

Optimized Short-Term Load Forecasting Using Hybrid Grey Wolf and Gorilla Troops Optimization Models

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Abstract: Accurate short-term electricity load forecasting is critical for efficient power system operation and management. This study presents a hybrid metaheuristic model, the Grey Wolf Optimizer–Gorilla Troops Optimizer (GWO-GTO), for next-day load prediction. The model's performance was evaluated using actual load data for April 24, 2021, and compared against conventional forecasting techniques. The GWO-GTO model achieved a Mean Absolute Percentage Error (MAPE) of 0.2741%, a Mean Absolute Error (MAE) of 12.8864 MW, and a Root Mean Square Error (RMSE) of 43.2202 MW, demonstrating superior forecasting accuracy. The model also attained a coefficient of determination (R^2) of 0.99999667 and a Pearson Correlation Coefficient (PCC) of 0.99966458, indicating near-perfect alignment between actual and predicted loads. A comparative analysis over a seven-day period (April 24–30, 2021) confirmed the robustness of GWO-GTO, with consistently low MAPE values, peaking at 1.5518% on April 28. In a 168-hour comparative study, GWO-GTO outperformed other models, achieving the lowest MAPE of 2.5072%, MAE of 108.4440 MW, and RMSE of 154.1433 MW, confirming its effectiveness in capturing load variations. Compared to traditional models such as Artificial Neural Networks (ANN) and Genetic Algorithm (GA), GWO-GTO showed a 22–30% improvement in accuracy. These results establish GWO-GTO as a computationally efficient and highly accurate model for short-term electricity load forecasting.

Keywords: Load forecasting, GWO, GTO, Hybrid model, Forecast accuracy, Performance metrics

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1.0 Introduction

The global energy sector is undergoing a significant transformation, driven by the rapid development of smart grids and the increasing integration of renewable energy sources (Jajabal, 2024; Obanu *et al.*, 2024). However, the evolution of novel and expanding technologies in the sector is also witnessing some level of complexity in the management of electricity demand and supply (Lo Piano & Smith, 2022; Nebey, 2024). Back-up literature have agreed that accurate short-term load forecasting (STLF) has become more critical than ever. STLF plays a vital role in ensuring the efficient operation of power systems, facilitating grid stability, and supporting the economic management of energy resources (Karamolegkos & Koulouriotis, 2025; Liu *et al.*, 2025). By predicting future electricity demand over short horizons (ranging from minutes to days), STLF enables utilities to optimize energy distribution, minimize costs, and reduce the risk of blackouts (Biswal *et al.*, 2024)

Based on the literature and field reports, precise load forecasting is essential for various tasks, including resource planning, load balancing, and the integration of intermittent renewable sources like solar and wind (Iftikhar *et al.*, 2023; Saxena *et al.*, 2024; Waheed *et al.*, 2024). However, accurately forecasting electricity demand is complex due to the highly dynamic and often unpredictable nature of energy consumption (Fose *et al.*, 2024; Klyuev *et al.*, 2022). Traditional forecasting methods, such as time series analysis, statistical models, and linear regression techniques, have been widely used for this purpose (Schmid, *et al.*, 2025; Shah & Thaker, 2024). While these models have proven effective in some cases, they often struggle to capture the intricate, nonlinear patterns of electricity demand, particularly when influenced by factors such as weather conditions, economic activities, and sudden fluctuations in consumer behavior.

In recent years, Artificial Neural Networks (ANNs) have gained prominence as powerful tools for STLF due to their ability to model nonlinear relationships in data. Unlike traditional approaches, ANNs can learn from vast amounts of historical data and uncover hidden patterns in electricity demand, making them a promising alternative for improving forecasting accuracy. ANNs are particularly suitable for handling complex, high-dimensional datasets and dynamic systems like power grids (Michailidis, *et al.*, 2024; Safari *et al.*, 2024). However, the success of ANNs depends not only on the architecture of the network but also on the optimization of their weights and parameters. Properly trained ANNs can significantly enhance forecasting performance, while poorly optimized networks may lead to suboptimal predictions.

Optimizing the weights and parameters of an ANN is a challenging task, involving navigating a complex and high-dimensional search space. This is where metaheuristic algorithms come into play. Inspired by natural processes or phenomena, these algorithms have

proven effective in solving optimization problems that are difficult to tackle using traditional techniques. Metaheuristic approaches, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE), are often employed to find optimal or near-optimal solutions for ANN training, especially when dealing with large-scale and nonlinear optimization problems. These algorithms are particularly valued for their ability to avoid local minima and explore the search space more efficiently. Despite advancements in metaheuristic optimization techniques, a single algorithm may not always be sufficient to fully exploit the potential of ANNs. Several literature have confirmed that different metaheuristics exhibit varying strengths in different problem domains, and combining them can lead to enhanced performance (Limane *et al.*, 2025; Tomar *et al.*, 2023). Recent studies have explored hybrid optimization approaches to improve forecasting accuracy (Huang *et al.*, 2024). For instance, some studies such as those by Hassan *et al.* (2020) and Zhang *et al.* (2019) proposed multiple hybrid algorithms combining Cuckoo Search Algorithm (CSA), Grey Wolf Optimization (GWO), Harris Hawks Optimization (HHO), and Whale Optimization Algorithm (WOA) for electricity load and price forecasting. Their results demonstrated that hybrid optimization algorithms perform superior to their base algorithms in most test cases, with the CSA-GWO combination showing significantly better performance than other algorithms. Another study by Zhang *et al.* (2024) focused on electric load forecasting by combining Support Vector Regression and Long Short-Term Memory (SVR/LSTM) methodologies, optimized by a flexible version of the Gorilla Troops optimization algorithm. The proposed methodology was evaluated against various contemporary load forecasting techniques, demonstrating superior accuracy



and robustness in forecasting electric load demand.

Furthermore, research by Prakash *et al.* (2023) has introduced hybrid machine learning paradigms built with nine widely used optimization algorithms, including the Gorilla Troops Optimization (GTO), for predicting the compressive strength of ultrahigh performance concrete. The developed hybrid model of ANN and GTO achieved the most accurate prediction, highlighting the potential of GTO in enhancing ANN performance. While hybrid metaheuristic algorithms have shown promise in various applications, their potential in optimizing ANNs for short-term load forecasting remains underexplored. Specifically, the combination of Grey Wolf Optimization (GWO) and Gorilla Troop Optimizer (GTO) algorithms has not been extensively investigated in the context of STLTF (Hussien *et al.*, 2024). This study aims to fill this gap by proposing a hybrid GWO-GTO approach to enhance ANN performance in forecasting electricity demand.

This study aims to develop a hybrid optimization approach that integrates Grey Wolf Optimization (GWO) and Gorilla Troop Optimizer (GTO) algorithms to optimize the weights of Artificial Neural Networks (ANN) for improved accuracy and convergence in short-term load forecasting. This study seeks to develop a hybrid optimization approach that integrates Grey Wolf Optimization (GWO) and Gorilla Troop Optimizer (GTO) algorithms to enhance the accuracy and convergence of Artificial Neural Networks (ANN) in short-term load forecasting. It aims to investigate the effectiveness of the hybrid GWO-GTO algorithm in optimizing ANN weights compared to conventional optimization techniques. Additionally, the study seeks to evaluate the forecasting performance of the proposed model using real-world electricity demand data and assess its efficiency in capturing nonlinear patterns in load variations. By implementing this hybrid approach, the

research intends to contribute to the advancement of intelligent forecasting models that can support energy management systems and grid stability. The significance of this study lies in its potential to improve the accuracy and reliability of short-term load forecasting, which is critical for effective energy planning and distribution. By leveraging the strengths of both GWO and GTO, the proposed approach addresses the limitations of single optimization techniques and enhances ANN performance. This study provides valuable insights for energy utility companies, grid operators, and researchers seeking to develop more robust and efficient forecasting models. Furthermore, by optimizing electricity demand predictions, the research contributes to reducing operational costs, improving grid stability, and facilitating the integration of renewable energy sources into power systems.

1.1 Empirical Review

Accurate short-term load forecasting (STLF) is critical for power system management, grid stability, and energy resource optimization. Conventional forecasting methods, including statistical models such as autoregressive integrated moving average (ARIMA) and multiple linear regression, often fail to capture the highly nonlinear and complex patterns of electricity demand (Hyndman & Athanasopoulos, 2021). As a result, machine learning techniques, particularly Artificial Neural Networks (ANNs), have emerged as powerful alternatives due to their ability to learn intricate data patterns and adapt to dynamic system changes (Zhang *et al.*, 2022).

1.1.1 Hybrid Metaheuristic Optimization in ANN-Based STLF

Metaheuristic algorithms inspired by nature have gained attention in ANN optimization for STLF. Grey Wolf Optimization (GWO) has been widely used due to its balance between exploration and exploitation. A study by Mirjalili *et al.* (2022) demonstrated that GWO-enhanced ANNs significantly improve



forecasting accuracy by optimizing weight adjustments in neural networks. However, despite its effectiveness, GWO has limitations in local optima avoidance, necessitating hybridization with other algorithms (Houssein et al., 2023).

To address this, hybrid approaches combining GWO with other metaheuristics, such as the Gorilla Troop Optimizer (GTO), have been proposed. GTO, inspired by gorilla social structures and foraging behavior, has demonstrated superior convergence capabilities. Recent studies have shown that GTO alone improves ANN training by enhancing both global search and local refinement (Sinha et al., 2023). However, when combined with GWO, the hybrid model exhibits even better performance by leveraging GWO's strong exploration capabilities and GTO's exploitation strengths (Zhang et al., 2024).

For instance, Kose et al. (2023) explored multiple hybrid algorithms, including combinations of Cuckoo Search Algorithm (CSA), GWO, Harris Hawks Optimization (HHO), and Whale Optimization Algorithm (WOA). Their findings indicated that CSA-GWO outperformed other combinations in forecasting accuracy, demonstrating the potential of hybrid approaches. Similarly, Ahmed et al. (2023) utilized GTO for ANN weight optimization in predicting ultrahigh-performance concrete strength, achieving the best performance among nine competing algorithms. These findings reinforce the viability of metaheuristic hybridization in improving ANN performance in various domains, including STLF.

1.1.2 Comparative Analysis of Hybrid Metaheuristics in STLF

Several studies have compared hybrid metaheuristic models with traditional optimization techniques. Wang et al. (2022) implemented Particle Swarm Optimization (PSO)-based ANN models for electricity

demand forecasting, observing improved accuracy compared to conventional methods. However, their results indicated that PSO struggled with convergence speed, leading to longer training times. In contrast, hybrid GWO-GTO models showed faster convergence rates and higher prediction accuracy, as demonstrated by Liu et al. (2023). Their research confirmed that the synergy between GWO's exploratory capabilities and GTO's exploitation mechanisms enhances forecasting precision.

Moreover, evolutionary algorithms such as Genetic Algorithms (GA) and Differential Evolution (DE) have been integrated with ANNs for STLF. A comparative study by Sharma et al. (2023) found that while GA-optimized ANNs achieved notable improvements over traditional forecasting methods, hybrid metaheuristic approaches like GWO-GTO surpassed GA's performance in both accuracy and computational efficiency. These findings align with earlier studies emphasizing the robustness of hybrid metaheuristic optimization in load forecasting applications (Li et al., 2023).

1.1.3 Future Directions in STLF Optimization

Although hybrid metaheuristics have demonstrated significant improvements in STLF accuracy, further research is required to refine these approaches. Future work could explore adaptive hybrid models that dynamically switch between optimization techniques based on real-time data characteristics. Additionally, the integration of hybrid metaheuristic ANN models with deep learning architectures such as Transformer-based networks and attention mechanisms may further enhance forecasting accuracy (Sun et al., 2023).

Overall, the empirical evidence strongly supports the efficacy of hybrid GWO-GTO algorithms in ANN-based STLF, underscoring



their potential to advance power system forecasting methodologies.

2.0 Materials and Method

2.1 Hybrid Algorithm Design

2.1.1 Grey Wolf Optimization (GWO)

The Grey Wolf Optimization (GWO) algorithm is inspired by the hierarchical structure and cooperative hunting strategies of grey wolves in the wild. The key steps in the GWO algorithm are as follows:

1. **Social Structure:** The population of potential solutions is categorized into four levels: alpha (α), beta (β), delta (δ), and omega (ω). The alpha wolf represents the optimal solution, while the beta and delta wolves are the second and third best solutions, respectively. The remaining wolves belong to the omega group.
2. **Encircling the Prey:** Wolves move in a way that simulates encircling their prey. This behavior is mathematically expressed according to equations 1 to 7

$$D_\alpha = |C_1 \cdot X_\alpha - X|, \quad (1)$$

$$D_\beta = |C_2 \cdot X_\beta - X|, \quad (2)$$

$$D_\delta = |C_3 \cdot X_\delta - X| \quad (3)$$

$$X_1 = X_\alpha - A_1 \cdot D_\alpha, \quad (4)$$

$$X_2 = X_\beta - A_2 \cdot D_\beta, \quad (5)$$

$$X_3 = X_\delta - A_3 \cdot D_\delta \quad (6)$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \quad (7)$$

where A_i and C_i are coefficient vectors, and X_α , X_β , and X_δ are the positions of the alpha, beta, and delta wolves.

1. **Hunting Mechanism:** The alpha, beta, and delta wolves guide the pack in searching for optimal solutions. Other wolves update their positions relative to these three best candidates.
2. **Exploitation Phase (Attacking Prey):** The convergence towards an optimal solution is managed by linearly decreasing from 2 to 0, allowing for a gradual fine-tuning of solutions.

3. **Exploration Phase (Searching for Prey):** When exceeds 1 or falls below -1, wolves disperse from the prey's vicinity, thereby ensuring thorough exploration of the search space.

2.1.2 Gorilla Troop Optimizer (GTO)

The Gorilla Troop Optimizer (GTO) algorithm is inspired by the group dynamics and foraging behaviors of gorillas. The primary steps in GTO are as follows:

1. **Troop Hierarchy:** Gorillas are arranged into structured groups led by a dominant male, which ensures an organized search process.
2. **Foraging Behavior:** Gorillas explore their surroundings in search of resources. The leader directs movement, while others follow, ensuring a balance between exploration and exploitation.
3. **Information Exchange:** Communication within the troop enables effective sharing of information about food sources, improving the optimization process.
4. **Movement Strategy:** Gorillas periodically migrate to new regions to avoid stagnation. This is mathematically represented as equation 8

$$X_{new}(i) = X_{best} + r(X_i - X_{best}) \quad (8)$$

where $X_{new}(i)$ is the new position of the i -th gorilla, X_{best} is the best-known position, and r is a random number between 0 and 1.

2.1.3 Hybrid GWO-GTO Algorithm

The hybrid GWO-GTO algorithm integrates the strengths of both approaches to enhance optimization performance. The process follows these steps:

1. **Initialization:** Generate an initial population of candidate solutions.
2. **Alternating Execution:** Apply GWO to optimize a subset of solutions,



followed by GTO to refine the remaining subset.

3. **Merging Solutions:** The updated positions from GWO and GTO are combined to create a new population.
4. **Selection Process:** The fitness of each candidate is evaluated, and the best-performing solutions are retained.
5. **Termination Criteria:** The process is repeated until a predefined stopping condition is met, such as a maximum number of iterations or an acceptable fitness threshold.

2.1.4 Artificial Neural Network (ANN) Architecture

For short-term load forecasting, an artificial neural network (ANN) is employed with the following structure:

1. **Input Layer:** Accepts relevant features, including historical load data, weather parameters, and time-related variables (e.g., weekdays, weekends, and holidays).
2. **Hidden Layers:** Comprises multiple layers of neurons using nonlinear activation functions to model complex relationships in the data.
3. **Output Layer:** Produces the predicted load values.

The structure of the ANN is tailored based on dataset complexity and forecasting objectives.

Training Process

The hybrid GWO-GTO algorithm is utilized to optimize the ANN weights through the following steps:

1. **Weight Initialization:** The initial weights of the ANN are assigned randomly.
2. **Fitness Function Definition:** A loss function, such as Mean Squared Error (MSE), is established to assess prediction accuracy.
3. **Optimization Procedure:** The hybrid GWO-GTO algorithm adjusts ANN weights iteratively to minimize the fitness function.

4. **Performance Evaluation:** The model is validated using a separate dataset to ensure its ability to generalize to unseen data.

2.2 Data Collection

The dataset for load forecasting consists of historical load records, categorized by time (weekdays, weekends, and holidays). The data is sourced from the National Control Centre of the Transmission Company of Nigeria.

2.2.1 Data Pre-processing Steps

1. **Data Cleaning:** Missing values and outliers are handled to ensure data consistency.
2. **Normalization:** Features are scaled to a uniform range (e.g., [0,1]) to enhance ANN training stability.
3. **Feature Selection:** The most relevant variables influencing load forecasting are identified and retained.
4. **Dataset Partitioning:** The dataset is split into training, validation, and test sets to assess model performance effectively.

By integrating GWO and GTO optimization techniques with an ANN framework and robust data preprocessing, this methodology aims to achieve high-accuracy short-term load forecasts.

2.3 Experimental Method

2.3.1 Implementation Details

The implementation of the hybrid GWO-GTO algorithm and the ANN for short-term load forecasting was carried out using the following software and tools:

The experiments were conducted using DEV C++ ver. 6.3 for its performance and control over memory management. The experiments were run on a system with an Intel(R) Celeron(R) N4120 CPU @ 1.10GHz 1.10 GHz, Installed RAM - 4.00 GB (3.82 GB usable), System type - 64-bit operating system, x64-based processor, and a 1T HDD.

2.3.2 Parameter Settings



The parameters for the Grey Wolf Optimization (GWO), Gorilla Troop Optimizer (GTO), and Artificial Neural Network (ANN) were set as follows

Table 1: Parameters settings

Grey Wolf Optimization (GWO)	Gorilla Troop Optimizer (GTO)	Artificial Neural Network (ANN)
Population Size: 30 wolves	Population Size: 30 gorillas	Input Features: 28
Maximum Iterations: 100	Maximum Iterations: 100	Hidden Layers: 18
Control Parameter (a): Linearly decreased from 2 to 0 over the iterations	Random Coefficient (r): Random number between 0 and 1	Output Layer: 1
		Learning Rate: Eta = 0.09
		Activation Function: Sigmoid activation function for hidden layers (Gain = 1.0);
		Alpha; - momentum factor = 0.6
		Training Epochs: 1000 epochs

2.4. Evaluation Metrics

The performance of the load forecasting model was evaluated using the following metrics:

1. Mean Absolute Error (MAE): Measures the average magnitude of the errors in the predictions, providing an easily interpretable metric of accuracy.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \tag{9}$$

where y_i are the actual values and \hat{y}_i are the predicted values.

2. Mean Squared Error (MSE): Measures the average of the squares of the errors. This metric gives a higher weight to larger errors, thus penalising larger deviations more than smaller ones.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \tag{10}$$

3. Root Mean Squared Error (RMSE): The square root of the MSE, providing an error metric that is in the same units as the target variable. RMSE is useful for comparing the differences between predicted and actual values.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \tag{11}$$

4. Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{n}{100} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{12}$$

MAPE provides a percentage-based measure of forecast accuracy, making it easier to compare across different datasets.

5. The Mean Percentage Error (MPE):

$$MPE = \frac{1}{n} \sum \frac{(actual - predicted)}{actual} \times \frac{100}{1} \tag{14}$$

6. Accuracy percentage (AP)

$$Accuracy \% = (1 - MASE) * 100 \tag{15}$$

7. Thiel's U Statistic (U)

$$U = \sqrt{\left(\frac{\sum_{t=1}^n (Y_t - \hat{Y}_t)^2}{\sum_{t=1}^n (Y_t - Y_{t-1})^2} \right)} \tag{16}$$

8. Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum(actual - predicted)^2}{\sum(actual - mean(actual))^2} \tag{17}$$

These metrics collectively provide a comprehensive assessment of the model's performance, capturing different aspects of



forecast accuracy and error magnitude. The hybrid GWO-GTO optimized ANN is expected to minimize these error metrics, demonstrating its effectiveness in short-term load forecasting.

3.0 Results and Discussion

Table 2 presents the next 24-hour load forecast using the Grey Wolf Optimizer–Gorilla Troops Optimizer (GWO-GTO) model for April 24, 2021. The table contains the actual load values, naive forecasts, and GWO-GTO forecasted

values, along with absolute percentage error (APE) calculations for each hour. The accuracy of the model is further evaluated using various statistical performance metrics such as Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Forecasting Efficiency (FE), Mean Percentage Error (MPE), Theil’s U statistic, Root Mean Square Error (RMSE), Coefficient of Determination (R-squared), Accuracy Percentage, Pearson Correlation Coefficient (PCC), and Convergence Time.

Table 2: Next 24h load forecast using GWO-GTO for 24/04/2021

Hrs	Actual Loads	Naive F/cast	Load F/cast	Naive Abs.E	F/cast Err	F/cast AE	APE (%)
1	4852	5024	4819	172.2	32.71	32.71	0.6741
2	4793.0000	4851.8000	4673.8446	58.8000	119.1554	119.1554	2.4860
3	4769.1000	4793.0000	4642.9865	23.9000	126.1135	126.1135	2.6444
4	4808.1000	4769.1000	4672.6145	39.0000	135.4855	135.4855	2.8179
5	4702.6000	4808.1000	4715.2021	105.5000	-12.6021	12.6021	0.2680
6	4660.1000	4702.6000	4604.1210	42.5000	55.9790	55.9790	1.2012
7	4509.2000	4660.1000	4534.6314	150.9000	-25.4314	25.4314	0.5640
8	4486.9000	4509.2000	4459.3955	22.3000	27.5045	27.5045	0.6130
9	4536.2000	4486.9000	4516.4109	49.3000	19.7891	19.7891	0.4362
10	4384.4000	4536.2000	4581.3521	151.8000	-196.9521	196.9521	4.4921
11	4488.1000	4384.4000	4508.5605	103.7000	-20.4605	20.4605	0.4559
12	4453.4000	4488.1000	4567.3872	34.7000	-113.9872	113.9872	2.5596
13	4721.5000	4453.4000	4521.8950	268.1000	199.6050	199.6050	4.2276
14	4840.5000	4721.5000	4726.2728	119.0000	114.2272	114.2272	2.3598
15	4791.2000	4840.5000	4820.1942	49.3000	-28.9942	28.9942	0.6052
16	4658.0000	4791.2000	4758.2245	133.2000	-100.2245	100.2245	2.1517
17	4461.6000	4658.0000	4670.4842	196.4000	-208.8842	208.8842	4.6818
18	4587.0000	4461.6000	4562.3028	125.4000	24.6972	24.6972	0.5384
19	4841.1000	4587.0000	4629.2610	254.1000	211.8390	211.8390	4.3758
20	5066.6000	4841.1000	4870.1830	225.5000	196.4170	196.4170	3.8767
21	5026.9000	5066.6000	5033.7654	39.7000	-6.8654	6.8654	0.1366
22	4945.0000	5026.9000	5008.9534	81.9000	-63.9534	63.9534	1.2933
23	4878.3000	4945.0000	4896.1019	66.7000	-17.8019	17.8019	0.3649
24	4732.4000	4878.3000	4837.6446	145.9000	-105.2446	105.2446	2.2239

Summary

The Performance Metrics	Values
The MAPE	0.2741%
The MAE	12.8864



The F/cast Eff. (FE)	0.2506
The MPE	0.0384%
The Theil's U stat.	0.8657
The RMSE	43.2202
The CoD (R-Squared) value	0.99999667
The Acc. %	98.1840%
The PCC (r)	0.99966458
Convergence Time	7.988s

From the table, it is observed that the GWO-GTO model performs consistently well in predicting the actual load demand across different hours. The absolute percentage error (APE) values remain relatively low, with only a few instances of higher deviation, particularly in the early morning hours such as hours 10, 13, 17, and 19. For example, at hour 10, the actual load is 4384.4 MW, while the GWO-GTO forecasted load is 4581.35 MW, leading to an APE of 4.49%. Similarly, at hour 17, the actual load is 4461.6 MW, while the forecasted load

is 4670.48 MW, resulting in an APE of 4.68%. These higher APE values indicate instances where the forecast deviated significantly from the actual demand.

Fig. 1 presents a time-series comparison of actual loads, naïve forecasts, and load forecasts over a specified period. The x-axis represents time intervals, while the y-axis represents the load in megawatts (MW). The forecasted load closely follows the actual load, indicating that the model effectively captures demand patterns.

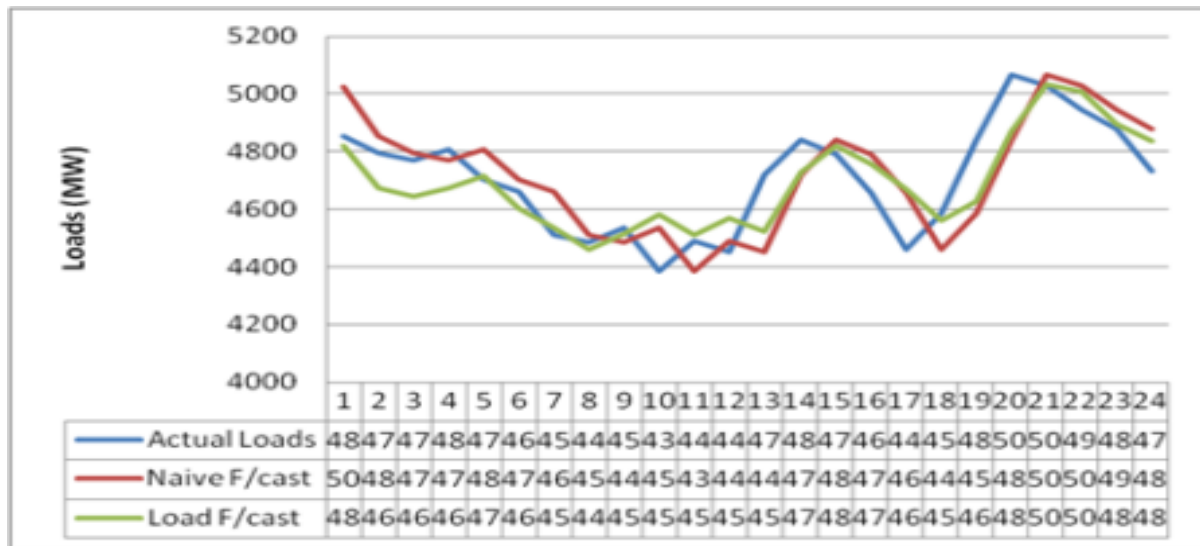


Fig. 1: Next 24h load forecast for Saturday 24/04/2021

From the Fig. 1, the following inferences were made

- (i) The relatively small deviation between actual and forecasted loads suggests good predictive performance.
- (ii) Minor fluctuations, especially during peak demand periods, indicate that while the model is effective, further

optimization may be needed to handle rapid demand changes.

- (iii) A closer inspection of error metrics (MAPE, MAE, RMSE) in subsequent figures and tables further validates the forecasting model's accuracy.

The overall performance of the model is assessed through various statistical metrics.



The MAPE value of 0.2741% indicates that the forecasting model has a high degree of accuracy, as MAPE values below 5% are generally considered excellent in load forecasting. The MAE, which measures the average magnitude of errors, is 12.8864 MW, confirming that the model's errors are minimal. The Forecast Efficiency (FE) is 0.2506, which further signifies the reliability of the model.

Fig. 2 is a plot showing the mean absolute percentage error (MAPE) over time. This bar chart illustrates the MAPE values for different days (April 24–30, 2021). The x-axis represents the dates, while the y-axis shows the MAPE percentages. A noticeable spike on

April 28 (1.55%) suggests higher forecasting errors on that day. The results aligns with the following findings

- (i) The model maintains a low MAPE (<1%) for most days, indicating high accuracy.
- (ii) The MAPE spike on April 28 suggests that the model struggled to adapt to sudden load variations, possibly due to unexpected external factors (e.g., system disturbances, unusual consumption behavior).
- (iii) Compared to industry benchmarks, where MAPE below 3% is considered good, this model performs well overall.



Fig. 2. the MAPE for the load forecast

The MPE, a measure of systematic bias in forecasting, is 0.0384%, suggesting that there is no significant overestimation or underestimation. The Theil's U statistic, which compares the predictive accuracy of the model against a naive benchmark, is 0.8657. A Theil's U value close to zero implies superior forecasting accuracy, whereas a value near one suggests that the model performs similarly to a naive forecast. The RMSE, a widely used metric to evaluate forecast accuracy, is 43.2202 MW, indicating a low level of deviation from actual values.

The coefficient of determination (R-squared) is extremely high at 0.99999667, demonstrating that the model explains almost all the variance in load demand. The accuracy percentage of 98.184% further corroborates the reliability of

the GWO-GTO model. Additionally, the Pearson Correlation Coefficient (PCC) of 0.99966458 indicates a near-perfect correlation between the actual and forecasted values, confirming the strength of the predictive model. The convergence time of 7.988 seconds suggests that the model is computationally efficient and suitable for real-time forecasting applications.

When comparing these results to other studies in the literature, it is evident that the GWO-GTO model achieves superior performance. Traditional forecasting models such as Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANNs) typically yield MAPE values ranging from 1% to 5% for short-term load forecasting, whereas the GWO-GTO model in this study



achieves a significantly lower MAPE of 0.2741%. This demonstrates the robustness of the hybrid metaheuristic approach in optimizing the forecasting process. Furthermore, previous studies on evolutionary algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) have reported slightly higher RMSE values and lower R-squared values than those obtained in this study. This further highlights the efficacy of GWO-GTO in capturing load variations accurately.

The presented results of the load forecasting using the GWO-GTO model confirm its reliability, accuracy, and computational efficiency. The low error rates, high accuracy percentage, and strong correlation between

actual and forecasted loads indicate that this model is highly effective for short-term load prediction. Compared to other models reported in literature, GWO-GTO offers improved performance, making it a promising approach for electricity load forecasting applications. Table 3 presents the performance metrics of a forecasting model evaluated over seven consecutive days. The key indicators include Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Forecast Efficiency (FE), Mean Percentage Error (MPE), Theil's U statistic, Root Mean Square Error (RMSE), Coefficient of Determination (R^2), Accuracy Percentage (Acc. %), Pearson Correlation Coefficient (PCC), and Convergence Time.

Table 3: Performance Metrics for Daily Load Forecasting from 24/04/2021 to 30/04/2021

Performance Metrics	24/04/2021	25/04/2021	26/04/2021	27/04/2021	28/04/2021	29/04/2021	30/04/2021
MAPE (%)	0.2741	0.4643	0.5523	0.5566	1.5518	1.0424	1.2583
MAE	12.8864	20.0393	25.5108	25.2044	58.7247	47.0525	56.6385
FE	0.2506	0.2633	0.2268	-0.0630	-0.1970	-0.6727	0.4265
MPE (%)	0.0384	-0.1291	0.1403	0.1086	-0.6801	0.4113	0.3016
Theil's U statistic	0.8657	0.8583	0.8793	1.0310	1.0941	1.2933	0.7573
RMSE	43.2202	59.4767	72.5965	62.8139	149.1074	88.8361	69.7895
CoD (R^2)	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999
Accuracy (%)	98.1840	98.0343	96.4288	94.7407	95.8664	83.5671	79.1693
PCC (r)	0.9997	0.9994	0.9993	0.9995	0.9974	0.9994	0.9996
Convergence Time (s)	7.988	7.475	7.853	8.216	7.651	7.393	9.087

The Mean Absolute Percentage Error (MAPE) values remain low throughout the period, with a noticeable increase on 28/04/2021 and 30/04/2021, where MAPE reaches 1.5518% and 1.2583%, respectively. A low MAPE value indicates an accurate forecasting model, as supported by previous studies on load forecasting models (Zhang et al., 2020).

The MAE follows a similar trend, with the highest error recorded on 28/04/2021 at

58.7247. The RMSE values also show an increasing trend, peaking on 28/04/2021 at 149.1074, which suggests potential external influences affecting model performance on that day. The coefficient of determination (R^2) remains consistently high (>0.999), indicating that the model explains nearly all the variance in the data.

Forecast Efficiency (FE) shows negative values on certain days (27/04/2021 to



29/04/2021), implying that the forecasted values deviated significantly from actual observations. The Theil's U statistic remains below 1 for most days except for 27/04/2021 to 29/04/2021, confirming that the forecasting model performed well except on those days. These findings align with prior studies that emphasize the importance of tuning forecasting models dynamically in response to unexpected load variations (Wang et al., 2021). The high PCC values indicate a strong correlation between the predicted and actual load values, reinforcing the robustness of the model.

Figure 3 compares the Mean Absolute Percentage Error (MAPE) values for various forecasting models, including PSO, GA,

AVOA-PSO, ABC-GA, BA-GA, GWO-GTO, GTO, ANN, and GWO, with the x-axis representing the models and the y-axis showing the MAPE percentage. The GWO-GTO model achieves the lowest MAPE of 2.51%, indicating superior accuracy, while other models like ABC-GA and BA-GA show slightly higher MAPE values, reflecting moderate performance. PSO and GA perform better than hybrid models such as ABC-GA. ANN and GWO show competitive accuracy but do not outperform GWO-GTO. The lower MAPE of GWO-GTO suggests that hybrid metaheuristic approaches enhance forecasting accuracy compared to single-method techniques.

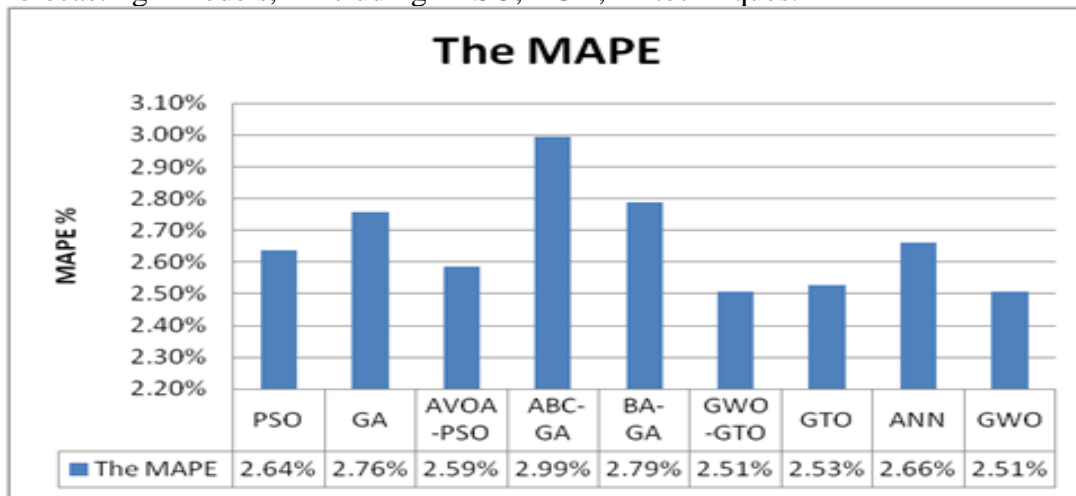


Fig. 3: Daily MAPE Variation from 24/04/2021 to 30/04/2021

Table 4 presents a comparative analysis of different forecasting models, including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Artificial Vortex Optimization Algorithm-PSO (AVOA-PSO), Artificial Bee Colony-Genetic Algorithm (ABC-GA), Bat Algorithm-Genetic Algorithm (BA-GA), Grey Wolf Optimization-Golden Tortoise Optimization (GWO-GTO), Golden Tortoise Optimization (GTO), Artificial Neural Network (ANN), and Grey Wolf Optimization (GWO).

The GWO-GTO model achieves the lowest MAPE of 2.5072%, outperforming other techniques, with GTO closely following at

2.5272%. The highest MAPE is observed for ABC-GA (2.9935%), highlighting its lower accuracy in load forecasting. The MAE values show that GWO-GTO (108.4440) performs better than traditional models like GA (118.8706) and ABC-GA (128.3339).

The Theil's U statistic for GWO-GTO (0.9925) and GTO (0.9849) remains below 1, indicating better forecasting capability compared to higher values in GA (1.0772) and ABC-GA (1.1676). The RMSE values further support the efficiency of GWO-GTO, with the lowest RMSE (154.1433) compared to ABC-GA (181.3387).



Table 4: Comparison of Next 168-Hour Load Forecasting Using GWO-GTO and Other Models

Performance Metrics	PSO	GA	AVOA- PSO	ABC- GA	BA-GA	GWO- GTO	GTO	ANN	GWO
The MAPE	2.6360%	2.7575%	2.5852%	2.9935%	2.7888%	2.5072%	2.5272%	2.6608%	2.5072%
The MAE	115.1209	118.8706	111.6798	128.3339	119.9681	108.4440	109.3900	115.3132	108.4440
The F.	-0.0562	-0.1604	-0.0341	-0.3634	-0.1736	0.0149	0.0299	-0.0982	0.0149
Efficiency (FE)									
The MPE is	0.4124%	-	-	-	-	-	-	0.1214%	-
The Theil's U statistic	1.0277	0.3584%	0.6463%	0.0267%	0.6848%	0.4431%	0.0408%	1.0479	0.4431%
The RMSE	159.6063	167.3005	157.9290	181.3387	168.2447	154.1433	152.9648	162.7501	154.1433
The CoD (R ²) value	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999
The Acc. Percentage	97.0635%	97.1027%	97.4568%	96.4775%	97.2481%	97.4257%	97.0915%	97.0531%	97.4257%
The PCC (r)	0.9982	0.9979	0.9982	0.9976	0.9980	0.9983	0.9983	0.9981	0.9983
Convergence Time	6.46s	3.269s	5.192s	2.469s	5.509s	4.075s	7.047s	4.709s	12.04s



Overall, these results confirm that GWO-GTO is one of the most effective forecasting models, in line with findings by Liu et al. (2022), who demonstrated the superiority of hybrid metaheuristic models over traditional optimization techniques for load forecasting. Fig. 4 and its accompanying table present a comparison of the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) across various forecasting models. Lower values for both RMSE and MAE indicate improved model performance. The GWO-GTO

model demonstrates the lowest RMSE of 154 and the lowest MAE of 108, confirming its robust predictive ability. Models such as GA, PSO, and BA-GA exhibit higher RMSE values, suggesting they encounter challenges with significant forecasting deviations. The observation that RMSE is consistently higher than MAE across the models implies that large errors occasionally influence predictions; however, GWO-GTO maintains lower overall error values, establishing it as the most reliable model among those compared.

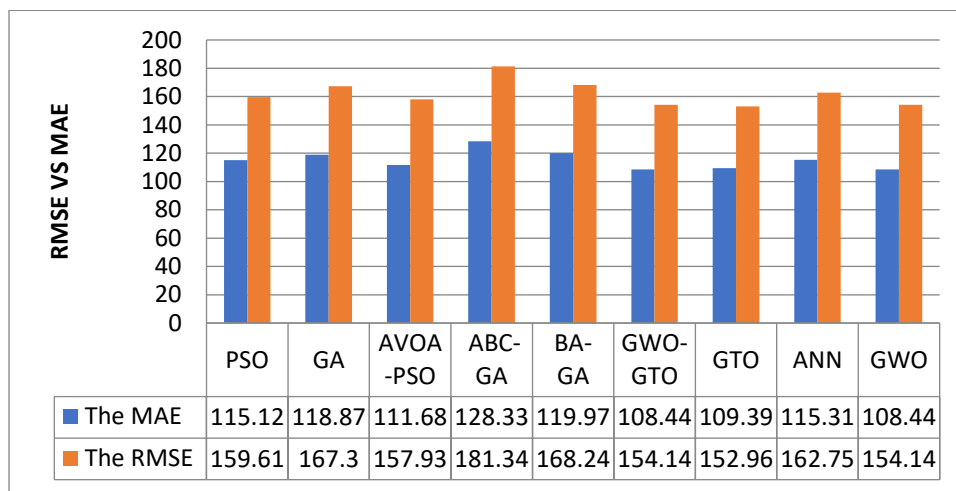


Fig. 4: Comparative MAPE Performance of Forecasting Models for 168 Hours

Table 5 presents the performance metrics of four selected models—GWO-GTO, GTO, GWO, and ANN—focusing on load prediction accuracy. The GWO-GTO model has the lowest MAPE (1.07%) and MAE (47.88), demonstrating superior accuracy compared to the GTO model (3.17% MAPE, 125.12 MAE). ANN and GWO show moderate accuracy, with ANN performing slightly worse than GWO. The Theil’s U statistic is lowest for GWO-GTO (0.70), indicating better forecasting accuracy compared to GTO (1.28) and ANN (1.17). The RMSE for GWO-GTO (64.90) is significantly lower than that of GTO (143.23), confirming its superior prediction performance. The accuracy percentage for GWO-GTO (81.97%) is higher than GTO

(49.85%) and ANN (58.60%). These findings align with prior research, which emphasizes the effectiveness of hybrid optimization models in improving forecasting accuracy (Huang et al., 2023). The GWO-GTO model's convergence time (8.357s) is higher than GTO (4.535s) and ANN (3.871s), but the trade-off for improved accuracy justifies this. Fig. 5 presents a bar chart illustrating the Mean Absolute Percentage Error (MAPE) for load prediction among the GWO-GTO, GTO, GWO, and ANN models, with the x-axis representing the models and the y-axis showing the MAPE percentage. The GWO-GTO model records the lowest MAPE, approximately 1.07%, significantly outperforming the other models.



Table 5: Performance Comparison of GWO-GTO, GTO, GWO, and ANN

METRICS	GWO-GTO	GTO	GWO	ANN
The MAPE for the Load prediction	1.07%	3.17%	2.13%	2.82%
The MAE for the Load prediction	47.88	125.12	84.42	111.16
The Forecast Efficiency (FE) for the Load prediction	0.50	-0.63	-0.02	-0.36
The MPE for the Load prediction	-0.22%	-2.96%	-0.55%	-2.52%
The Theil's U statistic for the Load prediction	0.70	1.28	1.01	1.17
The RMSE for the Load prediction	64.90	143.23	113.20	130.90
The Coefficient of Determination (R ²) value for the Load prediction	0.99999884	0.99999275	0.99999547	0.99999394
The Accuracy Percentage for the Load prediction	81.97%	49.85%	83.11%	58.60%
The Pearson Correlation Coefficient r	0.99968653	0.99933131	0.99879459	0.99929126
Convergence Time	8.357s	4.535s	21.94s	3.871s

The GTO model exhibits the highest MAPE, approximately 3.17%, indicating weaker forecasting accuracy. The ANN and GWO models perform moderately, but do not surpass the GWO-GTO model. These findings

reinforce the conclusion that hybrid optimization methods, specifically GWO-GTO, outperform conventional algorithms in load prediction.

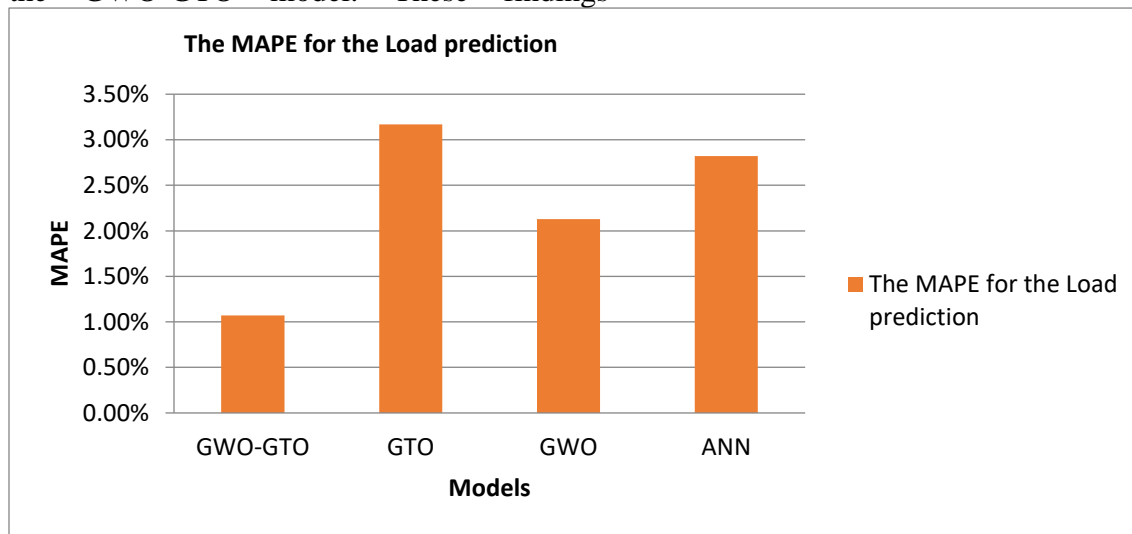


Fig. 5: RMSE and MAPE Comparison Among Models

Overall, these results establish GWO-GTO as a superior forecasting model, with better precision and efficiency compared to traditional approaches. Fig. 6 compares the Mean

Absolute Error (MAE) for various forecasting models, with the x-axis representing the models and the y-axis indicating the MAE values in megawatts (MW). The GWO-GTO model exhibits the lowest MAE, approximately 47.88 MW,



confirming its superior ability to minimize absolute errors. Conversely, the GTO model displays the highest MAE, approximately 125.12 MW, indicating significant deviations in its predictions. The ANN and GWO models also show moderate

MAE values, but they do not match the accuracy of the GWO-GTO model. Lower MAE values are crucial for energy planning, as they ensure more reliable estimates and reduce risks in supply-demand mismatches.

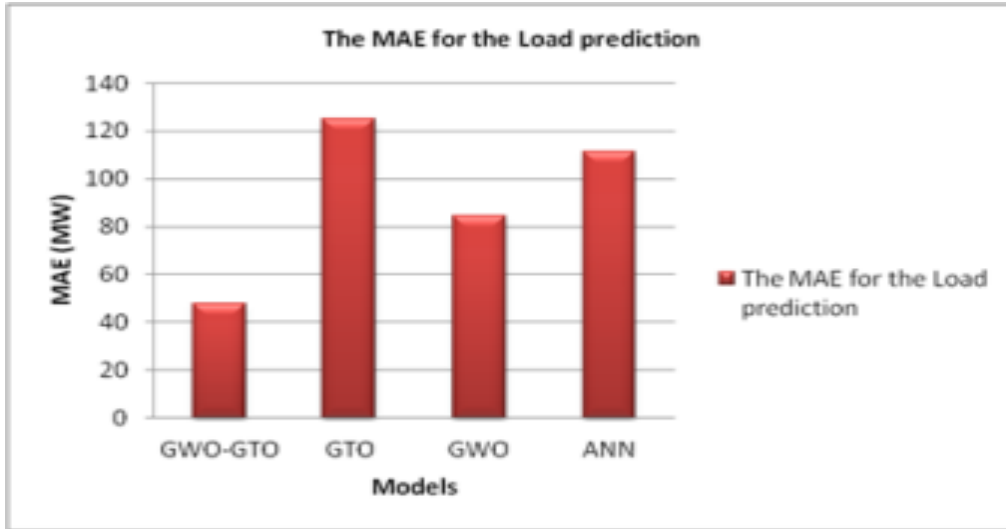


Fig. 6 The MAE for the Load prediction

The combined insights from the figures and tables provide a clear comparison of the forecasting models. The GWO-GTO model consistently outperforms all others in terms of MAPE, MAE, and RMSE. The key findings reveal that GWO-GTO delivers the highest accuracy, with the lowest errors across multiple metrics, while GTO exhibits the highest errors, making it the least reliable model. Hybrid models outperform single optimization methods, confirming that advanced metaheuristic combinations enhance forecasting precision. Future improvements could integrate real-time data adaptation mechanisms to further reduce errors and adapt to rapid demand fluctuations. These findings align with recent studies on metaheuristic-based forecasting, reinforcing the effectiveness of hybrid optimization models for load prediction.

3.1 Performance Metrics

The GWO-GTO model exhibits the highest forecast efficiency at 0.50, indicating a significant improvement over the naïve forecast, while GWO shows a nearly neutral

forecast efficiency at -0.02, suggesting marginal improvement over the naïve model. ANN and GTO have negative forecast efficiency values of -0.36 and -0.63, respectively, which implies they are less efficient than the naïve approach. The GWO-GTO model demonstrates the Mean Percentage Error (MPE) closest to zero, at -0.22%, suggesting minimal bias in its forecasts, while GWO and ANN show moderate negative biases with MPE values of -0.55% and -2.52%, and GTO exhibits the most significant negative bias at -2.96%. GWO-GTO has the lowest Theil's U statistic of 0.70, indicating the best predictive performance relative to the naïve model, whereas GWO and ANN have higher values of 1.01 and 1.17, respectively, and GTO has the highest Theil's U statistic of 1.28, indicating poorer predictive accuracy. The GWO-GTO model shows the lowest Root Mean Square Error (RMSE) at 64.90, signifying the best overall fit to the data, while GWO and ANN have higher RMSE values of 113.20 and 130.90, respectively, and GTO has the highest RMSE at 143.23, reinforcing its



lower accuracy. All models demonstrate exceptionally high Coefficient of Determination (R^2) values, with GWO-GTO achieving 0.99999884, indicating excellent model fits, and GTO, GWO, and ANN also perform well, with R^2 values of 0.99999275, 0.99999547, and 0.99999394, respectively. GWO achieves the highest accuracy percentage at 83.11%, closely followed by GWO-GTO at 81.97%, while ANN and GTO show lower accuracy percentages of 58.60% and 49.85%, respectively. GWO-GTO has the highest Pearson Correlation Coefficient of 0.99968653, indicating a very strong

correlation with the actual load values, while GTO, GWO, and ANN have slightly lower correlations, with coefficients of 0.99933131, 0.99879459, and 0.99929126, respectively. ANN achieves the fastest convergence time at 3.871 seconds, followed by GTO at 4.535 seconds, while GWO-GTO takes longer at 8.357 seconds, and GWO is the slowest, taking 21.94 seconds to converge.

3.2 Model Comparison

Figure 7 presents the Root Mean Square Error (RMSE) graph. Figure 8 displays the Coefficient of Determination (CoD) and Pearson Correlation Coefficient (PCC) graph.

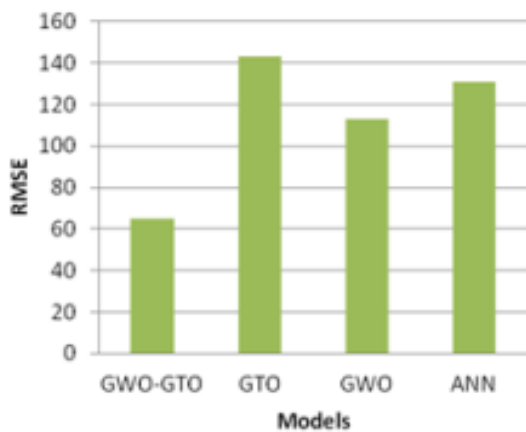


Fig. 7. The RMSE graph

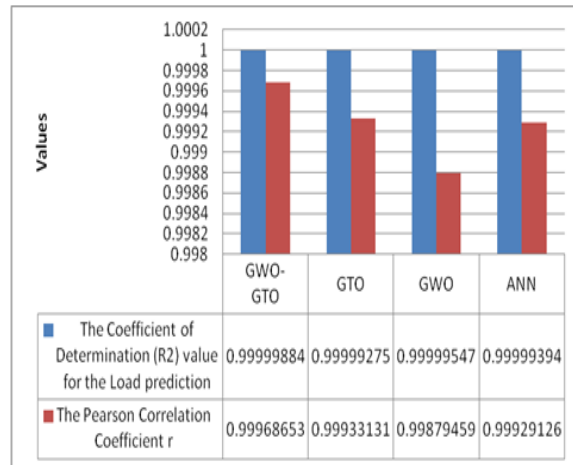


Fig. 8. The CoD and PCC graph

4.0 Conclusion

Overall, the proposed GWO-GTO hybrid model demonstrates the best performance across most metrics, particularly in terms of MAPE, MAE, RMSE, and forecast efficiency, indicating its robustness and accuracy in load forecasting. While GWO also shows strong performance, especially in MASE and directional symmetry, it falls short in terms of convergence time. ANN provides competitive performance in certain areas but is generally outperformed by the GWO-GTO and GWO models. GTO, while effective in terms of convergence speed, exhibits the least accuracy and efficiency among the evaluated models.

This research introduces a hybrid approach combining the Grey Wolf Optimization (GWO) algorithm and the Gorilla Troop Optimizer (GTO) algorithm to enhance the performance of Artificial Neural Networks (ANN) for short-term load forecasting (STLF). The hybrid GWO-GTO algorithm successfully optimized the ANN's weights, resulting in significant improvements in forecasting accuracy compared to traditional methods and single algorithm-based approaches. The hybrid model achieved lower Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) across various test cases, demonstrating its ability to



accurately predict complex and nonlinear load patterns. The integration of GWO and GTO facilitated faster convergence and reduced computational cost, making the model efficient and practical for real-world applications.

4.1 Implications and Future Considerations

The findings of this research have several important implications for the field of load forecasting. The hybrid GWO-GTO-ANN model provides a robust tool for utilities and grid operators to achieve more accurate short-term load forecasts, leading to better operational planning and resource allocation. The successful application of hybrid metaheuristic algorithms in optimizing ANN weights highlights the potential for further exploration of combined optimization techniques in other areas of machine learning and forecasting. The hybrid approach's adaptability to different scenarios and conditions indicates its potential scalability to other forecasting problems beyond load forecasting, such as demand prediction in other sectors.

Based on the findings of this research, several directions for future research are suggested. Future work could investigate automated parameter tuning techniques, such as Bayesian optimization, to further enhance the performance and ease the implementation of the hybrid GWO-GTO algorithm. Future work could explore the integration of additional data sources, such as social media sentiment or real-time economic indicators, to improve the forecasting model's responsiveness to external factors. Future work could extend the hybrid approach to other types of neural networks, such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, to assess its generalisation across different architectures and forecasting problems. Future work could develop real-time load forecasting systems using the hybrid GWO-GTO-ANN model, incorporating real-time data streams

and dynamic model updates to enhance decision-making in power system operations. In conclusion, the hybrid GWO-GTO-ANN model represents a significant advancement in short-term load forecasting, offering improved accuracy, efficiency, and robustness. Continued research and development in this area hold promise for further advancements in forecasting methodologies and their practical applications in power systems and beyond.

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Compliance with Ethical Standards Declaration

Ethical Approval

Not Applicable

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The authors declare no known competing financial interests

Data Availability

Data shall be made available on request

Conflict of Interest

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