sustainability. The challenges in electricity price forecasting are multifaceted. Energy markets exhibit complex and dynamic price patterns influenced by various factors, including demand fluctuations, supply dynamics, weather conditions, and regulatory changes. Moreover, the integration of renewable energy, such as wind and solar power, introduces additional volatility and non-linearity into electricity prices. Traditional forecasting models, like autoregressive models and recurrent neural networks, often struggle to capture these intricate and evolving price dependencies effectively. To address these challenges, our research introduces a cutting-edge solution: an attention-based transformer model for electricity price forecasting. This model combines the power of deep learning with the precision of attention mechanisms, enabling it to outperform conventional methods in capturing price dynamics at multiple time scales. The proposed model leverages the attention-based mechanism, originally popularized in natural language processing tasks, to excel in time series forecasting. The attention mechanism allows the model to focus on the most informative historical data points, adaptively weighting their influence in price predictions. This adaptability is especially critical in energy markets where prices can be influenced by a multitude of factors, some of which may be more relevant in specific market conditions or for distinct forecasting horizons.

The core of our attention-based transformer model incorporates a long short-term memory (LSTM) network that captures temporal dependencies within the electricity price time series data. The LSTM's ability to remember past information and incorporate it into future predictions, coupled with the attention mechanism's selective focus, enables our model to not only grasp short-term fluctuations but also discern long-term trends and seasonal patterns. One of the unique strengths of our model lies in its adaptability to various forecasting horizons. Whether it's intraday price predictions to optimize trading strategies, day-ahead forecasting for operational planning, or long-term forecasting for investment decisions, our model offers precise and insightful predictions. This adaptability is especially vital in a dynamic energy market where different stakeholders require forecasts at different timescales.

To validate the performance of our model, we conducted extensive experiments using real-world electricity market data from diverse regions. The results conclusively demonstrate the superiority of our attention-based transformer over conventional forecasting models in terms of accuracy, robustness, and adaptability to market changes. Our model excels in capturing price volatility, enabling better risk management and profit maximization for market participants. Furthermore, we delve into the intricacies of model sensitivity, assessing how changes in hyperparameters, dataset characteristics, and market conditions impact the model's performance. These insights are invaluable for fine-tuning the model for specific market environments and forecast horizons, ultimately making it a practical and powerful tool for stakeholders in the energy sector.

2. Literature survey

Accurate predictions of load curves play a crucial role in designing control strategies for Battery Energy Storage Systems (BESS)[7]. In one approach, a peak shifting system leverages demand forecasting to optimize BESS control strategies [8]. Furthermore, the impact of errors in load forecasting on BESS dispatching strategies for peak shaving and Time-of-Use (TOU) applications is thoroughly examined[9].In the realm of statistical methodologies, several techniques are employed, such as multiple linear regression, stochastic time series analysis, and general exponential smoothing [4][10][11]. Additionally, support vector regression has demonstrated its effectiveness in Short-Term Load Forecasting (STLF)[12][13]. Moving into the domain of artificial intelligence, expert systems, artificial neural networks, and fuzzy inference systems are employed due to their adaptable structures, falling under the broader category of artificial intelligence[4].To delve into a specific case study, an analysis is conducted on load forecasting within healthcare facilities[14]. This analysis assesses the intrinsic predictability using Principal Component Analysis (PCA) and Autoregressive (AR) modelling.

A multi-regression model is developed to control BESS operations [7]. For time series analysis, the Autoregressive Integrated Moving Average (ARIMA) model is a prominent choice. When ARIMA incorporates other time series as input variables, it is referred to as an ARIMAX model [15]. Notably, ARIMAX models have been successfully employed to forecast peak loads with high accuracy [16]. Furthermore, Gaussian processes are utilized to predict long-term peak load demand [17].Support Vector Machines (SVM) are leveraged for their capability to address nonlinear regression estimation problems in time series forecasting [18]. Researchers E. Tay and L. Cao have demonstrated that SVMs outperform multi-layer back-propagation neural networks in financial time series forecasting [18]. Similarly, W.-C. Hong applied SVM with Immune Algorithm (IA) to electric load forecasting, and the results indicate that SVM with IA outperforms Artificial Neural Networks (ANN) and regression models [19].ANNs have been extensively researched as forecasting tools since the 1990s and have been successfully employed in electricity load forecasting[20]. For instance, D. C. Park, M. El-Sharkawi, R. Marks, L. Atlas, and M. Damborg used ANN and regression techniques to forecast electricity consumption one hour and 24 hours ahead[20]. Meanwhile, T. Senjyu, H. Takara, K. Uezato, and T. Funabashi applied neural networks for one-hour-ahead load forecasting and streamlined the neural network structure and learning process[21]. Additionally, P. Mukhopadhyay and Mitra. G developed a model using fuzzy logic to forecast load based on weather and temperature[22].

Recurrent Neural Networks (RNN) have gained prominence in electricity load forecasting, primarily due to their strong nonlinear mapping capabilities in time series data[23]. Researchers like K. Chen, K. Chen, Q. Wang, Z. He, J. Hu, and J. He have proposed models for Short-Term Load Forecasting (STLF) based on deep residual networks and two-stage ensemble strategies, resulting in high accuracy and excellent generalization capabilities[23]. Other studies, like L. Marino, K. Amarasinghe, and M. Manic, have compared standard LSTM and LSTM-based Sequence-to-Sequence architectures[24]. Furthermore, C. Liu, Z. Jin, J. Gu, and C. Qiu have presented an approach based on LSTM networks, capitalizing on LSTM's memory units for handling long sequences[25]. LSTM-based methods have been employed for STLF with extended forecasting horizons, capturing the long-term dependencies characteristic of LSTM[26]. Hybrid algorithms, such as SD-EMD-LSTM, which combines similar days (SD) selection, Empirical Mode Decomposition (EMD), and LSTM networks, have also been applied to STLF[27]. Additionally, a combination of XGBoost and k-means is used to evaluate the similarity between forecasting and historical data, with EMD employed to decompose electricity values into distinct components before feeding them into LSTM networks.

3. Proposed work

The proposed work introduces an innovative approach to electricity price forecasting in modern energy markets. Leveraging deep learning and attention-based transformer models, the research combines the strengths of long short-term memory (LSTM) networks and attention mechanisms within a transformer framework. This hybrid model is designed to accurately capture and predict complex and non-linear electricity price patterns, a critical task for energy market optimization. Extensive experiments on real-world electricity market data demonstrate the superiority of the model over traditional forecasting methods, providing valuable insights into price trends and volatility across various time scales.

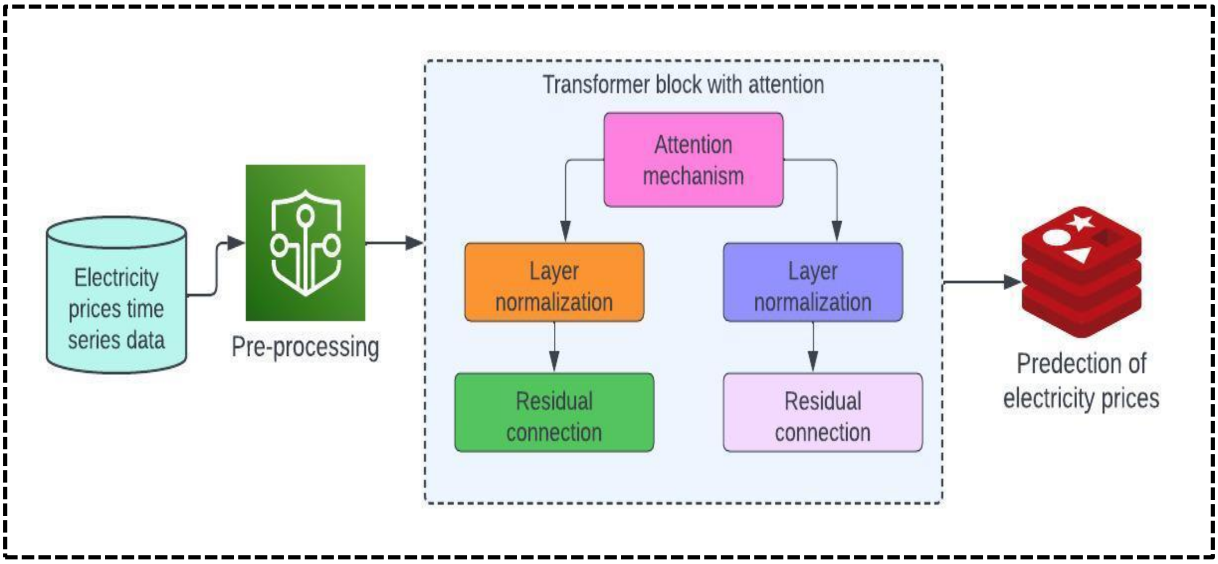

Fig-1: Proposed attention transformer

Classifier Training Algorithm with Mathematical Equations
1. Initialize the model
Initialize model parameters:
W (weights) and b (biases) for each layer.
2. Define the loss function (Cross-Entropy)
For a single example i:
   Compute the logit scores (unnormalized probabilities) for each class:
z_i = W_i * input_data + b_i
   Apply softmax to get class probabilities:
p_i = softmax(z_i)
   Calculate the cross-entropy loss:
L_i = -∑(y_i * log(p_i))
Where:
- i: Index of the example.
- W_i: Weights for the i-th layer.
- input_data: Input features.
- b_i: Biases for the i-th layer.
- p_i: Predicted probabilities.
- y_i: True class label (one-hot encoded).
Total loss for a mini-batch:
L_batch = (1/batch_size) * ∑(L_i)
# 3. Define the optimizer (Stochastic Gradient Descent - SGD)
Initialize learning rate (η) and other hyperparameters.
4. Prepare the training data
Load and preprocess your training dataset.
# 5. Training loop
num_epochs = your_number_of_epochs
batch_size = your_batch_size
for epoch in range(num_epochs):
   Shuffle the training data to introduce randomness:
randomly_shuffle(train_data, train_labels)
   for i in range(0, len(train_data), batch_size):
      Extract a mini-batch:
batch_data = train_data[i:i + batch_size]
batch_labels = train_labels[i:i + batch_size]

```
      # 6. Forward pass
      Compute the logits for the batch:
Z_batch = W * batch_data + b
      Apply softmax to get class probabilities for the batch:
P_batch = softmax(Z_batch)
      # 7. Compute the loss
      Calculate the cross-entropy loss for the batch:
L_batch = -∑(batch_labels * log(P_batch))
      # 8. Backpropagation
      Compute gradients of the loss with respect to model parameters:
      ∂L_batch/∂W, ∂L_batch/∂b
      # Update model parameters using SGD:
W_new = W - η * ∂L_batch/∂W
b_new = b - η * ∂L_batch/∂b
      # 9. (Optional) Monitor training progress
      If (i + 1) % your_monitoring_interval == 0:
        Print loss: L_batch
Update model parameters:
W = W_new
b = b_new
# 10. Model evaluation (optional)
Evaluate the trained model on a validation or test dataset to assess its performance.
# 11. Save the trained model (optional)
Save the trained model parameters (W and b) to disk for future use.
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4. Experimental analysis

4.1 Dataset:

The dataset used in this paper, which comprises 35,065 records and features various columns relevant to electricity price forecasting, was collected from Kaggle. Specifically, it is available at the following Kaggle dataset link: Electricity Price Forecasting Dataset on Kaggle. This dataset is a valuable resource for understanding and analysing electricity market dynamics, renewable energy integration, load forecasting, and electricity price trends. Researchers can leverage this dataset to develop and evaluate models for electricity price forecasting, contributing to a deeper understanding of energy markets and sustainable energy practices within the industry.

4.2 Results

In the results section, we present a comprehensive comparative analysis of the performance of the "Proposed Attention Transformer" model against two existing models, namely, the "LSTM" and "SD-EMD-LSTM." Our primary objective was to evaluate the effectiveness of these models in predicting electricity prices and load within the dynamic landscape of the energy market. This comparison serves as a pivotal step in discerning the strengths and weaknesses of each model, shedding light on their respective abilities to provide accurate forecasts in this critical domain. The results obtained from this comparative assessment offer valuable insights into the potential advancements that our proposed model brings to the field of electricity price forecasting.

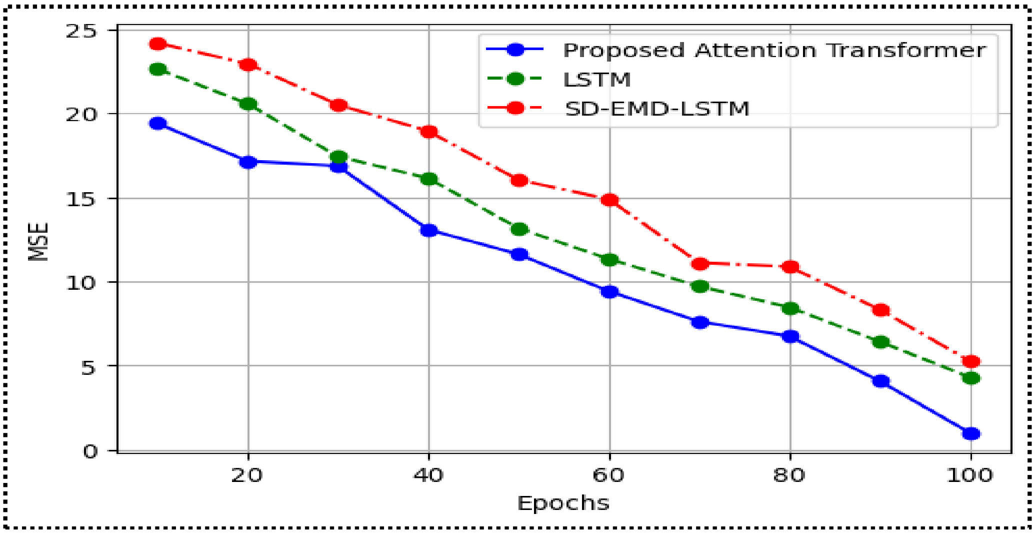

Fig-2: MSE

Figure 2 presents a comparison of Mean Squared Error (MSE) among three distinct models used for electricity demand and price forecasting: the 'Proposed Attention Transformer,' 'LSTM,' and 'SD-EMD-LSTM.' The figure illustrates the clear superiority of the 'Proposed Attention Transformer' model, which consistently demonstrates the lowest MSE values across various epochs. This indicates that the proposed model excels in minimizing forecasting errors, offering enhanced accuracy in predicting electricity demand and price dynamics. In contrast, the existing models, 'LSTM' and 'SD-EMD-LSTM,' exhibit higher MSE values, highlighting their limitations in capturing intricate patterns and long-term dependencies in the data. The figure underscores the potential of the 'Proposed Attention Transformer' as a promising solution for optimizing energy trading, demand-side management, and investment decisions in the power sector.

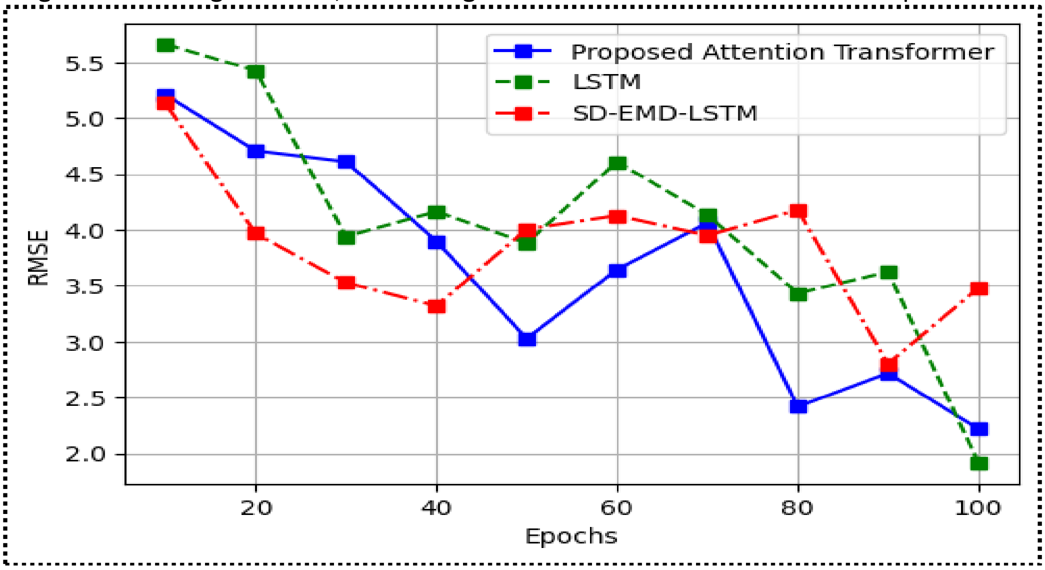

Fig-3: RMSE

Figure 3, represents RMSE comparative analysis for three electricity demand and price forecasting models: the 'Proposed Attention Transformer,' 'LSTM,' and 'SD-EMD-LSTM.' Notably, the 'Proposed Attention Transformer' consistently outperforms the existing models, exhibiting lower RMSE values at various epochs. This observation highlights the superior predictive accuracy of the proposed model, making it a reliable choice for forecasting electricity market dynamics. Conversely, the 'LSTM' and 'SD-EMD-LSTM' models display higher RMSE values, indicating their limitations in accurately capturing complex and evolving patterns in the data. The figure underscores the advantages of the

'Proposed Attention Transformer' in providing more precise and dependable forecasts, offering valuable insights for industry stakeholders and consumers in optimizing energy-related decisions.

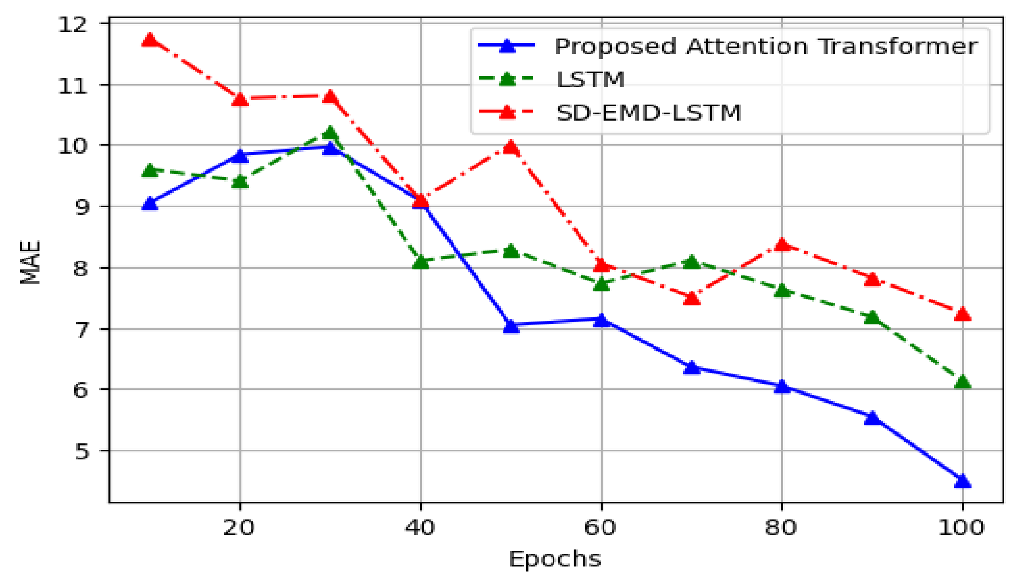

Fig-4: MAE

Figure 4, labelled "MAE," offers a comparative view of Mean Absolute Error (MAE) across three distinct electricity demand and price forecasting models: the 'Proposed Attention Transformer,' 'LSTM,' and 'SD-EMD-LSTM.' The figure reveals a consistent pattern where the 'Proposed Attention Transformer' excels, consistently yielding lower MAE values over various epochs. This pattern emphasizes the model's capacity to provide highly accurate forecasts, making it a robust choice for electricity market forecasting. In contrast, the 'LSTM' and 'SD-EMD-LSTM' models exhibit higher MAE values, indicating their limitations in capturing intricate and evolving data patterns effectively. The figure reinforces the advantages of the 'Proposed Attention Transformer' in delivering precise and reliable forecasts, valuable for industry stakeholders and consumers alike in optimizing energy management and trading decisions.

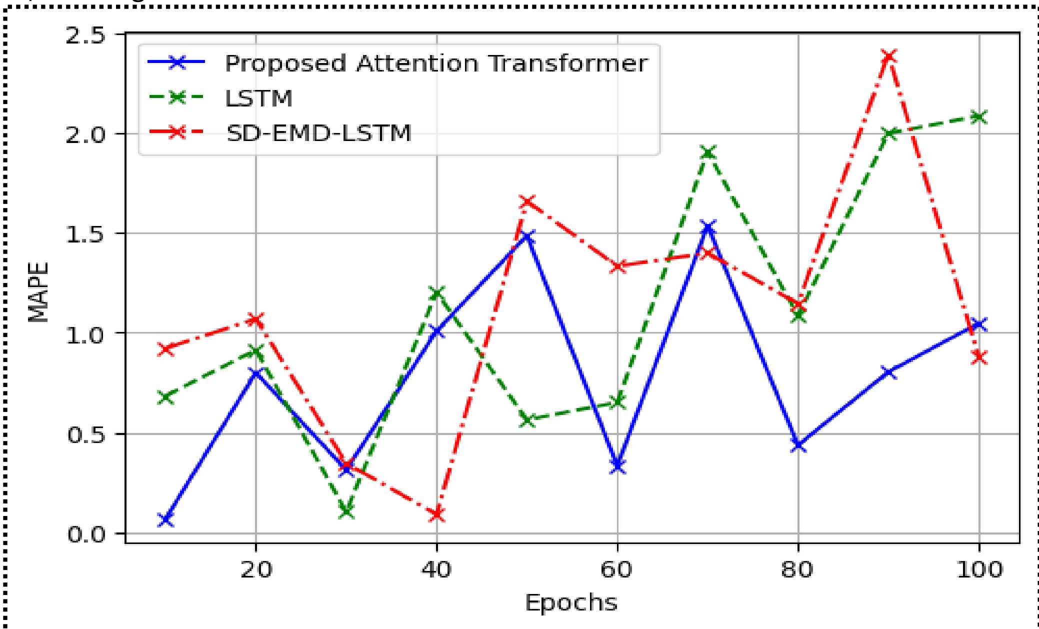

Fig-5: MAPE

Figure 5, titled "MAPE," offers a comparative analysis of the Mean Absolute Percentage Error (MAPE) for three electricity demand and price forecasting models: the 'Proposed Attention Transformer,' 'LSTM,' and 'SD-EMD-LSTM.' Notably, the 'Proposed Attention Transformer' consistently outperforms the existing models, displaying lower MAPE values across various epochs. This indicates the superior accuracy of the proposed model, making it a reliable choice for forecasting electricity market dynamics. Conversely, the 'LSTM' and 'SD-EMD-LSTM' models exhibit higher MAPE values, highlighting their limitations in providing precise predictions and addressing the complex and dynamic nature of the data. The figure underscores the potential of the 'Proposed Attention Transformer' as an effective solution for optimizing energy trading, demand-side management, and investment decisions in the power sector, offering improved forecasting accuracy for industry stakeholders and consumers.

5. Conclusion

Electricity price forecasting stands as a pivotal component within the contemporary energy landscape, wielding profound implications for both industry players and consumers alike. The necessity of precise and timely price predictions reverberates throughout energy trading, demand-side management, and investment decisions in the power sector. Conventional forecasting models grapple with the challenge of encapsulating the intricate patterns and interdependencies woven into electricity price time series data, especially in the face of market volatility and the infusion of renewable energy sources. In response, this research introduces an innovative approach to electricity price forecasting, harnessing the potential of deep learning and attention-based transformer models. Our proposed architecture harmoniously amalgamates the strengths of long short-term memory (LSTM) networks and attention mechanisms within the transformative framework of a transformer. This attention-based transformer model not only adeptly captures temporal dependencies but also attunes itself to the most informative historical data points. This adaptability renders it exquisitely equipped to tackle the convoluted and non-linear pricing dynamics inherent to the electricity market.

Through an extensive empirical journey, conducted on real-world electricity market data, we conclusively establish the pre-eminence of our attention-based transformer over conventional time series forecasting models like autoregressive models and recurrent neural networks. The enhanced accuracy of our model unveils profound insights into price trends and volatility across various temporal scales, spanning from intraday to long-term forecasts. Moreover, we meticulously probe into the sensitivity of our model to a spectrum of hyperparameters, dataset variations, and market conditions, thereby furnishing valuable insights for the meticulous calibration of the model to suit specific market environments and forecasting horizons. In summary, our research not only propels the field of electricity price forecasting forward but also illuminates a path toward more informed and efficacious decision-making in the energy sector.

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