Load Forecasting And Scheduling Model For Electricity Spot Trading And Its Deep Learning Optimization

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The transition toward renewable and sustainable energy sources has increased volatility and uncertainty in modern power grid operations. The intermittent nature of renewable generation, together with rapidly changing demand patterns, necessitates the development of advanced load forecasting and scheduling models, particularly for participants in electricity spot markets. Spot trading involves real-time electricity transactions, where accurate demand prediction is essential to maximize economic returns while ensuring grid stability. Reliable load forecasting enables market participants and grid operators to anticipate demand variations, optimize generation dispatch, and reduce operational risks. Despite significant progress in forecasting techniques, unforeseen events such as extreme weather conditions, system disturbances, and market fluctuations continue to challenge prediction accuracy. The primary objective of this study is to investigate and evaluate efficient load forecasting and scheduling models tailored for electricity spot trading systems. Additionally, the research aims to identify innovative forecasting strategies that significantly outperform conventional methods, highlighting their practical advantages. To validate the effectiveness of the proposed approach, the developed models are benchmarked against traditional techniques. The results demonstrate that the proposed forecasting and scheduling methods achieve superior accuracy and efficiency.

Keywords: load forecasting, electricity spot trading, sustainable energy sources, scheduling model

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1. Introduction

The effective management of power networks has become increasingly important as electricity demand fluctuates due to industrial expansion, urbanization, and the growing use of electronic devices. This highlights the critical role of load forecasting and scheduling models, which ensure the reliability, efficiency, and sustainability of power systems. As electric power networks evolve to improve reliability, safety, affordability, and efficiency, there is a pressing need for more precise and effective load forecasting. The rapid development of urban and rural areas, increased population mobility, and the integration of new energy sources like electric vehicles have accelerated changes in power loads. Spatial power load forecasting is essential for generation planning, grid planning, effective utilization, sustainable development, and dispatching. The proposed model enhances grid stability by providing more accurate load forecasts, which are particularly important as renewable energy sources like wind and solar increase, helping manage generation variability and ensuring balanced supply to prevent grid disruptions.

The complexity of geographical load forecasting has increased due to shifts in grid loads caused by the incorporation of new energy sources and electric vehicles. In the modern energy sector, load forecasting and scheduling models are essential for creating a more resilient and sustainable energy system, especially as renewable energy sources become more unpredictable and demand patterns evolve. Load forecasting and scheduling are vital for improving operational efficiency and reducing costs in electricity spot trading systems, ensuring a steady flow of electricity by accurately forecasting future demand and aligning power generation accordingly. This is especially important in short-term trading markets, where precision and planning are key. The advancements in computing, data availability, and technology have revolutionized these processes. AI techniques, particularly time-series machine learning, have transformed power load forecasting by capturing complex nonlinear patterns. Support Vector Regression (SVR) and kernel-based methods excel in handling nonlinear tasks, while Feedforward Neural Networks (FNN) are useful for modeling complex relationships without predefined input-output mappings. Accurate scheduling models help optimize resource allocation, predict peak demand, and reduce oversupply, enhancing market efficiency and cutting operational costs.

Short-term load forecasting benefits from the strengths of Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU), which excel in processing sequential data and capturing temporal dynamics. Hybrid models combining various algorithms, such as LSTM and Convolution Neural Networks (CNNs), leverage LSTM's temporal capabilities and CNN's ability to extract spatial features, enhancing forecasting accuracy. Another approach integrates LSTM with Empirical Mode Decomposition (EMD) to decompose load sequences into frequency components for a more detailed analysis. The primary contributions of this work include:

- Exploring a novel deep learning model for load forecasting and bidding strategies, aiming for high-accuracy demand prediction and optimized bidding strategies.
- Extracting deep features using RBM to enhance the forecasting process, identifying key features directly from the data for more accurate and robust load forecasting and scheduling.
- Developing an improved optimization algorithm-assisted deep learning technique to predict electric load, combining deep learning and optimization algorithms to achieve high accuracy in forecasting electric loads.

2. Material and methods

The advancements in deep learning techniques for load forecasting and scheduling models tailored for electricity spot trading have made significant progress, addressing the complexities of electricity demand forecasting and energy management optimization. Various studies have contributed to this field, such as Tian et al. [1], who used a continuous-time Markov chain to estimate the likelihood of remaining in a secure state for real-time safety quantification, allowing users to tailor security methods. Kathirgamanathan et al. [2] conducted performance evaluations comparing ensemble deep learning with single deep learning and machine learning methods, utilizing historical load and weather-related data to enhance load prediction. Wei et al. [3] proposed a spatial electrical demand forecasting method based on a GCN and LDTW, while Nepal et al. [4] combined the ARIMA model with clustering techniques like K-means to predict campus power peak loads. Lu et al. [5] suggested an improved Short-Term Nodal Load Forecasting (STNLF) method using LASSO for feature reduction. Mohammad [6] introduced an improved ANN model with an Adaptive Backpropagation Algorithm (ABPA) for better long-term electricity consumption predictions. Mohammad and Young [7] proposed a Deep Neural Network (DNN)-based Energy Load Forecasting system for smart grids, while Bendaoud and Nadir [8] implemented a unique CNN for Short-Term Load Forecasting (STLF) in Algeria. Zhang et al. [9] suggested a Time Augmented Transformer (TAT) for short-term load forecasting, while Corte-Real et al. [10] integrated CNN and LSTM networks in a Home Energy Management System (HEMS) for optimizing electric battery management.

The proposed model leverages real-time load predictions to inform the bidding strategy in electricity spot trading. By adjusting bids dynamically based on anticipated demand, market participants can ensure competitive pricing, reducing the risk of over or under-bidding. Accurate load forecasting enables traders to optimize their bids, minimizing costs and maximizing profitability. The dataset, including hourly electricity demand and weather-related variables, is used to forecast load fluctuations, directly influencing the bidding strategy and enhancing both profitability and grid stability.

Lee et al. [11] characterized a hybrid deep learning scheduling technique to improve learning efficiency and precision in environments with dynamic, biased information from multiple smart meter sources, using cosine similarity analysis to identify power usage patterns. Hamad and Ismael [12] used a 2-year sub-dataset for correlation analysis of yearly datasets. El-Azab et al. [13] integrated four machine and deep learning methods, training data with and without external variables like calendar dates and temperatures. Xiong et al. [14] applied Deep Reinforcement Learning (DRL) in an Energy Management System (EMS) to lower electricity costs and improve Quality of Service (QoS) using Deep Q-learning. Lu et al. [15] proposed a load-characterizing method based on trends using candlestick charts for load assessment. Gasparin et al. [16] compared deep learning architectures for one-day-ahead prediction and assessed real-world datasets to advance electricity demand forecasting. Habib et al. [17] used random simulation of EV charging patterns and a forecasting model to investigate risks related to Residential Distribution Networks (RDNs), with recursive feedback inputs for peak-day forecasts. Faraji et al. [18] proposed a two-level corrective Load Forecasting procedure using MLP-ANNs and FF-ANNs to improve forecast accuracy. Jawad et al. [19] developed the Least Cost Electric Load Forecasting Model (lcELFM) by applying correlated weather conditions to reduce forecasting errors. Khani [20] optimized PtG storage for gas load management, using an innovative scheduling model for gas demand forecasts. Devarajan [21] introduced an improved BP neural network algorithm for workload forecasting in cloud computing, which the proposed work adapts by integrating BP neural networks with ARLSTM for enhanced load forecasting in electricity spot trading. This integration improves forecasting accuracy, scheduling efficiency, and market bidding strategies, enhancing grid stability and economic performance. Effective load forecasting and scheduling are critical for electricity spot trading, as accurate demand prediction ensures cost efficiency and grid stability [22]. Conventional forecasting models often lack flexibility and adaptability, making it difficult to accommodate dynamic variables and real-time data. The proposed model addresses these limitations, offering a more flexible, scalable, and accurate approach to navigate the complexities of modern electricity markets.

2.1. Data acquisition

The dataset employed in the model for forecasting load and scheduling in the context of electricity spot trading is detailed in the following section

Electricity Load Forecasting Dataset: It is taken from the link of https://www.kaggle.com/datasets/saurabhshahane/electricity-load-forecasting with access: 2024-02-16. The dataset draws from an extensive array of data sources, each contributing crucial elements to the forecasting framework. Including a diverse set of factors vital for accurate load forecasting, these sources provide data on an hourly basis. The acquired data is denoted as G_m^r and $m = 1, 2 \dots M$ where the total volume of data sourced from these online platforms is represented M.

2.2. Deep features using RBM

A Restricted Boltzmann Machine (RBM) [23] is an unsupervised learning algorithm used in deep learning, consisting of two layers: a visible layer that represents observable variables and a hidden layer that learns patterns in the data. The likelihood of the visible units in an RBM is defined by the joint energy function: An RBM is structured as a bipartite graph with two separate layers: visible units, denoted as $K \in \{0, 1\}$ and hidden units is represented as $\epsilon\{0, 1\}$. Each visible unit is connected to every hidden unit through a matrix of weightsy, yet there are no intra-layer connections among units within the same layer. The gathered data G_m^r is the input to this RBM model. The likelihood of the visible units in an RBM is defined using a set of variables θ, according to a joint energy function $k.h, \theta$. That is mathematically displayed in Eq. (1).

$$G(K, h) = \frac{1}{M(\theta)h} \sum \exp(k.h, \theta) G_m^r \tag{1}$$

In this context, the symbols k and h represent the vectors of visible and hidden variables respectively. The term $\exp(k.h, \theta)$ denotes the exponential function of a variable and displayed mathematically in Eq. (2).

$$T(\theta) = \sum_{k,h} \sum \exp(k.h, \theta) \tag{2}$$

Here, $E(k.h, \theta)$ represents the energy function of the RBM, characterized without constraints, involving the parameters θ. RBM is defined in Eq. (3)

$$E(k.h, \theta) = \sum_{ab} v_a y_a k_a - \sum_{ab} v_b y_b k_b \tag{3}$$

In this context, the variables a and b denote the indices of the visible and hidden units respectively. The biases for the visible and hidden units are represented by b_a for visible units and c_a for hidden units respectively. Given the absence of direct interactions among hidden variables, their distribution can be straightforwardly determined in Eq. (4) and Eq. (5).

$$T\left(k_a/h\right) = \sigma\left(b_b + \sum_a k_a y_{ab}\right) \tag{4}$$

$$T\left(k_a/h\right) = \sigma\left(c_a + \sum_b y_{ab} k_a\right) \tag{5}$$

RBMs are widely used for dimensionality reduction, feature learning, and as building blocks for more complex models like DBNs. They learn complex distributions without supervision, making them powerful for tasks involving large, complex datasets. The features extracted by RBMs provide a more efficient representation of the data, enhancing ARLSTM's ability to capture temporal patterns in load forecasting. Finally, the extracted feature K_m^r is obtained; this is used for the subsequent prediction process. Fig. 1 shows the pictorial view of RBM for feature extraction.

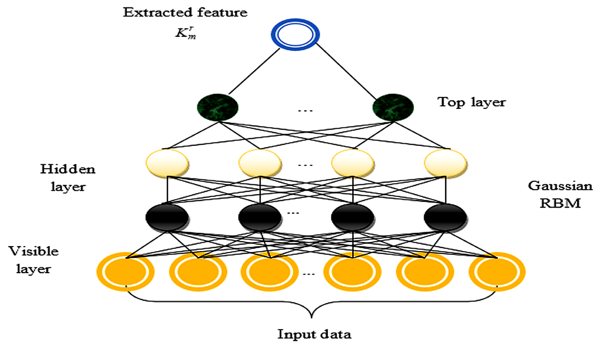

Fig. 1. Pictorial view of RBM for feature extraction

2.3. Improved Heuristic Algorithm

The meta-optimization technique referred to as the OOA [24] is employed to ensure balance between the exploration and exploitation stages. This algorithm models the hunting behavior of ospreys during their prey-catching endeavors. The operational phases of the OOA including both hunting and gathering are designed to mimic the osprey's proficiency in capturing prey. Compared to Genetic Algorithms and Particle Swarm Optimization, OOA) offers superior exploration capabilities, mimicking nature's hunting behavior to avoid local optima. This results in more efficient global optimization, especially for complex forecasting and scheduling tasks.

Startup: The ability of each member within the population to navigate the search space is leveraged to find the optimal solution. In the exploration phase, the osprey's position is represented through a vectorial model. The initial positioning of the osprey is outlined in Eq. (6).

$$z_{j,k} = sl_k + t_{j,k}\left(yu_k - op_k\right), \tag{6}$$

In this context, the random number is represented as $t_{j,k}$, falling within a specified range $[0,1]$. Moreover, the osprey is considered an analog to the solution for the problem; hence its objective function is also articulated in vector form. The quality of the proposed solution is evaluated using the objective characteristic of the Osprey.

Exploration phase: This phase encompasses both the evaluation of potential locations and the execution of the capture maneuver. Ospreys possess exceptionally keen eyesight, enabling them to spot fish even beneath the water's surface. Once the prey's position is pinpointed, the osprey can dive toward the seabed to initiate its hunt. An osprey with an enhanced ability to concentrate can effectively hunt in submerged environments. The allocation of a pair of fish to each osprey is represented through Eq. (7).

$$RT_j = \left\{L_l \mid l \in \{1,2\ldots U\} \wedge S_l < S_j\right\} \cup \{K_{BEST}\} \tag{7}$$

Thus, the outstanding osprey is denoted as K_{BEST}, and the group of fish targeted by the osprey is represented as RT_j. Subsequently, if this new osprey location enhances the objective function, the former position is replaced by this updated one in line with Eq. (8).

$$T_j = \begin{cases} T_j^{q1}, T_j^{q1} < T_j \\ T_j \text{ Ootherwise} \end{cases} \tag{8}$$

Exploitation phase: In addition to relocating to a new spot with the chosen fish for peaceful consumption, the osprey adjusts its position within its hunting territory. This shift in location boosts the convergence capability of the OOA and enhances its power of exploitation. Subsequently, if the osprey's new position improves its primary function, Eq. (9) is used to update the original location with the new one.

$$T_j = T\begin{cases} T_j^{q2}, T_j^{q2} < T_j \\ Y_j \text{ otherwise} \end{cases} \tag{9}$$

This denotes the iteration counter limitu, the impact on the objective function T_j^{q2}, the new position of the Osprey across dimensions jand k correspondingly, the total count of iterations, which is expressed as U. The OOA algorithm pseudocode is stated in the algorithm 1.

2.4. Adaptive Residual LSTM for load prediction

The Residual Long Short-Term Memory (RLSTM) [25] network enhances traditional LSTM by introducing residual connections, addressing the vanishing gradient problem, and improving the training of deep models. The RLSTM's ability to capture intricate dependencies makes it ideal for tasks like time series forecasting. The Adaptive Residual LSTM (ARLSTM) further refines this model by adapting its structure, improving its capacity to handle forecasting challenges and learn from complex sequential data, leading to higher accuracy in predictions. The cell state at the time R is denoted by K_R and the hidden state by L_R holding information from past time steps. This information in the cell state can be modified through the actions of three gates: the input gate a, the forget gate b, and the output gate c,

Algorithm 1. Developed OOA

Start
Create the variables and constraints
number of iteration value and population is fixed
Initialize the objective function and population matrix
For $j = 1$ to O
    While $j > J_{max}$
        Phase 1
            The position of the fish is modernized using Eq. (7).
            j^{th}OOA is upgrading the using Eq. (8).
        Phase 2
            j^{th}OOA is upgrading the using Eq. (9).
    End while
End for
The best solution is stored

which manage the cell state's data for adding or removing information. At each time step R, the block calculates the new output L_R and updates the cell state K_R using the current input K_R and K_R the network's previous states K_{R-1} and L_{R-1}. This involves recurrent connections linking the input, the hidden states and the cell states. Each gate is influenced by the input vector and the previous cycle's hidden state. Recent research has integrated numerous enhancements to the initial LSTM model, further developing its architecture and enhancing its capacity. The formulas for the gates are mathematically modeled in Eq. (10) to Eq. (13).

$$a_R = \sigma_g \left(T_R y_R + K_R L_{R-1} + S_R \right) \tag{10}$$

$$b_R = \sigma_g \left(T_b y_R + K_b L_{R-1} + S_R \right) \tag{11}$$

$$c_R = \sigma_g \left(T_c y_R + K_c L_{R-1} + S_c \right) \tag{12}$$

$$U_R = \sigma_g \left(T_U y_R + K_U L_{R-1} + S_U \right) \tag{13}$$

Here σ represents the activation function of the gate, specifically a sigmoid function and T, K and S denotes the weights for inputs, the weights for recurrent connections and the biases respectively.

The primary goal of residual learning is to reformulate the objective of the layers to focus on learning an approximated residual function. This approach facilitates the learning of higher-level representations by providing a clearer path for representational learning. The formula expressing this concept can be displayed in Eq. (14):

$$A = f(B, K) + B \tag{14}$$

In this context, $f(B, K)$ represents the residual function that the relevant layers aim to learn, with A and B being the input and output vectors of the layers under consideration, respectively. Despite the potential for vanishing gradients as more layers are added, residual learning facilitates the learning of the identity function across any number of layers by allowing the residual $f(B, K)$ to be zero.

Proposed Prediction Model: ARLSTM networks represent a sophisticated evolution in the realm of neural networks, specifically designed to enhance the prediction capabilities of sequential data models. This advancement is particularly pivotal in fields such as load prediction.

The obtained feature K_m^r is fed as input to this model, the count of residual blocks in an RLSTM model is critical as it defines the depth of the network. Integrating residual connections into the LSTM architecture allows for more efficient gradient flow during training, addressing the vanishing gradient problem. This leads to improved learning, especially in deeper networks, and better prediction accuracy compared to standard LSTMs. Various parameters such as the number of residual blocks, the number of hidden neurons and the total number of epochs within the RLSTM are tuned to reduce the errors and improve accuracy and precision with the help of the OOA algorithm. Eq. (15) depicts the mathematical formulation of the objective function for the proposed system.

$$\lambda = \underset{\{R_{\text{RLSTEM}}, H_{\text{RLSTM}}, E_{\text{RLSTM}}\}}{\arg\min} \left(\frac{1}{\text{aur}} + \frac{1}{\text{pion}} \right) \tag{15}$$

From the above equation, the variable $Rb_{\text{RLSTEM}}, H_{\text{RLSTM}}, E_{\text{RLSTM}}$ defines the number of residual blocks, the number of hidden neurons and the total number of epochs in RLSTM. The range of these parameters are [3-10], [5-255] and [5-50] respectively. Also the variable aurand piondefines the accuracy and precision. Fig. 2 shows the recommended view of the heuristic approach and deep learning-based load prediction model.

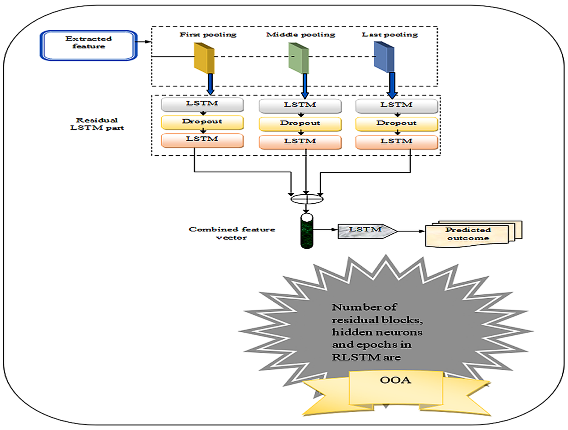

Fig. 2. Recommended view of heuristic approach and deep learning-based load prediction model

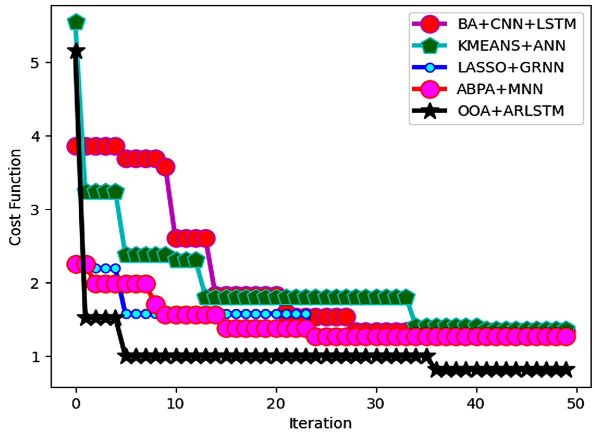

Fig. 3. Convergence assessment of the proposed OOA-ARLSTMalgorithm compared with conventional models

3. Result and discussions

3.1. Comparative analysis of convergence graph

The convergence assessment depicted in Fig. 3 showcases the performance of the IOOA-based approach for load forecasting and scheduling. By the 30th iteration, this method demonstrates a notable improvement in cost efficiency compared to several established models utilized in this domain, namely BA+CNN+LSTM, KMEANS+ANN, LASSO+GRNN, and ABPA+MNN. Specifically, the OOA-based system achieves cost savings of 11.5%, 23.5%, 55%, and 56.25% over these respective models. This analysis underscores the economic advantage of employing the OOA-ARLSTM model for load forecasting and scheduling tasks. . The model adapts to sudden shifts in demand and supply by continuously updating its predictions with new data, enhancing its ability to forecast during unforeseen events. This dynamic adjustment ensures better responsiveness to market changes, increasing robustness.

3.2. Comparative analysis of the proposed model compared with an existing model

The performance of the epoch analysis in load forecasting and scheduling plays a pivotal role in enhancing the efficiency and reliability of the system, as demonstrated in Fig. 4. Particularly, the performance comparison at epoch 25 as delineated in Fig. 2(f), showcases the superiority of the OOA-ARLSTM-based approach over traditional models including BA+CNN+LSTM [26], KMEANS+ANN [27], LASSO+GRNN [28], and ABPA+MNN [29]. The MAPE is a crucial metric for evaluating the accuracy of forecasting models, with lower values indicating higher precision. At the highlighted epoch, the MAPE values for the compared models are as follows: OOA-ARLSTM based model at 5.61%, BA + CNN + LSTM at 6.20%, KMEANS+ANN at 34.76%, LASSO+GRNN at 11.8%, and ABPA+MNN at a similar or possibly higher rate, indicating a disparity not explicitly detailed in the provided context. The OOA-ARLSTM-based model's MAPE of 5.61% underscores its enhanced prediction accuracy and efficiency in forecasting load demands and scheduling, outstripping the performance of both conventional models and those integrating advanced algorithms and neural network architectures.

3.3. Numerical analysis of the recommended model

Table 1 details a numerical comparison of the OOA-ARLSTM-based strategy for load forecasting and scheduling against a range of established models. When compared to the BA+CNN+LSTM, KMEANS+ANN, LASSO+GRNN, and ABPA+MNN models, the improvements offered by the proposed model are quantified at 40.83%, 44.52%, 78.83%, and 21.39% respectively. This underscores that the suggested OOA-ARLSTM-based model outshines the conventional models in performance. The model improves decision-making by providing accurate load forecasts that enable energy traders to make more informed bids. This leads to reduced energy costs, optimized resource allocation, and enhanced profit margins by predicting demand accurately and minimizing wastage.

4. Conclusion

This work has made significant contributions to electricity load forecasting and scheduling for spot trading, demonstrating the effectiveness of advanced predictive models in improving forecast accuracy and reliability. The model outperforms existing approaches, offering potential for more

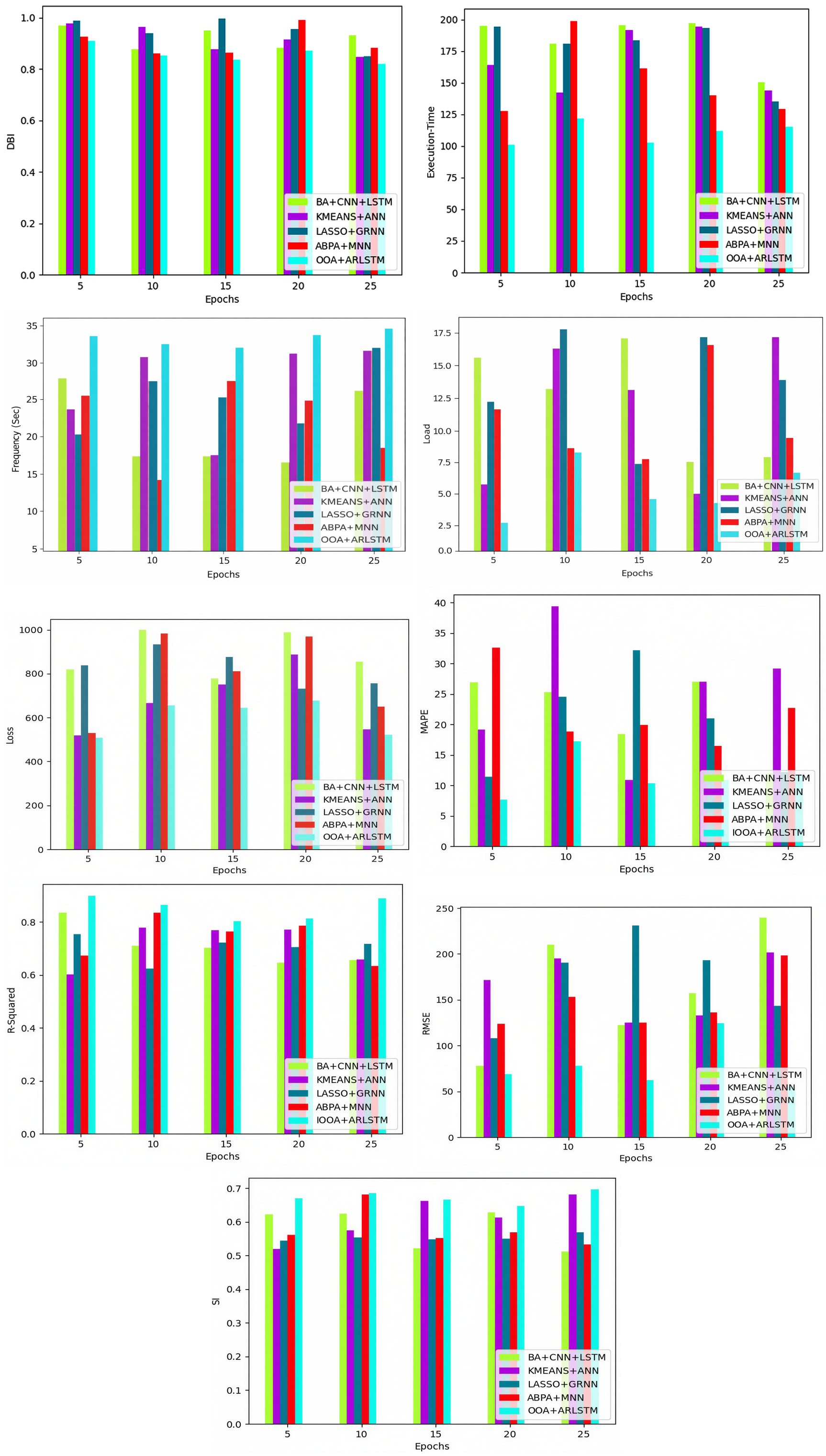

Fig. 4. Performance of epoch analysis for recommended load forecasting and scheduling model compared with existing model regarding (a) DBI, (b) Execution time, (c) Frequency, (e) Load, (f) Loss, (g) MAPE, (h) R-Squared, (i) RMSE and (j) SI

efficient and sustainable electricity market operations by optimizing energy utilization and reducing costs. It also contributes to environmental sustainability by minimizing fuel consumption and carbon emissions. The model

Table 1. Statistical Analysis of the Deep Learning and Heuristic Approach based Load Forecasting and Scheduling Model

Terms/Measures	BA+CNN+LSTM [26]	KMEANS+ANN [27]	LASSO+GRNN [28]	ABPA+MNN [29]	ARLSTM
"Best"	1.341647	1.372405	1.271179	1.273675	0.816565
"Standard deviation"	3.868347	5.545285	2.199589	2.259336	5.150059
"Mean"	2.027022	1.953929	1.481649	1.463432	1.077208
"Median"	1.546948	1.812295	1.271179	1.273675	1.00517
"Worst"	0.937707	0.726094	0.279837	0.283302	0.608581

is adaptable to real-world applications, particularly in extreme weather conditions and market disruptions, enhancing grid stability and market efficiency. Future research will focus on expanding its use in multi-market environments, integrating price forecasting, and validating its performance on real utility-scale data.

Declarations

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Conflicts of interests: Authors do not have any conflicts.

Data Availability Statement: The data generated and analyzed during the current study are available from the author upon reasonable request but are not yet publicly available due to ongoing research.

Code availability: Not applicable.

Authors' Contributions: Xue Li, Sheng Huang, Binghui Zhao is responsible for designing the framework, analyzing the performance, validating the results, and writing the article. Jianheng Lin, Yun Ren is responsible for collecting the information required for the framework, provision of software, critical review, and administering the process.

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