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Demand Forecasting and Resource Scheduling of Independent Energy Storage Market in Power Grid with Deep Learning

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Abstract: - The power grid presents several obstacles for demand forecasting and resource scheduling, such as a substantial amount of data, a growing number of factors influencing the demand profile, uncertainty in the generation profile of distributed energy from renewable sources, and a shortage of historical data. Here, we provide a unique market-oriented energy storage method based on artificial intelligence (AI) that aims to optimize operational profit in the electricity market between consumers, energy storage, and grid service providers. The approach is divided into two parts; the first is the Residual Network-50 (GR-ResNet-50) algorithm, which is used to overcome future uncertainties related to load needs and power pricing. The second uses deep learning based on the Radial Heap Basis Algorithm (RHBA) to determine the most effective charging or discharging operation considering the grid peak states, load demand, and the state of the batteries. The performance of the proposed method in this study is compared with the conventional method in terms of 0.007% of low MAPE and 20 seconds of less execution time. The research shows that the proposed strategy significantly lowers on-peak power, improves operational profit, and improves effective performance.

Keywords: Power Grid, Deep Learning, Energy Storage System, Economic, Forecasting, Scheduling, Optimization And Renewable Resources

1. INTRODUCTION

Integrating renewable energy sources into power grids introduces variability and intermittency, posing significant challenges to grid stability and reliability [1]. Energy storage systems play a pivotal role in mitigating these challenges by storing excess energy during low-demand or high-renewable generation periods and releasing it during peak-demand or low-generation periods [2]. Efficient demand forecasting and resource scheduling are crucial for optimizing the operation of independent energy storage systems in power grids [3]. Traditional forecasting and scheduling methods often rely on simplistic models and heuristics, which may not fully capture the complex dynamics of energy markets and grid operations [4]. In the rapidly evolving landscape of energy markets and power grid management, deploying energy storage systems is increasingly widespread. These systems are essential in balancing supply and demand, improving grid stability, and facilitating the integration of renewable energy sources [5]. A key challenge in maximizing the value of energy storage assets, particularly in market-driven business environments, is optimizing their charging and discharging strategies [6]. Traditionally, energy-saving optimization has relied on heuristic approaches or simplified models that only partially capture the complexity of market dynamics and operational constraints [7].

Furthermore, accurate demand forecasting and efficient resource planning are essential for effective energy conservation management [8]. This paper proposes combining deep learning-based demand forecasting and resource planning techniques to address these challenges to optimize energy storage systems' charging and discharging strategies in market-oriented trading environments within power grids [9]. By improving the capabilities of deep learning models, it aims to improve the accuracy of demand forecasts, enabling more informed decision-making regarding the optimal allocation of energy storage resources. In addition, deep learning-based resource planning algorithms will dynamically adjust charging and discharging strategies in response to real-time market signals, grid conditions, and operational requirements [10]. By harnessing the power of deep learning, we seek to unlock the full potential of energy storage assets, thereby contributing to developing more resilient, sustainable, and efficient power grids.

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In [11], a two-level optimization approach was presented for the distribution system, which contemplates the demand response, electrical energy storage, and energy resources. The first level determines optimal bidding strategies for electric vehicles and demand response aggregators. The second level focuses on real-time optimization of system resources. This integrated framework could improve efficiency, cost savings, and resilience in active distribution systems. However, computational complexity and reliance on assumptions about market behavior and resource availability may occur. In [12], a distribution market operator and a microgrid operator integration were presented to optimize microgrid operation in the electricity market. The mixed integer linear programming formulation enables detailed decision-making considering various resource and grid conditions. However, limitations may include the computational complexity associated with stochastic modeling and potential challenges in accurately modeling and predicting uncertainties. In [13], energy management control was presented using a matrix-based system to innovatively integrate individual and social priorities, designing effective energy trading and integrated network energy distribution.

Using a recurrent neural network for real-time demand forecasting improves its forecasting capabilities. Optimizing energy flows leads to significant economic and energy savings. However, challenges may arise in implementing and scaling the model in diverse social settings and ensuring reliable real-time predictions. In [14], a trade-based battery energy storage system (BESS) planning model was presented to optimize resource allocation and address energy trade advantage loss in distribution markets. Formulated as a reciprocal iterative, multi-objective two-stage optimization problem, it first optimizes internal resource allocation, including PV systems, wind turbines, gas turbines, and BESS. Subsequently, a double-sided auction model called the Average Price Market (APM) mechanism was introduced to reduce discrepancies between time-of-use (ToU) electricity prices and feed-in tariffs. However, its complexity may pose challenges regarding computational load and real-time processing.

In [15], an energy management scheme suitable for interconnected multi-microgrids was presented to address the challenges posed by increased DER integration and high energy storage system costs. The project aims to reduce operational costs for each microgrid while maximizing the use of renewable energy sources (RERs) without disrupting loads. It works by scheduling resources based on daily price curves and RER forecasts and optimizing energy costs through real-time trading with neighboring microgrids. The scheme efficiently corrects the mismatch between forecasted generation and load through energy trading or scheduling stored energy. The main contributions of this paper are as follows: Deep learning with optimization-based demand forecasting and resource scheduling is proposed for power grid energy storage problems with economic issues. The energy sources such as photovoltaic, fuel cell diesel generators, wind turbines, and energy storage systems are combined into the microgrid. The objective function proposed in this paper is to determine the demand and schedule energy sources based on an effective energy storage system. Proposed a GR-ResNet-50 for optimal demand forecasting and incremental cost reduction of the power grid. Proposed an RHBA for best scheduling of charging/discharging of the energy storage system. Demand response programs further strengthen the techno-economic benefits of microgrid operation.

The structure of the paper is as follows. The proposed system's modeling is explained in section 1. The demand forecasting, resource scheduling, and battery model power regulation for energy storage systems are presented in section 2. Section 3 presents the simulation findings and the related discussion, and Section 4 offers the conclusion.

2. SYSTEM MODELLING

The microgrid system includes PV panels, wind power, fuel cells, diesel generators, EV charging points, and energy storage systems. From the perspective of energy storage, this is essentially an arbitrage strategy to make money by charging the energy storage system during low-priced electricity purchases from the power grid, discharging it during high-priced electricity purchases, and then selling electricity to consumers. This profit-seeking technique is only feasible if future power prices and needs can be precisely predicted, as it is predicated on the market margin for electrical costs. Additionally, a thorough analysis of all the variables influencing the energy storage system's lifespan and financial gains must be done to calculate the charge and discharge amounts.

Furthermore, it is essential to consider the profit in both the immediate and distant future to optimize operational profit. Fig. 1 provides an overview of the proposed approach.

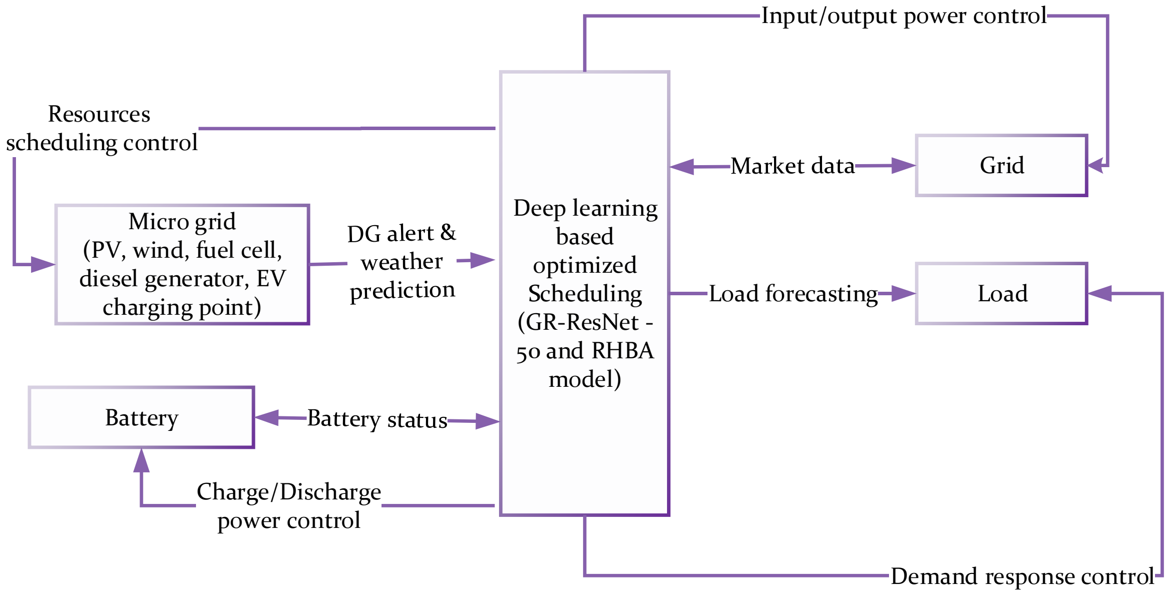


Fig. 1 Proposed methodology

Based on the historical and weather data, the GR-ResNet-50 approach is used in the first stage to anticipate the electricity price and load demand patterns for the next 24 hours. The weather, cloud patterns, and consumer choices are all uncertain. Therefore, load demand, wind generation, and solar power do not preserve the projected profiles. Future uncertainties regarding demand and electricity generation are taken into consideration during optimization. The RHBA approach calculates the energy storage system's future optimal charging or discharging power based on projected pricing, power demands, and SOC. The proposed RHBA aims to discover a way to fulfill the constraints while achieving specific goals due to the demands of less computing time. These include figuring out how much power is exchanged with the primary grid and how much electricity the energy storage system needs to charge and discharge during the day. Furthermore, power losses cannot be broken because of the microgrid connections' significant resistance and low voltage.

2.1. Proposed GR-ResNet-50 algorithm for demand forecasting

The electricity demand in the real world is highly affected by load connections, socio-economic features, user factors, weather data, etc. Since current electricity prices and load demands are utilized to determine the future total benefit, it is necessary to precisely estimate these variables to determine the ideal energy storage system power at the hour. The deep learning model with optimization for time-series data forecasting is covered in this section. The paper proposes the GR-ResNet-50 model, which is composed of two parts: The greedy randomized function and the ResNet-50 method. The Greedy method is an iterative randomized sampling method where each GR iteration gives an outcome to the issue. Each GR iteration is divided into two stages: the first stage uses an evolving randomized greedy function to develop a preliminary solution effectively; the subsequent stage applies a local search process to the generated solution in an attempt to find a better solution, which helps to enhance the convolutional layer of ResNet-50.

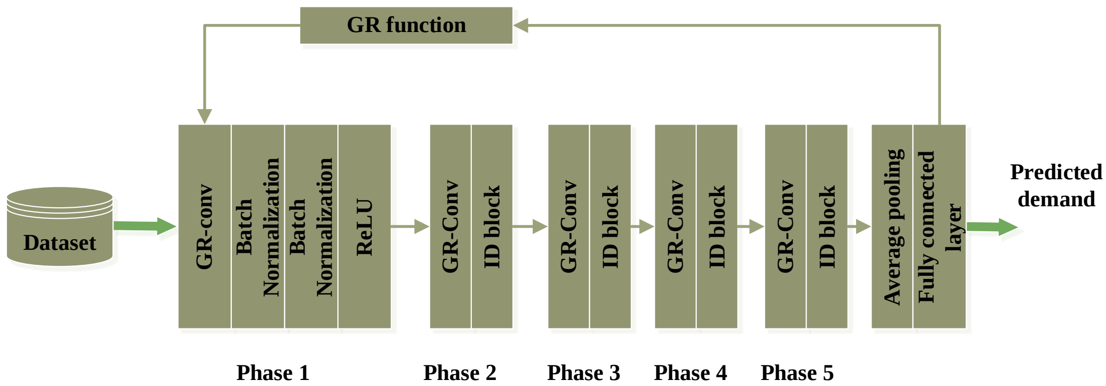


Fig.2 Proposed GR-ResNet-50 in demand forecasting of power grid system

Moreover, the incremental electricity cost has been predicted by this condition. The proposed GR-based ResNet50 comprises sixteen residual blocks, each with several convolutional layers connected by residual connections, as illustrated in Fig. 2. The design has fully linked layers, a softmax output layer for demand forecasting, and pooling layers. Here, the convolution layer feature extraction function is improved by the GR approach function. The historical weather, electric load, and market data are given as the input of the GR-ResNet-50 algorithm. ResNet-50's convolutional layers apply a randomized function to the input information to extract features from the data. A ResNet-50 solution is constructed during the GR building stage one component at a time.

An adaptable greedy function produces a list of potential demands from which each element is randomly chosen. The process accepts the dimension m as input, sets the parameters $d_1 ....d_m$, and λ, and outputs the outermost layer $k*$. The weather, industrial, historical, and economic data are given as the input of the proposed GR-ResNet-50 model. Before proceeding with the G-ResNet-50 method, apply a data cleaning procedure for repairing or eliminating inaccurate, corrupted, improperly formatted, duplicate, or insufficient data from a dataset. After data cleaning, the greedy method selects the significant features from the dataset. The essential features are season, hour, temperature, rainfall, solar, humidity, electricity cost, etc. The GR function has two stages of execution: one is the construction stage, and the other one is the best local search stage. The cardinality of the steps and limited condition of the construction stage for features are estimated using eqn. (1) and (2).

$$\Gamma = \max\{| d_i^0 | : 1 \le i \le m\} \tag{1}$$

$$d = \{i : | d_i^0 | \ge \lambda.\Gamma, 1 \le i \le m\} \tag{2}$$

furthermore, a randomly chosen element s from set d is placed to the cover $k*$. Additionally, the greedy function is modified, meaning that for every set d_i^0, where $i = 1, ...m$, members of set d_i^0 are eliminated. The first answer is the starting point for the iterative local search phase, which looks for a better solution. The process of creating a limited candidate range involves selecting characteristics from the candidate list based on their respective score values. Lastly, an arbitrary feature is chosen and returned from limited candidate range.

$$R = \{i \in data\,list \mid filter[i] \ge d_{\min} + \lambda(d_{\max} - d_{\min})\} \tag{3}$$

A non-improved response is accepted within a specific probability when it is initialized with a parameter called historical weather data, energy consumption, and load demand. After Extracting the data features from the GR function, the batch normalization function is applied. A batch normalization layer is used to normalize the activations after the GR convolutional layer, and then an activation function for ReLU is employed to add uncertainty. ReLU can be prevented from the issue of vanishing gradients and is a computationally beneficial function since it is piecewise linear. To further downsample the feature map by a value of two for each parameter, a max pooling layer and a stride are added at the end. Its purpose is to preserve the most significant information while shrinking the spatial dimensions of the feature maps generated by the convolutional layers. It can aid in preventing overfitting and lowering the network's computing cost. The method preserves the most significant characteristics in the feature map that are input while reducing noise and the impact of minute fluctuations by choosing the highest possible value in each interval.

Moreover, it generates a dimensional feature map that feeds into the ResNet50 architecture's later convolutional blocks. The output of the preceding layer is transformed into a single-dimensional vector by flattening layers, which is subsequently fed into the fully linked layer. Usually employed as the last layers of a neural network, fully connected layers produce the final predictions. Every neuron in this layer gets inputs from every other neuron in the layer before it. The weighted total of these inputs is then used to calculate each neuron's output, which is subsequently analysed using an activation function. Finally, the optimal demands are predicted for further State of Charge (SoC) optimized conditions.

2.2. RHBA of battery energy storage system

Maximizing dependability and minimizing user energy costs are the goals of the BESS combined system's objective function for effective energy management and resource scheduling. The Radial Heap Basis Algorithm combines the Heap optimizer procedure with the neural network function. The RHBA is based on the feed-forward network, which includes input hidden and output layers. The conditions of the heap optimizer approach tune the parameters of the radial network. The RHBA model in BESS and energy scheduling is illustrated in Fig.3. The model's prediction consumption, cost, constraints data, and generation are given to the RHBA model input. The normalized input variables are distributed to the hidden units of the hidden layer by the input layer. Every covert unit executes a radial basis function with dimensions equivalent to various input variables linked to a center vector. Consider the input and output data for training problems using eqn. (4),

$$(a_i, b_i),\ i = 1,2.....M \tag{4}$$

Where, $a_i \in \Re^s, b_i \in \Re,$, the number of input for charge/discharge condition in state of charge of battery is denoted as s, and M is the total amount of data. The m^{th} input vector's difference from the node center is the activity of the l^{th} node, which can be found using the following formula:

$$\chi_1(u(m)) = \left\| u(m) - \hat{u}_h \right\| = \sqrt{\sum_{i=1}^{M} (u_i(m) - \hat{u}_{i,h})^2},\ m = 1,.....M \tag{5}$$

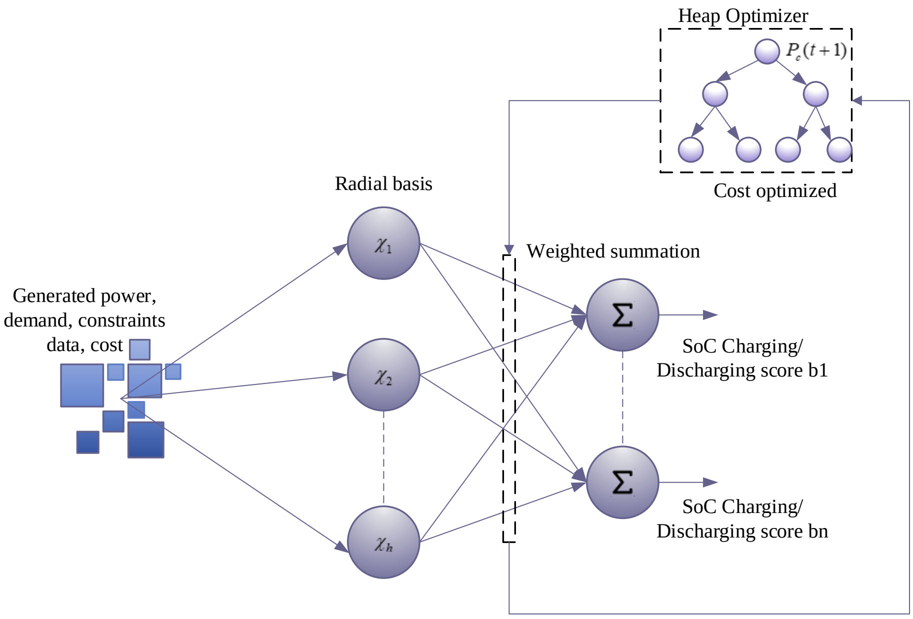


Fig.3. Proposed RHBA in BESS optimization and energy scheduling

The input data vector is represented as $u^T(m) = [u_1(m),.....u_s(m)]$ and the centre of the hidden unit is considered as $\hat{u}_l^T(m) = [\hat{u}_{i,h},.....\hat{u}_{s,h}]$. A radially symmetric function is the activation function for every node. In this study, the thin plate spline function is used:

$$w(\chi) = \chi^2 \log(\chi) \tag{6}$$

Then, the hidden unit outcome is considered as using eqn.(7),

$$y(m) = [g(\chi_1(u(m), \chi_2(u(m).....\chi_h(u(m)))] \tag{8}$$

The hidden unit liner integrated output is expressed using eqn. (9).

$$\hat{b}_n(m) = y(m).W_n = \sum_{h=1}^{H} W_{H,n} g(\chi_h(u(m))) \tag{9}$$

Where, W_n is the synaptic weights vector of the output. Once the radial basis centers and nonlinearities in the hidden layer have been fixed, the heap optimizer of the hidden layer outputs to the actual observed outputs (goal values) is usually used to determine the synaptic weights. The heap optimizer is applied for the optimal solution of radial function in BESS. The fitness performance of the algorithm is applied using eqn. (10),

$$F = \beta\delta(E) + \alpha \frac{|f|}{|v|} \tag{10}$$

Where, $\delta(E)$ is the radiation function weights vector error value, $|f|$ selected features for cost optimization, $\beta \in [0,1], \alpha = (1-\beta)$. Finding a balance between heap optimizer capacities for BESS, the data are initialized in the algorithm such as the trained load demand, SoC, per unit cost. Assign and estimate the optimization issues constraints with its condition. Initialize the heap optimizer parameters. Evaluate the exploitation and exploration phases of heap algorithm in the energy management phases are expressed using eqn. (11),

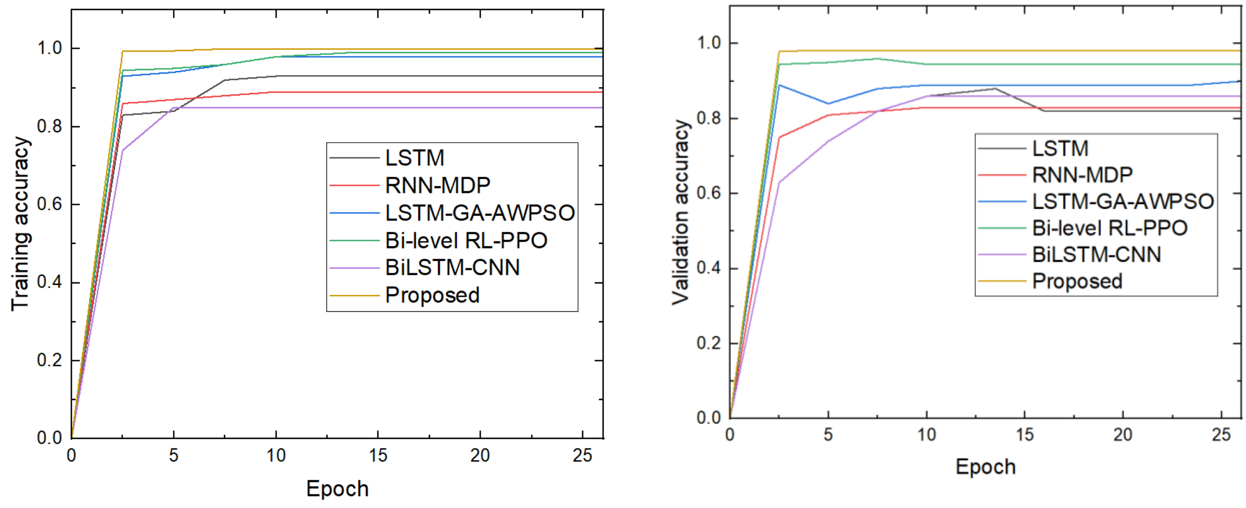
$$P_c(t+1) = \begin{cases} P_g(t) & P_c(t) \le o \\ P_g(t) + \alpha\vec{\delta}\left|P_g(t) - P_{pv}(t)\right| & P_g(t) > 0 \, and \, P_{load}(t) - P_{pv}(t) \le 0 \\ P_{char}(t) + \alpha\vec{\delta}\left|P_g(t) - P_{pv}(t)\right| & \overline{P}_{char}(t) > 0 \, and \, P_{load}(t) - P_{pv}(t) \le 0 \, and \, f(SoC) < f(P_c(t)) \\ P_{disc}(t) + \alpha\vec{\delta}\left|P_g(t) - P_{pv}(t)\right| & \overline{P}_{dichar} > 0 \, and \, P_{load}(t) - P_{pv}(t) \le 0 and \, f(SoC) \ge f(P_c(t)) \end{cases} \tag{11}$$

The optimization procedure will terminate when the maximum number of iterations is reached. If not, the process is repeated, beginning at step one.

3. RESULT AND DISCUSSION

This research is implemented using MATLAB 2019b software in the Windows platform. We use a data set from Kaggle, one of the most significant data science archives, to construct a GR-ResNet-50 model for forecasting the energy demand and RHBA for BESS optimization to demonstrate this process. In simulations, the proposed approach is compared to other demand forecasting models in BESS, such as LSTM, AFC-ANN [10], MI-ANN [45], and Bi-level [46]. The previously described models were chosen as benchmarks because of their more remarkable architectural resemblance to the suggested model. Performance is assessed using various criteria: cost, demand power, accuracy, and MAPE. Accuracy is a percentage (%) expressed as accuracy = 100-MAPE. The time the forecasting technique takes to execute is the execution time, said in seconds. Moreover, the performance of the proposed system is compared with the conventional methods such as Long Short-Term Memory Network (LSTM) [16], recurrent neural networks with Markov decision process (RNN-MDP) [17], Long Short-Term Memory With Genetic Algorithm–Adaptive Weight Particle Swarm Optimization (LSTM-GA-AWPSO) [18], Bi-

Level Reinforcement Learning Proximal Policy Optimization (Bi-level RL-PPO) [19] and Bidirectional Long Short-Term Memory Network With Convolutional Neural Network (BiLSTM-CNN) [20]. The training and validation accuracy proposed by the GR-ResNet-50 model for forecasting the demand is compared with the earlier models illustrated in Fig. 4. The model's accuracy steadily increases as the number of training and validation epochs rises.



(a) (b)

Fig.4 Accuracy rate of a) Training and b) validation

The RHBA-based GR-ResNet-50 energy-management model learns and trains on microgrid operating status data to optimize energy scheduling. Figure 5 shows the simulation findings for the best power from the PV, wind, fuel cell, and diesel generator power grid. The illustration shows adequate wind power resources available between 23:00 and 6:00 when electricity demand is at its highest. It indicates that wind power and higher grid output are prioritized. When the impact on the environment and system operation costs are considered, the load demand between 6:00 to 9:00 and 13:00 to 19:00 exceeds the combined production of PV, wind, and fuel cells.

Additionally, there is enough sunshine between 9:00 and 15:00. Electricity generation from PV is scheduled ahead of electricity generation from diesel generators. The wind energy is completely absorbed, and the microgrid's stability is increased between 8:00 to 14:00 and 15:00 to 23:00 when electricity demand is at its highest. Diesel generators, batteries, and PVs work together to maximize production, but PV output comes first. PVs are almost running at maximum efficiency. Each distributed power source will buy electricity from the primary power grid to satisfy the grid load requirement once it exceeds its nominal power limit.

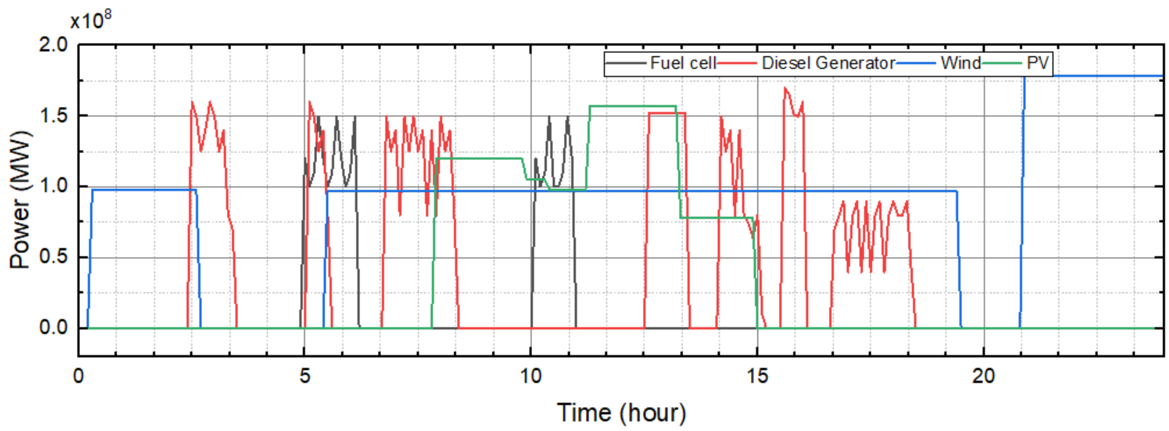
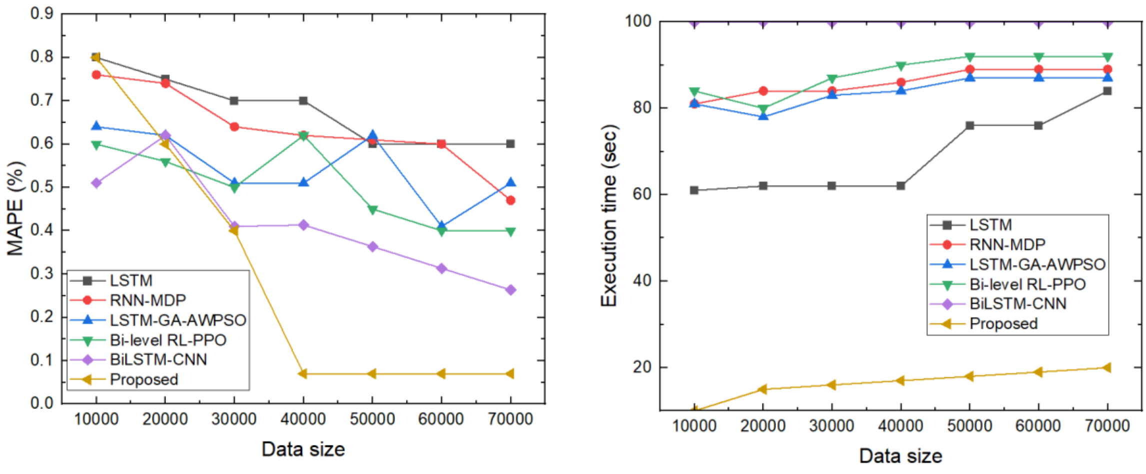


Fig.5 Predicted power values from the simulation results



(a) (b)

Fig.6 Computation of scalability analysis for proposed and conventional methods a) MAPE (%) and b) Execution time (sec)

After that, a comparison is made between the estimated and accurate hourly power usage statistics. The more accurately the prediction model describes the experimental data, the smaller its MAPE and execution value are; the scalability and accuracy of the proposed model are confirmed by computing the prediction model's MAPE. The altered input samples, characteristics, weights, bias, and the accordingly predicted outcomes examine the model's scalability. Fig. 6(a-b) demonstrates that these parameters affect the MAPE and execution time for the existing and proposed models. As the number of data sets rises from 0 to 40000, the accuracy of the demand prediction gets better and trends toward stability. It is confirmed by Fig. 6 (b) that the execution time rises with the number of samples and vice versa. Because the RHBA method is used for BESS optimization and the GR-ResNet-50 approach is used for forecasting, the suggested model is comparatively scalable compared to the benchmark models. The independent energy management cost has been reduced by the proposed models, which is compared with the conventional methods detailed in Fig. 7.

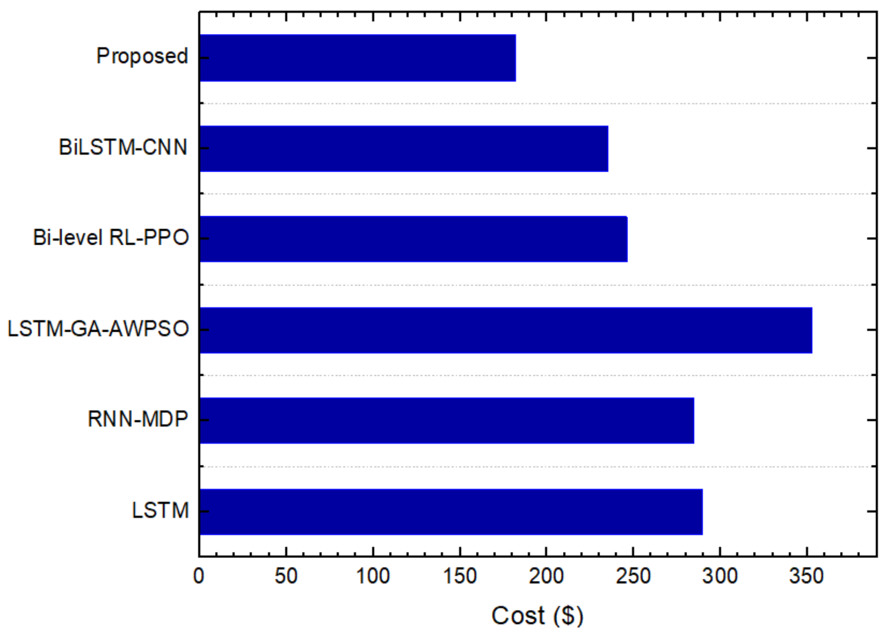


Fig.7. Independent energy management cost optimization

While optimism is an effective pricing strategy when cost reduction is the primary objective, resource scheduling variable load optimization is more straightforward and effective in cost-reduction circumstances. But as all users try to transfer load in short hours, optimization might lead to rebound peaks. The combined deep learning and optimization model subsequently decrease the peak-to-average ratio and electrical consumption. While compared with the earlier models, the proposed model has achieved significantly less amount for energy management that is highly significant for market economics in real time procedure.

4. CONCLUSION

Recently, the influence on a country's social and economic policy has been significant in assessing and controlling electricity consumption. Considering short-term data dependencies, a combined deep learning and optimization model is developed in this work to anticipate demand prediction and battery charging/discharging optimization. The method optimally forecasts demand using the GR-ResNet model for a user-specified period and its subsequent time frame. Based on training, validation, execution time, and MAPE, the demand desired outcomes are compared with the traditional approaches. High forecasting scalability and reliable scheduling algorithms have been attained by the proposed deep learning model, which aims to optimize renewable energy sources and reduce daily electricity expenses. Less MAPE, good training and validation accuracy, shorter execution times, and optimized energy costs were all attained by the suggested approach. Future research will be done to enhance the current design by including PV, wind, and several BESSs in congestion management.

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