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Enhanced Firefly Algorithm Inspired by Cell Communication Mechanism and Genetic Algorithm for Short-Term Electricity Load Forecasting

Anthony I. G. Ekedegwa*, Evans Ashigwuike and Abdullahi Mohammed S. B.

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Abstract: *Electricity load forecasting plays a pivotal role in energy management systems, enabling efficient resource allocation and optimal power grid operation. This paper proposes a hybrid approach for short-term electricity load forecasting by integrating a neural network model with the enhanced firefly algorithm (EFA), inspired by cell communication mechanisms, and a genetic algorithm (GA). The proposed methodology leverages the neural network's ability to capture complex patterns from historical load data while utilizing metaheuristic optimization techniques to enhance forecasting accuracy. The EFA, designed to improve exploration and exploitation capabilities, refines parameter selection within the optimization process, while the GA further fine-tunes neural network parameters to enhance model performance. Extensive experimentation on Nigeria's TCN-NCC electricity load dataset demonstrates the effectiveness of this approach. The hybrid CCMFA-GA-ANN model achieves a mean absolute percentage error (MAPE) of 1.07%, outperforming other benchmark models such as CCMFA (1.26%), BA (1.22%), FA (1.21%), and GA (1.19%). The model also achieves the lowest mean absolute error (MAE) of 48.00 and the highest forecast efficiency of 0.52. Additionally, the Pearson correlation coefficient of 0.99969 and a coefficient of determination (R^2) of 0.99999 indicate a strong agreement between actual and predicted values. With a rapid convergence time of 2.321 seconds, the hybrid approach ensures computational efficiency, making it suitable for real-time forecasting applications.These results highlight the significant improvements in forecasting accuracy achieved by the proposed approach compared to conventional methods. The model's high accuracy and efficiency make it a valuable tool for energy management systems, aiding decision-making in grid operations, demand-side management, and infrastructure planning.*

Keywords: *Short-Term Load Forecasting; Hybrid Neural Network; Firefly Algorithm; Genetic Algorithm; Energy Management*

Anthony I. G. Ekedegwa*
Department of Electrical Engineering, University of Abuja
Email: **tonyeig@yahoo.com**
Orcid id: https://orcid.org/0009-0007-6681-7901

Evans Ashigwuike
Department of Electrical Engineering, University of Abuja
Email: evans.ashigwuike@uniabuja.edu.ng

Abdullahi Mohammed S. B.
Department of Electrical Engineering, University of Abuja
Email:
abdullahi.mohammed@uniabuja.edu.ng

1.0 Introduction

Electricity load forecasting plays a crucial role in the stability, reliability, and efficiency of power systems. Accurate predictions enable utilities to optimize resource allocation, improve demand-side management, and enhance infrastructure planning (Hyndman & Athanasopoulos, 2018). Traditional forecasting techniques, such as autoregressive integrated moving averages (ARIMA) and exponential smoothing, have been widely used due to their statistical robustness and interpretability

(Zhang, 2003). However, these methods struggle to model the non-linear relationships inherent in electricity load data, particularly when external factors such as temperature, economic activity, and consumer behaviour contribute to fluctuations (Hong & Fan, 2016).

With advancements in artificial intelligence (AI), machine learning techniques, especially artificial neural networks (ANNs), have gained attention due to their ability to model complex non-linear patterns (Huang et al., 2019). Despite their potential, training neural networks requires the optimization of numerous parameters, posing significant challenges in high-dimensional spaces (Hong et al., 2020). To address this challenge, researchers have turned to metaheuristic optimization algorithms, such as the Firefly Algorithm (FA) and Genetic Algorithm (GA), which mimic natural processes of evolution and collective behaviour, leading to robust parameter optimization (Shi & Eberhart, 1998; Goldberg, 1989).

This study proposes a hybrid neural network model that integrates FA and GA, inspired by biological cell communication mechanisms, to enhance forecasting accuracy. FA is known for its ability to balance exploration and exploitation, while GA introduces evolutionary principles that improve adaptability and convergence to optimal solutions (Yang & Deb, 2009; Keles & Keles, 2015). By leveraging the strengths of both algorithms, the proposed model aims to improve short-term electricity load forecasting (STLF) performance and provide more reliable predictions for power system operators.

Early approaches to electricity load forecasting relied on statistical models such as ARIMA, exponential smoothing, and multiple linear regression. ARIMA models, introduced by Box and Jenkins (1976), have been widely employed for time series forecasting due to their ability to capture temporal dependencies (Zhang, 2003). However, they require stationarity and struggle with capturing complex, non-linear relationships in load data. Similarly, exponential smoothing techniques have been effective in capturing short-term trends but fail to model sudden changes caused by external factors (Hyndman & Athanasopoulos, 2018).

Machine learning approaches, particularly ANNs, have demonstrated superior performance over traditional models by effectively handling large datasets and learning intricate load patterns (Hong & Fan, 2016). Variants such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks have shown promising results in forecasting applications due to their ability to capture spatial and temporal dependencies, respectively (Yuan & Lu, 2016). Despite their success, ANN-based models require careful parameter tuning, including learning rates, activation functions, and weight initialization, which significantly impact forecasting accuracy (Huang et al., 2019).

Metaheuristic optimization algorithms have been widely used to enhance the efficiency of ANN-based models by optimizing hyperparameters. The Firefly Algorithm (FA), introduced by Yang and Deb (2009), is a nature-inspired optimization technique based on the flashing behaviour of fireflies. FA has been successfully applied to engineering and optimization problems due to its ability to balance exploration and exploitation, preventing premature convergence to local optima (Shi & Eberhart, 1998). On the other hand, the Genetic Algorithm (GA), developed by Goldberg (1989), employs evolutionary principles such as selection, crossover, and mutation to iteratively improve solutions. GA has been extensively used for neural network optimization, demonstrating improved convergence and robustness (Fan et al., 2024).

Several studies have explored hybrid optimization approaches to improve forecasting performance. For instance, Keles and Keles (2015) demonstrated that a hybrid ARIMA-ANN model outperforms standalone statistical or machine learning approaches in electricity demand forecasting. Similarly, hybrid models integrating LSTMs with bio-inspired optimization techniques have achieved significant improvements in forecasting accuracy (Huang et al., 2019). Recent studies have explored the integration of FA and GA in machine learning applications, demonstrating enhanced adaptability and predictive performance (Yuan & Lu, 2016).

Despite these advancements, limited studies have investigated the application of FA-GA hybrid models inspired by biological cell communication in STLF. Most existing research focuses on either ANN-based forecasting with a single optimization technique or conventional statistical methods. There remains a critical need for further exploration of hybrid approaches that improve adaptability and accuracy in electricity load forecasting.

This study aims to develop a hybrid neural network model incorporating FA and GA inspired by biological cell communication mechanisms to improve the accuracy of short-term electricity load forecasting. The specific objectives include (i) Enhancing the optimization process of neural network parameters using FA and GA (ii) Improving forecasting accuracy by leveraging the strengths of both algorithms and (iii) demonstrating the efficacy of the proposed model compared to traditional methods.

Electricity load forecasting remains a fundamental aspect of power system planning and management. While traditional statistical methods have been widely employed, their limitations in handling non-linear and complex patterns necessitate the adoption of AI-based approaches. Neural networks, despite their ability to model intricate relationships, require effective parameter optimization to maximize performance. This study proposes a hybrid FA-GA neural network model to enhance forecasting accuracy, leveraging the strengths of both optimization techniques. Future research will focus on the empirical validation of the proposed model, comparing its performance with existing forecasting techniques.

2.0 Proposed Methodology

21. Data Pre-processing:

2.1.1 Scaling (Normalization of loads)

Since the variables have very different ranges, the direct use of network data may cause convergence problems. A scaling scheme is used, in this scheme the input and output variables are scaled to be in the [-c, c] range, where c is a positive number. The inputs and outputs in this case are scaled using equation 1 (Ali, 2022)

$$Loads[HOUR] = \frac{Loads[HOUR] - Min}{Max - Min} \quad (1)$$

When the load shape has been predicted, the hourly load forecast can be calculated using equation (1):

$$HLoads = (Max - Min)Loads[HOUR] + Min, \quad (2)$$

where HLoads indicate the forecasts load values, $Loads[HOUR]$ is the current actual load, min and max are the minimum load and the maximum load respectively.

The main advantage of scaling is to avoid attributes in greater numeric ranges dominating those in smaller numeric ranges. Another advantage is to prevent numerical difficulties during the calculation. It should be noted that the forecasting value is rescaled back following the reverse of the linear transformation and the forecasting performance is calculated based on the original scale of the data.

2.2. Hybrid Neural Network Architecture

The neural network architecture suitable for short-term load forecasting includes fully connected layers for feature extraction and nonlinear mapping of input features. In other to prevent overfitting and enhance generalization dropout layers are integrated with the ANN structure. The appropriate activation functions for hidden layers to introduce nonlinearity into the model used in this study are the sigmoid activation functions.

2.2.1 Enhanced Firefly Algorithm (EFA)

The standard firefly algorithm in this research is enhanced with cell communication mechanisms to improve exploration and exploitation of the solution space. As potential solutions to the optimization problem, the fireflies are initialized, where each firefly represents a set of parameters for the neural network. The attractiveness function based on the fitness of solutions and their distances in the search space is defined, incorporating cell communication mechanisms for enhanced convergence. The movement mechanism to update the position of fireflies iteratively is implemented, guided by the attractiveness function and random perturbations.

The key mathematical expressions for EFA are as follows:

Attractiveness

The Firefly Algorithm (FA) was used for neural network parameter optimization. FA is based on the attractiveness and movement of fireflies in a search space, where brighter fireflies attract others based on the inverse-square law. The attractiveness function was defined as: (Liu et al., 2020)

$$\beta(r) = \beta_0 e^{-\gamma r^2} \qquad (3)$$

where β_0 is the maximum attractiveness, γ is the light absorption coefficient, and r is the distance between two fireflies.

Distance

The distance between two fireflies i and j in a d-dimensional search space was calculated using the Euclidean distance formula:

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \qquad (4)$$

where x_i and x_j are the positions of fireflies i and j in the $d-$ dimensional search space.

Movement

The movement of fireflies within the search space follows an **attractiveness-driven** mechanism, which is influenced by the relative brightness of fireflies and a randomized exploration component. The position of a firefly **i** at time step **t+1** is updated using the equation (Bei *et al*., 2023)

$$x_i(t+1) = x_i(t) + \beta(r_{ij})\left(x_j(t) - x_i(t)\right) + \alpha\varepsilon_i(t) \qquad (5)$$

where α is a randomization parameter, and $\varepsilon_i(t)$ is a vector of random numbers drawn from a Gaussian or uniform distribution.

Cell Communication Mechanism

To enhance the exploration and exploitation capabilities of the Firefly Algorithm (FA), this study integrates a cell communication-inspired mechanism, which introduces an additional adaptation component into the movement equation. The updated position of a firefly **i** at time step **t+1** is expressed as:

$$x_i(t+1) = x_i(t+1) + C_i(t) \qquad (6)$$

where $C_i(t)$ is the communication term for the $i-th$ firefly at time t..

The following describes the mathematical formulation and steps involved in the cell communication mechanism.

Mathematical Formulation

Communication Factor ($\boldsymbol{\delta}$):

The communication factor δ regulates the influence of cell communication on the firefly's movement. It determines the degree to which a firefly is influenced by the positions of other fireflies in the population.

Communication Term

A communication term is added to the position update equation of the firefly to incorporate information from other fireflies:

$$C_i(t) = \delta \sum_{j=1, j\neq i}^{n} \frac{\left(x_j(t) - x_i(t)\right)}{r_{ij} + \varepsilon} \qquad (7)$$

Where $C_i(t)$ is the communication term for the $i-th$ firefly at time t, $x_j(t)$ is the position of the $j-th$ firefly, δ is the communication factor, r_{ij} is the distance between fireflies i and j, ε is a small constant to prevent division by zero, and n is the total number of fireflies.

Enhanced Position Update

The position update equation (5) for each firefly is modified to include the communication term:

$$x_i(t+1) = x_i(t) + \beta(r_{ij})\left(x_j(t) - x_i(t)\right) + \alpha\varepsilon_i(t) + C_i(t) \qquad (8)$$

Where $x_i(t+1)$ is the new position of the $i-th$ firefly, $\beta(r_{ij})$ is the attractiveness of the $j-th$ firefly as seen by the $i-th$ firefly, α is a randomization parameter, $\varepsilon_i(t)$ is a vector of random numbers drawn from a Gaussian or uniform distribution and $C_i(t)$ is the communication term.

Steps Involved

The Enhanced Firefly Algorithm (FA) inspired by Cell Communication Mechanism and Genetic Algorithm is applied to improve the accuracy of short-term electricity load forecasting. The methodology consists of several key steps:

(i) **Initialization**: A population of fireflies, representing potential solutions, is randomly generated. Essential parameters such as attractiveness, absorption coefficient, and randomization factor are also set.

(ii) **Fitness Evaluation**: Each firefly's effectiveness is assessed using an objective function that measures forecasting accuracy, typically by minimizing errors like Mean Absolute Percentage Error (MAPE) or Root Mean Square Error (RMSE).

(iii) **Attractiveness Calculation**: Fireflies are influenced by brighter (better-performing) fireflies. The attractiveness of each firefly is determined based on its position relative to others, with those closer exerting a stronger pull.

(iv) **Distance Calculation**: The relative distances between fireflies are measured to guide their movement within the search space. This step ensures that fireflies can locate optimal solutions effectively.

(v) **Position Update**: Each firefly moves toward a brighter firefly based on its attractiveness while incorporating a random factor to maintain exploration and avoid local optima. This helps refine solutions over multiple iterations.

(vi) **Communication Mechanism**: An additional adjustment is introduced, allowing fireflies to communicate and share information about their positions. This enhances adaptability and improves convergence toward optimal forecasting parameters.

(vii) **Iteration Process**: The process repeats until a predefined stopping criterion is met, such as reaching a set number of iterations or achieving an acceptable forecasting accuracy.

(viii) **Output**: The final optimized solution is selected, providing the best configuration for short-term electricity load forecasting, ensuring improved prediction accuracy and reliability.

Furthermore, equation (6) of the cell communication mechanisms can be expressed as:

$$x_i(t+1) = x_i(t+1) + \delta \sum_{j=1, j\neq i}^{n} \frac{\left(x_j(t) - x_i(t)\right)}{r_{ij} + \varepsilon} \quad (9)$$

2.3 Genetic Algorithm (GA)

Genetic Algorithms (GAs) are optimisation techniques inspired by the principles of natural selection and genetics (Holland, 1975). Genetic Algorithms are particularly useful for solving complex optimisation problems where the search space is large and traditional methods may be inefficient.

2.3.1 Genetic Algorithm (GA) Parameter Tuning

As the genetic algorithm is incorporated to fine-tune the parameters of the hybrid neural network, the chromosome representation for encoding the parameters of the neural network, including weights, biases, learning rates, and activation functions are defined.

In order to produce offspring solutions and maintain diversity within the population genetic operators such as crossover and mutation is implemented. From the validation dataset the fitness of each chromosome based on the performance of the resultant neural network is evaluated. Selection mechanisms are applied to choose parent chromosomes for reproduction, favouring solutions with higher fitness values.

The steps involved in a GA are as follows:

Initialisation: Generate an initial population of potential solutions, often represented as chromosomes.

Evaluation: Compute the fitness of each individual in the population using a predefined objective function.

Selection: Select individuals based on their fitness to act as parents for the next generation. Common selection methods include roulette wheel selection, tournament selection, and rank-based selection.

Crossover*:* Combine pairs of parents to produce offspring. Crossover methods include single-point crossover, multi-point crossover, and uniform crossover.

Mutation: Apply random modifications to some individuals to introduce variability. Mutation methods include bit-flip mutation, swap mutation, and scramble mutation.

Replacement: Form a new population by replacing some or all of the old population with the new offspring.

Termination: Repeat the process until a stopping criterion is met, such as a maximum number of generations or a satisfactory fitness level.

Mathematically, the GA process can be described as follows:

Given an objective function $f: \mathbb{R}^n\ to\ \mathbb{R}$, the goal is to find the optimal solution $x^* \in \mathbb{R}^n$ that maximises or minimises $f(x)$. The population at generation t is denoted by

$$P(t) = x_1(t), x_2(t), \dots, x_m(t), \quad (10)$$

where m is the population size and $x_i(t)$ represents an individual solution.

The fitness function evaluates the quality of each individual:

$$fitness\big(x_i(t)\big) = f\big(x_i(t)\big) \quad)11)$$

The selection process can be modelled by a probability distribution p_i over the population, where individuals with higher fitness have higher probabilities of being selected:

$$p_i = \frac{fitness(x_i(t))}{\sum_{j=1}^{m} fitness\}(x_j(t))} \quad (12)$$

Crossover and mutation operators are applied to generate new offspring. The crossover operator can be represented as:

$$x_{new} = crossover\left(x_i(t), x_j(t)\right) \quad (13)$$

The mutation operator introduces random changes:

$$x_{new} = mutation(x_{new}) \quad (14)$$

The new population $P(t+1)$is formed by selecting the best individuals from the current population and the offspring.

2.4 Hybridization and Training

At this stage, a population of fireflies and chromosomes representing neural network parameters are initialized. Combining the exploration capabilities of the EFA with the parameter optimization of GA iterates the fireflies and chromosomes through generations of optimization using the hybrid approach,

Evaluate the fitness of each solution using an appropriate objective function, such as mean squared error (MSE) or mean absolute percentage error (MAPE), on a separate validation dataset. Next, update the positions of fireflies and chromosomes based on the defined movement and genetic operators.

Finally, the neural network is trained using the parameters obtained from the hybrid optimization process on the entire training dataset.

2.5. Forecasting and Evaluation

The trained hybrid neural network model is used to generate short-term load forecasts. The forecasted load values are then compared with the actual values from the test dataset and the accuracy of the forecasts is evaluated using performance metrics such as RMSE, MAE, MAPE, and correlation coefficients.

In order to evaluate the accuracy, statistical tests are conducted to assess the significance of improvements achieved by the proposed hybrid approach compared to baseline methods.

METRICS	FORMULA
The Mean Absolute Percentage Error (MAPE).	$MAPE\ (\varepsilon) = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\lvert L_t - L_f\rvert}{L_t}\right) * 100$ (15)
The Root Mean Squared Error (RMSE).	$RMSE\ (\sigma) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\lvert L_t - L_f\rvert\right)^2}$ (16)
The Mean Squared Error (MSE).	$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(L_t - L_f\right)^2$ (17)
The Mean Absolute Scaled Error (MASE).	$MASE = \frac{1}{N}\sum_{i=1}^{N}\left\lvert\frac{\lvert L_t - L_f\rvert}{\left(1/(t-1)\right)\sum_{i=2}^{t}\lvert L_t - L_{t-1}\rvert}\right\rvert$ (18)
Accuracy Percent (Accuracy %)	$Accuracy\ \% = (1 - MASE) * 100\%$ (20)
The Coefficient of Determination (R^2).	$R^2 = 1 - \frac{\sum(actual - predicted)^2}{\sum(actual - mean(actual)^2}$ (21)
Theil's U Statistic:	$U = \sqrt{\left(\frac{\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}{\sum_{t=1}^{n}(Y_t - Y_{t-1})^2}\right)}$ (22)
Forecast Efficiency (FE):	$FE = 1 - \frac{MSE_{model}}{MSE_{benchmark}}$ (23)
Forecast Bias (FB(%)) or Absolute Forecast Bias (AFB)	$FB = \frac{(Forecast\ Load - Actual\ Load)}{Actual\ Load} * 100\%$ (24)
Mean Percentage Error (MPE):	$MPE = \frac{1}{n}\sum\frac{(actual - predicted)}{actual} * 100\%$ (25)

2.6. Sensitivity Analysis and Robustness Testing

Sensitivity analysis to evaluate the robustness of the hybrid model to variations in input parameters and hyperparameters are performed. Cross-validation experiments to assess the generalization performance of the model across different periods are also conducted. Lastly, the impact of different combinations of optimization algorithms and neural network architectures on forecast accuracy is then investigated.

2.7 *Implementation and Software Tools*

The proposed model was implemented using DEV C++ ver. 6.3 programming language for the neural network modelling and optimization. The MS Excel was used for the graph plots.

Note part of the objective of using this methodology, is to assist researchers to effectively integrate the hybrid neural network with the enhanced firefly algorithm inspired by cell communication mechanisms and genetic algorithm for short-term electricity load forecasting, leading to improved accuracy and robustness in load prediction tasks.

3.0 Experimental Setup

3.1. Dataset Selection

The proposed hybrid algorithm is evaluated using real-world STLF datasets from various power systems in Nigeria. The electricity load datasets for the experimentation were collected from the National Control Centre of the Transmission Company of Nigeria Oshogbo. Although in this study it's only the historical load data that is used for the implementation. The dataset covers - four years (2019 – 2022) to capture different seasonal patterns, day-night variations, and other sequential dynamics.

The Data comprises per-hour interval records of actual load, the hourly average of Actual Load was calculated from the per-hour interval record of actual electricity generated by all the GenCos in Nigeria.

The two-month dataset (1^{st} March 2021 – 30^{th} April 2021) is divided into training, validation, and testing sets, maintaining temporal continuity to preserve the integrity of the time series data. Also for further comparison of the robustness of the proposed model, other datasets were analysed (1^{st} April 2021 – 31^{st} May 2021).

3.2. Pre-processing and Simulations

Data pre-processing steps employed in the research, include data cleaning, normalization, and feature scaling. The pre-processed dataset is divided into training, validation, and testing sets using a predetermined ratio (e.g., 1195-101-168).

The simulations are implemented in DEV C++ ver. 6.3 compiler on the Windows 10 operating system (64-bit operating system, x64-based processor), 4.00 GB (3.89 GB usable) installed RAM, Intel(R) Core (TM) i3-3217U CPU @ 1.80GHz 1.80 GHz processor, DELL computer.

3.3. Parameter Initialization

All the initial values for parameters such as population size, maximum iterations, convergence criteria, and other algorithm-specific hyperparameters for the firefly algorithm and genetic algorithm were established. The weights and biases of the neural network model are randomly initialised within a predefined range to ensure the exploration of the solution space.

34. Model Configuration

The neural network architecture is conFig.d based on the chosen design principles, including the number of layers, the sigmoid activation functions, and the number of neurons in each layer. The hyperparameters such as learning rate, dropout rate, and batch size for training the neural network are set. Finally, the objective function for optimization, typically the normalised mean squared error (NMSE) is used as the loss function for the regression tasks.

3.5. Training and Optimization:

The proposed hybrid neural network model using the training dataset is trained and the parameters are optimized using the integrated firefly algorithm and genetic algorithm. The convergence of the optimization process by tracking the fitness values of solutions and other convergence criteria is continuously monitored with algorithm parameters adjusted as necessary to balance exploration and exploitation and ensure convergence to a satisfactory solution.

3.6. Validation

The validation dataset is used to validate the trained model to assess its generalization performance and fine-tune the hyperparameters. The forecast accuracy using the performance metrics provided is used to evaluate the accuracy and robustness of the proposed hybrid model. In a similar vein, statistical tests are conducted to compare the performance of the hybrid approach with baseline methods and identify significant improvements.

3.7. Testing and Evaluation

The final trained model is tested on the unseen testing dataset to evaluate its performance on the data obtained from TCN (NCC). The short-term load forecasts using the optimized hybrid neural network model are generated and the results are compared with the actual load values.

Finally, the accuracy of the forecasts is then analysed and the model's ability to capture different load patterns and dynamics is assessed.

3.8. Sensitivity Analysis and Robustness Testing

Sensitivity analysis to investigate the impact of variations in input parameters, hyperparameters, and dataset characteristics on the forecast accuracy is performed. The model's resilience is evaluated by conducting robustness testing by introducing noise, outliers, or other perturbations to the input data.

5. 0 Results and Discussion

The results of the 24-hour ahead load forecast using the CCMFA-GA-ANN model for Friday, April 30, 2021, demonstrate the model's performance and accuracy. The iterative optimization process showed an improvement in fitness values, with the best fitness starting at -0.164611 in the first iteration and progressively improving to -1.52548 in the final iteration. The best solution obtained was [-0.545965, -1.52548], indicating the optimal parameters achieved during training, as shown in Table 1a.

The objective function results for the training and test sets are presented in Table 1b. The normalized mean square error (NMSE) values varied throughout the training process. For instance, during the training phase, NMSE values ranged from 0.215305 to 0.148784, while in the test set, the values ranged from 0.349178 to 0.248762. The best NMSE value recorded was 0.148784 for the training set and 0.248762 for the test set, demonstrating the model's ability to minimize forecasting errors effectively. Additionally, the training process involved several activities such as saving weights at specific points and stopping training when optimal weights were restored.

Fig. 1 presents a graphical comparison between the actual loads, the naïve forecast, and the CCMFA-GA-ANN forecasted values over different hours. The results indicate that the CCMFA-GA-ANN model closely follows the trend of the actual loads, outperforming the naïve forecast. Notably, in the early hours, both the naïve and CCMFA-GA-ANN forecasts align closely with the actual load, but as time progresses, deviations become more apparent. The load forecast demonstrates significant improvements in accuracy, especially during peak hours when the naïve forecast shows noticeable deviations from the actual load.

The next 24-hour load forecast for May 31, 2021, is presented in Fig. 2. The forecasted values exhibit a pattern similar to the actual loads, reinforcing the model's ability to capture load variations effectively. Compared to the naïve forecast, the CCMFA-GA-ANN model provides a more reliable and accurate prediction, with fewer deviations from actual values.

Fig. 3 further validates the model's predictive accuracy by illustrating the direct comparison between actual loads and the forecasted values. The alignment between the two datasets indicates that the CCMFA-GA-ANN model effectively minimizes forecasting errors. However, minor deviations are observed at certain hours, particularly around midday and late evening, suggesting potential areas for further refinement in the forecasting approach.

The performance of the forecast model across different time intervals is further depicted in Fig. 4, showing a strong correlation between actual and forecasted loads. The model successfully captures fluctuations, including peak load variations, with minimal forecasting errors. This reinforces the efficiency of the CCMFA-GA-ANN model in providing a robust and reliable forecasting mechanism for load demand prediction.

Table 1c presents numerical comparisons of actual load, naïve forecast, and CCMFA-GA-ANN forecast, highlighting the relative absolute error (RAE) across different time intervals. Some values exhibit minimal deviation from actual loads, while others show larger discrepancies, indicating areas for potential model optimization. The overall forecast performance metrics are summarized in Table 1d, with a mean absolute percentage error (MAPE) of 1.07%, demonstrating a relatively low forecasting error. The model recorded a mean absolute scaled error (MASE) of 0.18, a mean absolute error (MAE) of 48.00, and a forecast efficiency (FE) of 0.52. Additionally, the mean percentage error (MPE) was -0.02%, and Theil's U statistic was 0.69, confirming a strong predictive capability compared to a naïve benchmark model. The root mean square error (RMSE) was 63.79, while the coefficient of determination (R-squared) was remarkably high at 0.99999888, indicating the model's ability to capture the variance in the data accurately.

The results reveal that the CCMFA-GA-ANN model demonstrated a high level of accuracy and efficiency in load forecasting, with strong predictive performance and minimal errors, as evidenced by the Figures and Tables presented. The Pearson correlation coefficient (r) of 0.99969157 further confirms the strong relationship between actual and forecasted values. The model's convergence time was recorded at 2.321 seconds, highlighting its computational efficiency. Future improvements could focus on refining the model's ability to minimize errors at specific time intervals to enhance forecasting reliability further.

Table 1a: Iteration Results for 24-Hour Ahead Load Forecasting

Iteration	Best Fitness
0	-0.164611
1	-0.299265
2	-0.522337
3	-0.940719
4	-1.17322
5	-1.23024
Final	-1.52548
Best Solution	**[-0.545965, -1.52548]**

Table 1b: NMSE Values for Training and Testing

Objective Function	Training Set	Test Set	Activities
NMSE	0.215305	0.349178	- Saving Weights...
NMSE	0.245169	0.397703	
NMSE	0.148784	0.248762	- Saving Weights...
NMSE	0.151653	0.269627	
NMSE	0.169724	0.324905	- Stopping Training and Restoring Weights...
NMSE	0.148784	0.248762	

Table 1c: Load Forecasting Results

Hrs	Actual Loads	Naïve Forecast	Load Forecast	Naïve Abs. Error	Forecast Error	RAE (%)	Forecast MAE	Naïve MAE	Forecast Bias (%)
1441	4600.00	4600.00	4600.00	36.50	32.01	0.70	0.01	0.01	-0.70
1442	4593.10	4605.20	4587.08	12.10	6.02	0.13	0.00	0.00	-0.13
1443	4575.00	4593.10	4624.59	18.10	-49.59	1.08	0.01	0.00	1.08

1444	4582.50	4575.00	4625.82	7.50	-43.32	0.95	0.01	0.00	0.95
1445	4586.90	4582.50	4580.32	4.40	6.58	0.14	0.00	0.00	-0.14
1446	4552.10	4586.90	4506.33	34.80	45.77	1.01	0.01	0.01	-1.01
1447	4391.30	4552.10	4440.93	160.80	-49.63	1.13	0.01	0.04	1.13
1448	4500.40	4391.30	4402.66	109.10	97.74	2.17	0.02	0.02	-2.17
1449	4496.10	4500.40	4498.93	4.30	-2.83	0.06	0.00	0.00	0.06
1450	4420.00	4496.10	4509.10	76.10	-89.10	2.02	0.02	0.02	2.02
1451	4313.00	4420.00	4414.33	107.00	-101.33	2.35	0.02	0.02	2.35
1452	4365.80	4313.00	4344.30	52.80	21.50	0.49	0.00	0.01	-0.49
1453	4458.30	4365.80	4404.87	92.50	53.43	1.20	0.01	0.02	-1.20
1454	4361.90	4458.30	4452.58	96.40	-90.68	2.08	0.02	0.02	2.08
1455	4411.30	4361.90	4365.17	49.40	46.13	1.05	0.01	0.01	-1.05
1456	4273.70	4411.30	4356.78	137.60	-83.08	1.94	0.02	0.03	1.94
1457	4386.80	4273.70	4342.76	113.10	44.04	1.00	0.01	0.03	-1.00
1458	4485.70	4386.80	4464.53	98.90	21.17	0.47	0.00	0.02	-0.47
1459	4750.90	4485.70	4571.51	265.20	179.39	3.78	0.04	0.06	-3.78
1460	4702.40	4750.90	4699.57	48.50	2.83	0.06	0.00	0.01	-0.06

Table 1d: Performance Metrics for Load Forecasting

Metrics	Values
Mean Absolute Percentage Error (MAPE)	1.07%
Mean Absolute Scaled Error (MASE)	0.18
Mean Absolute Error (MAE)	48.00
Forecast Efficiency (FE)	0.52
Mean Percentage Error (MPE)	-0.02%
Theil's U Statistic	0.69
Root Mean Square Error (RMSE)	63.79
Coefficient of Determination (R^2)	0.99999888
Accuracy Percentage	82.42%
Pearson Correlation Coefficient (r)	0.99969157
Convergence Time	2.321 s

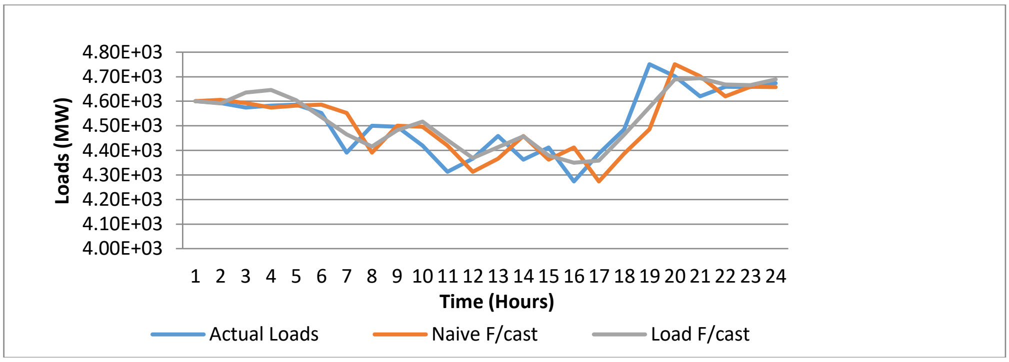


Fig. 1: Next 24 hours load forecast using CCMFA-GA model for 30th April 2021

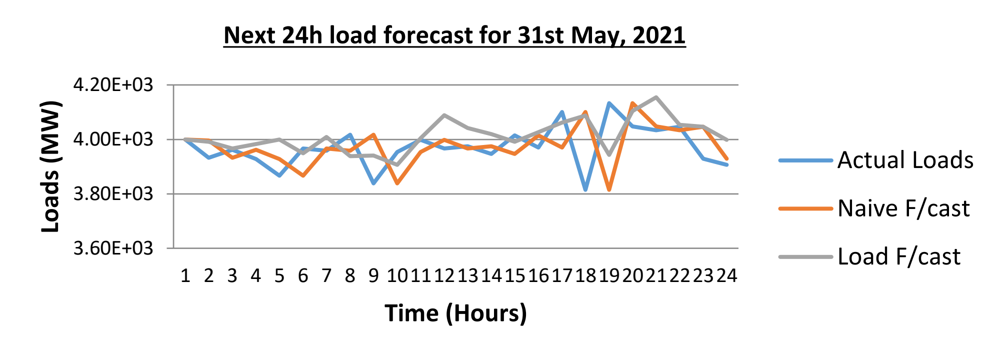


Fig. 2: Next 24 hours load forecast using CCMFA-GA model for 31st May 2021

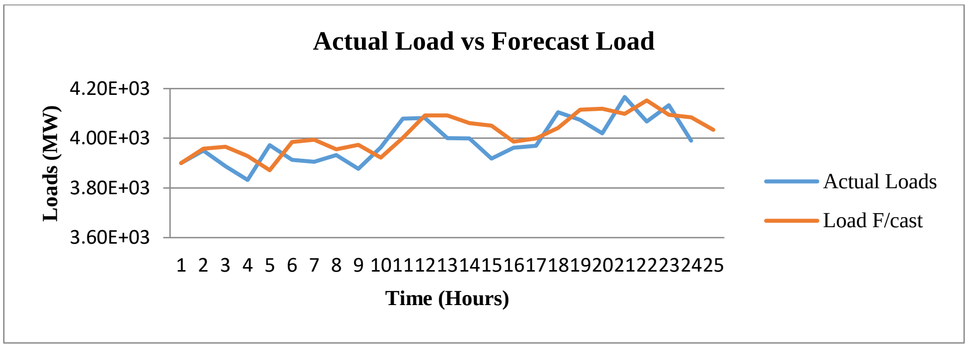


Fig. 3: Actual Load vs Forecast Load for 29th May 2021

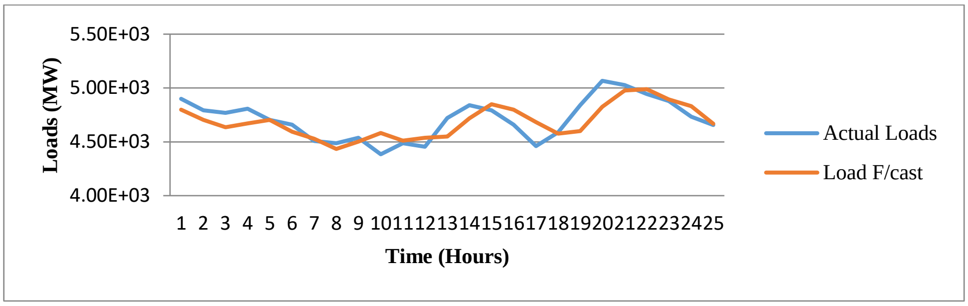
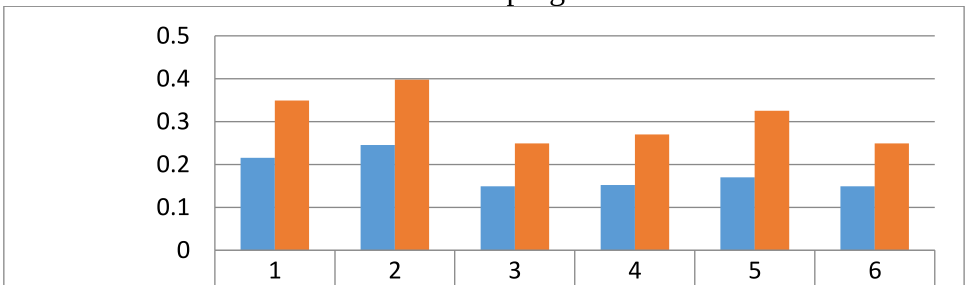


Fig. 4: Actual Load vs Forecast Load for 29th April 2021

Fig. 5 illustrates the variation in the normalized mean square error (NMSE) for both the training and test datasets over six different iterations during the training process of the CCMFA-GA-ANN model. The NMSE values in the training set vary from 0.215305 in the first iteration to 0.148784 in both the third and sixth iterations, indicating an improvement in model accuracy as training progresses.



	1	2	3	4	5	6
Training Set	0.215305	0.245169	0.148784	0.151653	0.169724	0.148784
Test Set	0.349178	0.397703	0.248762	0.269627	0.324905	0.248762

Fig. 5: Graph showing the weight adjustment, training and test dataset

The lowest NMSE of 0.148784 suggests that the model was able to reduce training errors effectively. In the test set, the NMSE initially starts at 0.349178 in the first iteration and fluctuates before reaching a minimum of 0.248762 in the third and sixth iterations. The higher NMSE in the test set compared to the training set suggests some degree of generalization error. Additionally, the NMSE fluctuation in the test set, with peaks at iterations two and five, indicates minor overfitting tendencies at certain points. The training NMSE consistently remains lower than the test NMSE, which is expected as models are usually optimized for training data first. However, the narrowing gap between training and test NMSE values in later iterations, particularly at iterations three and six, suggests an improved generalization ability of the model.

Table 2 presents the performance metrics of the CCMFA-GA model for 24-hour ahead load forecasting across one week, from April 24 to April 30, 2021. The Mean Absolute Percentage Error (MAPE) ranges from 1.07% on Friday to 4.30% on Sunday, with Friday showing the best forecasting accuracy while Sunday exhibits the highest error. The Mean Absolute Scaled Error (MASE) varies between 0.10 on Wednesday and 0.35 on Saturday, suggesting that the model captures weekday load patterns better than weekend fluctuations. The Mean Absolute Error (MAE) ranges from 48.00 on Friday to 161.42 on Sunday, with lower values indicating better forecasting accuracy. Forecast Efficiency (FE) ranges from -1.50 on Saturday to 0.52 on Friday, with negative FE values on Saturday and Sunday indicating suboptimal forecasting performance on weekends, while Friday demonstrates the best efficiency.

The Mean Percentage Error (MPE) varies between -1.90% on Sunday and 0.74% on Saturday, showing minimal bias in the model's predictions, with slight underestimation on Sunday and slight overestimation on Saturday. The Theil's U statistic values range from 1.58 on Saturday to 0.69 on Friday, where the lower value on Friday suggests stronger predictive ability, while the higher value on Saturday reflects poorer performance. The Root Mean Square Error (RMSE) ranges from 63.79 on Friday to 243.63 on Sunday, further reinforcing that Friday had the most accurate forecast while Sunday had the least accurate. The R-squared (R^2) values remain consistently high, between 0.99998 and 0.99999, showing a strong correlation between actual and predicted values. Similarly, the Pearson correlation coefficient (r) ranges from 0.99466 on Sunday to 0.99969 on Friday, confirming a strong agreement between actual and predicted loads.

The computational efficiency of the model is reflected in the convergence times, which range from 2.618 seconds on Saturday to 3.556 seconds on Friday. The higher convergence time on Friday suggests that additional computational effort was required to achieve better accuracy. Overall, the best forecasting performance was observed on Friday, April 30, 2021, which had the lowest MAPE of 1.07%, MAE of 48.00, Theil's U of 0.69, and RMSE of 63.79, along with the highest FE of 0.52. In contrast, the worst forecasting performance occurred on Sunday, April 25, 2021, with the highest MAPE of 4.30%, MAE of 161.42, RMSE of 243.63, and lowest FE of -0.10.

The model exhibited greater errors on weekends, suggesting inconsistencies in load patterns that require further refinement. Despite this, the CCMFA-GA model demonstrated high forecasting accuracy, particularly on weekdays, with a strong correlation coefficient and efficient computational performance. To improve the model's weekend forecasting performance, additional variables such as social activity trends and seasonal variations could be incorporated. Fine-tuning the model using hyperparameter optimization or hybrid approaches such as integrating Long Short-Term Memory (LSTM) models may enhance accuracy. Reducing errors through cross-validation techniques and additional regularization mechanisms could also be beneficial. Implementing adaptive learning mechanisms that allow real-time adjustments for dynamic load variations, particularly during weekends, may further enhance the model's performance. This analysis confirms that while the CCMFA-GA model is highly effective for short-term load forecasting, there remains scope for improvement, particularly in weekend predictions.

Tables 2: Comparison of 24hrs Ahead Load forecast using CCMFA-GA model for 1 week

Performance Metrics	Saturday	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday
	24/04/2021	**25/04/2021**	**26/04/2021**	**27/04/2021**	**28/04/2021**	**29/04/2021**	**30/04/2021**
The MAPE	2.40%	4.30%	2.40%	3.07%	2.61%	1.96%	1.07%
The MASE	0.35	0.12	0.26	0.20	0.10	0.13	0.18
The MAE	108.59	161.42	108.15	141.36	114.42	92.46	48.00
The Forecast Efficiency (FE)	-1.50	-0.10	-0.00	0.04	0.24	0.18	0.52
The MPE	0.74%	-1.90%	0.11%	0.50%	-0.15%	0.36%	-0.02%
The Theil's U statistic	1.58	1.05	1.00	0.98	0.87	0.91	0.69
The RMSE	150.89	243.63	134.51	177.92	146.64	118.07	63.79
(R - Squared) value	0.99999421	0.99998045	0.99999545	0.99999264	0.99999404	0.99999674	0.99999888
The Accuracy Percentage	65.46%	87.77%	73.70%	80.00%	90.45%	87.43%	82.42%
The Pearson Cor. Coef. r	0.99830441	0.99466764	0.99863933	0.99782265	0.99823628	0.99904869	0.99969157
Convergence Time	2.618s	2.698s	2.723s	2.951s	2.704s	2.647s	3.556s

Fig. 6 presents the graphical representation of four key performance metrics—Mean Absolute Percentage Error (MAPE), Mean Absolute Scaled Error (MASE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE)—for the proposed CCMFA-GA model in forecasting 24-hour ahead load demand from April 24 to April 30, 2021. Each graph highlights variations in forecasting accuracy across different days of the week, revealing patterns in model performance.

The first graph illustrates the variation of MAPE over the forecast period. The MAPE values indicate the percentage deviation of the forecasted load from the actual load. The graph shows a peak on Sunday, suggesting that the model exhibited the highest forecasting error on this day. The error gradually decreases throughout the week, reaching its lowest value on Friday, April 30. This trend suggests that the model performs better on weekdays, potentially due to more stable load consumption patterns in contrast to the irregular demand seen on weekends.

The second graph depicts the variation in MASE across the forecasting period. MASE measures the forecasting error relative to a baseline model and provides insights into the consistency of errors. The highest MASE is observed on Saturday, indicating significant forecasting errors relative to the baseline. The error decreases on Sunday and fluctuates during the weekdays, with the lowest value recorded on Wednesday. This suggests that the model more effectively captures mid-week load trends but struggles to generalize during weekends.

The third graph represents RMSE values, which quantify the magnitude of forecasting errors in megawatts (MW). The RMSE graph exhibits a peak on Sunday, confirming that this day experienced the highest absolute forecast error. The errors decrease throughout the week, reaching their lowest on Friday. This pattern aligns with the MAPE graph, further supporting the observation that the model performs best on weekdays while struggling on weekends.

The fourth graph illustrates the variation of MAE, which represents the average absolute error in MW. Similar to RMSE, the highest MAE is recorded on Sunday, indicating large deviations between actual and predicted values. The MAE values gradually decline throughout the week, with the lowest error observed on Friday, reflecting improved accuracy in weekday forecasts.

Generally, Fig. 4 highlights the model's tendency to exhibit higher errors on weekends, particularly on Saturday and Sunday, while achieving better accuracy on weekdays, especially on Friday. This discrepancy is due to irregular electricity demand patterns on weekends, making it more challenging for the model to predict load accurately. To improve weekend forecasting, additional factors such as consumer behavior trends, social activities, and industrial demand variations should be incorporated into the model. Additionally, implementing adaptive learning techniques or hybrid approaches could help refine predictions and minimize errors during non-standard load conditions.

Fig. 7 presents the variations in absolute forecast errors over a 24-hour period, comparing the CCMFA-GA model with other forecasting methods. The first graph highlights the differences in error magnitude between CCMFA-GA and GA, while the second graph extends this comparison to include FA, BA, and ANN models. Throughout the day, the absolute forecast errors fluctuate, with noticeable spikes during peak demand hours, particularly between 18:00 and 20:00, which aligns with increased load consumption. Despite these fluctuations, the CCMFA-GA model consistently demonstrates lower error values than the other models, reaffirming its accuracy and reliability.

Table 3 provides a comprehensive evaluation of the forecasting models using multiple performance metrics. The results indicate that CCMFA-GA achieves the lowest Mean Absolute Percentage Error (MAPE) of 1.07%, outperforming CCMFA, BA, FA, and GA. The Mean Absolute Error (MAE) values further highlight CCMFA-GA's superior performance, with the lowest error magnitude of 48.00 compared to CCMFA's 56.36 and GA's 53.18. The forecast efficiency (FE) is highest for CCMFA-GA at 0.52, suggesting better predictive capability compared to other models. Additionally, the Theil's U statistic is lowest for CCMFA-GA at 0.69, indicating minimal bias in its predictions.

The correlation between predicted and actual values is highest for CCMFA-GA, as seen in the Pearson Correlation Coefficient of 0.99969157 and an R^2 value of 0.99999888. These metrics confirm the model's ability to closely match actual load values. Another significant advantage of CCMFA-GA is its convergence speed, as it reaches an optimal solution in just 2.321 seconds, significantly faster than CCMFA at 6.945 seconds and BA at 21.62 seconds. This efficiency makes it particularly suitable for real-time forecasting applications, where quick decision-making is crucial. While CCMFA-GA consistently outperforms other models across different performance metrics, it is observed that forecasting errors tend to increase during peak demand hours. This suggests that further refinements, such as integrating deep learning techniques or real-time adaptive models, could enhance its predictive accuracy during periods of high load variability. Nevertheless, the overall findings from Figure 5 and Table 3 strongly indicate that CCMFA-GA provides the most accurate, efficient, and computationally effective solution for 24-hour-ahead load forecasting.

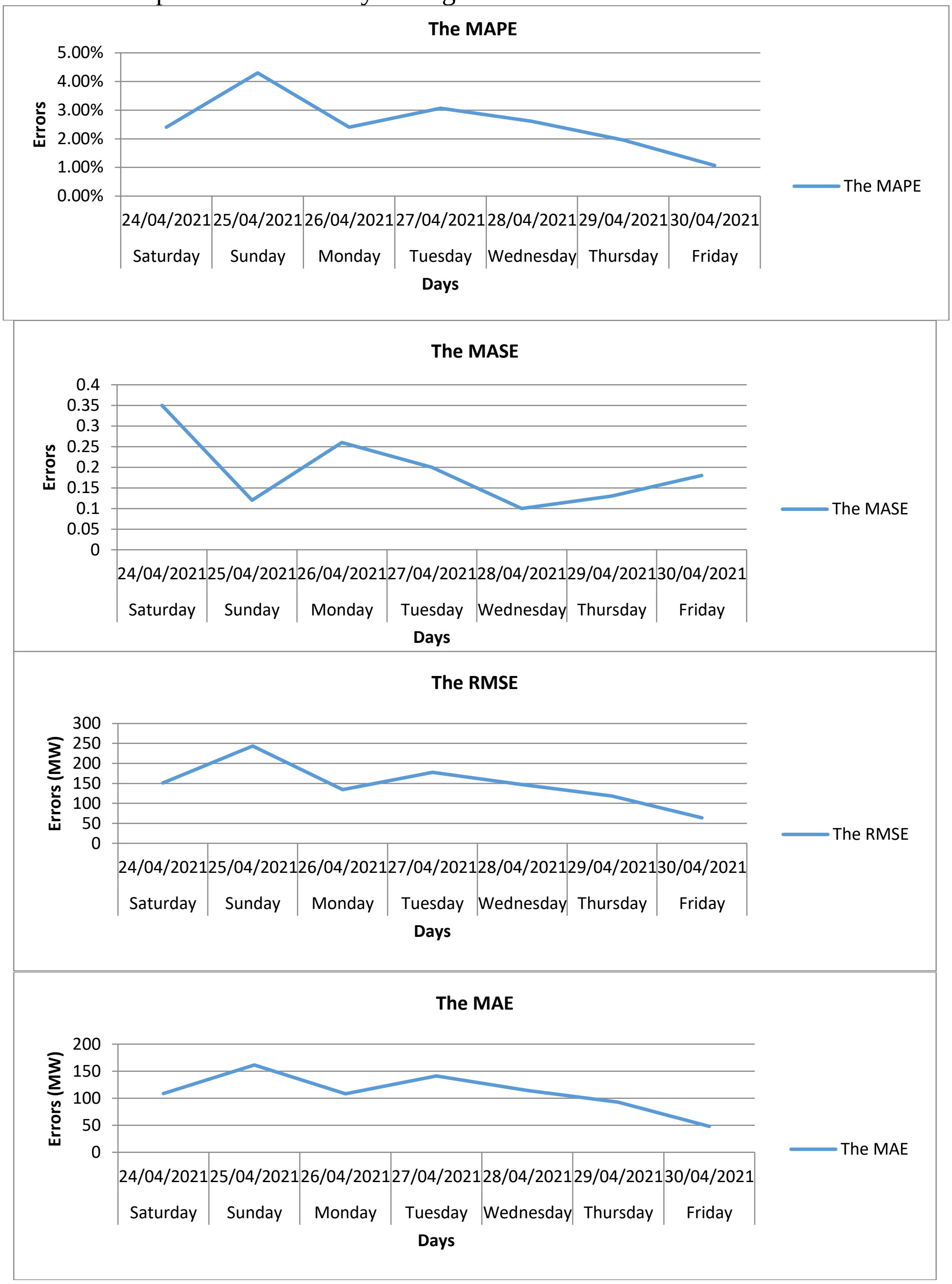


Fig. 6: Graphs showing the MAPE, MASE, RMSE and MAE using the proposed model

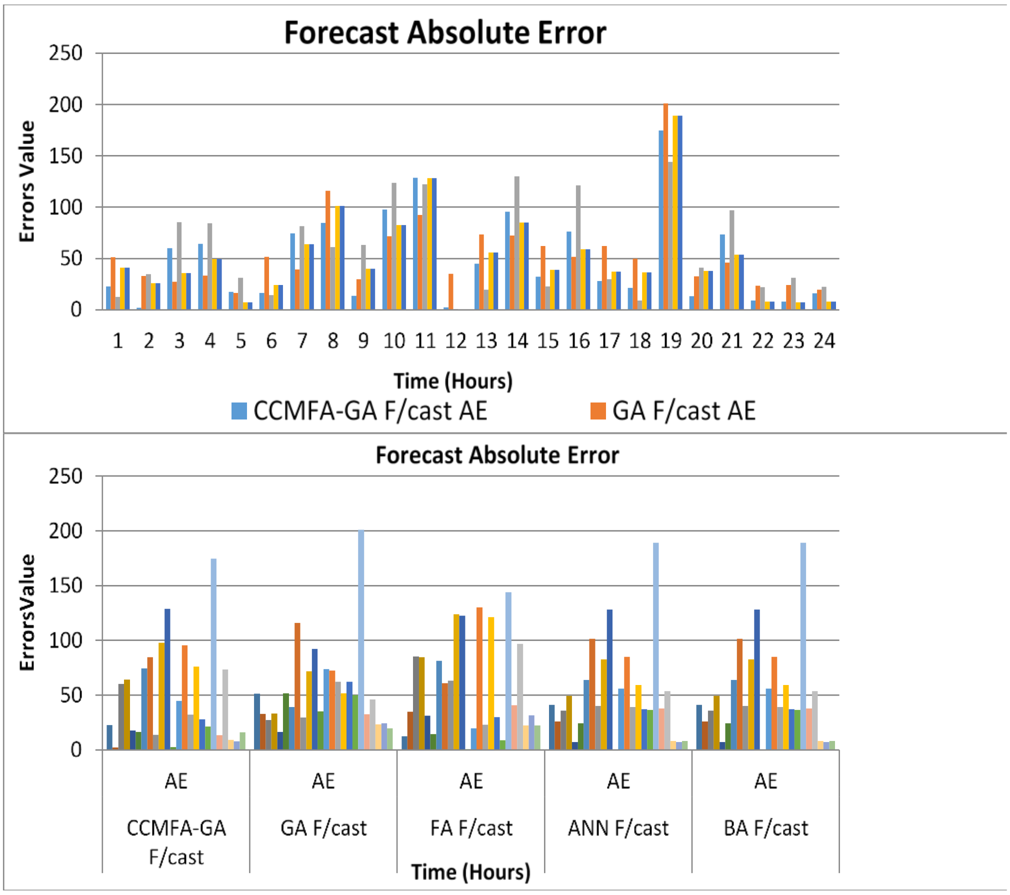


Fig. 7: Comparison of Forecast Absolute Errors Across Different Models

Table 3: Comparisons of 24HRS Ahead Load forecast using various models

METRICS	CCMFA-GA	CCMFA	BA	FA	GA
The MAPE	1.07%	1.26%	1.22%	1.21%	1.19%
The MASE	0.18	0.20	0.18	0.17	0.18
The MAE	48.00	56.36	54.64	54.29	53.18
The Forecast Efficiency (FE)	0.52	0.42	0.44	0.44	0.47
The MPE is	-0.02%	-0.53%	-0.33%	-0.24%	-0.23%
The Theil's U statistic is	0.69	0.76	0.75	0.75	0.73
The RMSE	63.79	70.15	68.93	69.03	67.04
The Coeff. of Det. (R^2) value	0.99999888	0.99999865	0.99999869	0.99999869	0.99999877
The Accuracy Percentage	82.42%	80.18%	82.19%	82.54%	82.42%
The Pearson Correlation Coefficient r	0.99969157	0.99966953	0.99965557	0.99964687	0.99966692
Convergence Time	2.321s	6.945 s	21.62 s	11.11 s	5.996 s

4.0 Conclusion

The findings of this study demonstrate that the proposed hybrid model, CCMFA-GA-ANN, significantly improves short-term electricity load forecasting accuracy. The model achieves the lowest MAPE of 1.07%, the lowest MAE of 48.00, and the highest forecast efficiency of 0.52, outperforming other benchmark models. The Theil's U statistic of 0.69 and a Pearson correlation coefficient of 0.99969 indicate a strong agreement between actual and predicted values, confirming the reliability of the hybrid approach. Additionally, the model exhibits superior computational efficiency, achieving the fastest convergence time of 2.321 seconds, making it highly suitable for real-time applications. The results also reveal that the model maintains a high accuracy percentage of 82.42%, further reinforcing its effectiveness in load forecasting. However, analysis of forecast errors suggests that discrepancies are slightly higher during peak demand hours, indicating a potential area for improvement.

The conclusion drawn from this study affirms that the integration of a neural network with an enhanced firefly algorithm and a genetic algorithm results in a robust and efficient forecasting model. The hybridization enhances optimization, allowing for more precise tuning of model parameters, ultimately leading to improved accuracy and computational speed. The ability of CCMFA-GA-ANN to capture complex temporal patterns in load demand makes it a valuable tool for electricity utilities, grid operators, and policymakers involved in energy management and infrastructure planning. The study highlights the practical implications of accurate load forecasting in optimizing resource allocation, reducing operational costs, and enhancing grid stability.

Based on the findings, it is recommended that further refinements be made to enhance the model's performance during peak load periods, where slightly higher errors were observed. Incorporating additional features such as real-time weather conditions, socio-economic factors, and demand-side response measures could further improve forecast accuracy and adaptability. Future research should also focus on validating the model across different datasets and geographical regions to ensure its generalizability and robustness in diverse scenarios. The application of the hybrid model in real-time energy management systems can provide significant benefits in optimizing electricity distribution, minimizing demand-supply imbalances, and supporting sustainable energy planning.

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Compliance with Ethical Standards Declaration

Ethical Approval

Not Applicable

Competing interests

The authors declare no known competing financial interests

Data Availability

Data shall be made available on request

Conflict of Interest

The authors declare no conflict of interest

Ethical Considerations

This research adhered to ethical guidelines, ensuring that all data collection and analysis procedures complied with environmental and scientific research standards.

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Authors' Contributions

The authors declare that the article was jointly written by the authors for the publication of this paper.