A comparative study of long short-term memory based long-term electrical load forecasting techniques with hyperparameter optimization

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ABSTRACT

Long-term load forecasting (LTLF) is crucial for reliable electricity supply, infrastructure planning, and informed energy policies, ensuring grid stability and efficient resource allocation. Traditional methods, like statistical models and expert judgment, rely on historical data but may struggle with dynamic changes in technology, regulations, and consumer behavior. Addressing challenges such as economic uncertainties, seasonal variations, data quality, and integrating renewable energy requires advanced forecasting models and adaptive strategies. This research aims to develop an efficient LTLF model for the Coimbatore region in Tamil Nadu, India, using long short-term memory (LSTM) networks. While LSTM has limitations in capturing long-term dependencies and requires high data quality and complex management, optimizing hyperparameters, including through the opposition-based hunter-prey optimization (OHPO) technique, is explored to enhance its predictive performance. The results show that the proposed OHPO-configured LSTM model for LTLF achieves superior performance compared to other techniques, with a mean square error (MSE) of 0.25, root mean square error (RMSE) of 0.5 and mean absolute percentage error (MAPE) of 0.27. This research underscores the significance of improving LTLF precision for informed decision-making in infrastructure planning and energy policy formulation.

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1. INTRODUCTION

Load forecasting is crucial for power system scheduling, operation, and planning, reducing the costs of building power facilities and optimizing startup costs of generating units. It is categorized into short-term, mid-term, and long-term forecasting [1], [2]. Traditional methods struggle with non-linear time series data, leading to the adoption of artificial intelligence (AI) methods like artificial neural networks (ANNs), recurrent neural networks (RNNs), fuzzy logic, and support vector machines (SVMs) for improved accuracy in long-term load forecasting (LTLF) [3]–[7]. Underestimating or overestimating long-term load results in significant operational issues and financial losses [8]. long short-term memory (LSTM) networks, designed for handling long-term dependencies, are increasingly used for LTLF, with optimization techniques enhancing their performance [9]–[15]. Hyperparameter optimization through methods like grid search or random search, though costly, is vital for LSTM performance [16], [17]. Techniques such as particle swarm optimization (PSO), genetic algorithms, and hunter-prey optimization (HPO) have been explored for better forecasting accuracy, with HPO needing opposition-based learning strategies to overcome local optima issues [18]–[24].

2. LITERATURE REVIEW

Mohammed and Al-Bazi [25] enhanced traditional ANNs with the adaptive back propagation algorithm (ABPA) for more accurate long-term load forecasts, achieving minimal mean absolute percentage error (MAPE) and mean square error (MSE) values. Another 2022 study proposed a linked demand strategy using wavelet decomposition, ELATLBO, and Bayesian optimization (BO) for predicting a metal industry microgrid's demand time series with minimal input data [26]. During coronavirus disease 2019 (COVID-19), an LSTM model with a simplex optimizer was used to estimate electric usage, improving forecasting accuracy by 5.6% [27].

A hybrid load forecasting system developed in 2022 achieved the lowest prediction error for three months and highest accuracy for six months [28]. The BO-particle swarm optimization (BO-PSO) algorithm, which eliminates gradient calculations, outperformed state-of-the-art algorithms in predictive accuracy [29]. HPO, based on predator-prey dynamics, showed strong optimization performance in multiple tests [30]. Advanced opposition-based learning (OBL) variations were classified to balance exploration and exploitation for algorithm success [31]. In 2024, research highlighted the need for accurate solar power generation forecasting, proposing the evolution of cub to predator (ECP) technique which achieved a prediction accuracy of 97.2%, surpassing other methods and optimizing renewable energy resource management [32].

3. PROPOSED METHOD

LTLF predicts future electricity demand to ensure reliable supply, optimize infrastructure, inform policy decisions, maintain grid stability, and promote economic efficiency in energy industries. Challenges in LTLF using traditional approaches include difficulties in capturing complex, non-linear relationships; limited adaptability to dynamic changes in technology, regulations, and consumer behavior; issues with data quality and availability; handling seasonal variations and weather sensitivity; integrating renewable energy sources; managing model complexity and interpretability; and addressing economic uncertainties. Overcoming these challenges requires advanced forecasting techniques, robust data management practices, and adaptive strategies to improve accuracy in predicting electricity demand over extended periods. This research endeavors to create an effective LTLF model tailored for the Coimbatore Region in Tamil Nadu, India, leveraging LSTM networks. Although LSTM struggles with capturing long-term relationships and needs high-quality data and complex management, this study explores improving its predictive accuracy by optimizing hyperparameters using the optimization techniques. Identifying the optimal hyperparameters for LSTM through manual or trial-and-error processes is time-consuming and computationally complex, necessitating the incorporation of optimization techniques. The research explores various optimization techniques, including particle swarm optimization (PSO), grey wolf optimization (GWO), and hunter-prey optimization (HPO). The top-performing hunter-prey optimization technique is enhanced with opposition-based learning and referred to as opposition-based hunter-prey optimization (OHPO).

3.1. Problem identification

Accurate LTLF is crucial for the power industry to manage future energy demands effectively. Traditional forecasting methods often struggle with complex variables like weather, economic conditions, and population trends. In Coimbatore, India, rapid urbanization and economic growth are driving increased electricity demand. To improve accuracy, new LTLF approaches are needed. Overcoming challenges requires advanced forecasting models, robust data management, and adaptive strategies to navigate the dynamic energy environment effectively.

3.2. Research objective

The objective of the research is to develop a novel LSTM-based approach for LTLF in Coimbatore, Tamil Nadu, and India, optimizing the model's accuracy through opposition-based hyperparameter optimization and evaluating its performance using error metrics like MSE, root mean square error (RMSE), and MAPE.

- To develop a novel approach for LTLF in the Coimbatore region of Tamil Nadu, India.

- Using an LSTM network for LTLF allows for learning order dependence in sequence prediction problems.
- To increase the accuracy of the forecasting model, we optimize the LSTM hyperparameters using opposition-based learning in the HPO technique.
- To assess how well the suggested method performs in relation to alternative comparison approaches using a range of error metrics, including MSE, RMSE, and MAPE.

3.3. Long short-term memory

LSTM is an ideal RNN architecture for long-term electricity demand forecasting due to its ability to learn sequential dependencies and patterns in historical data, enabling accurate future predictions. It effectively addresses vanishing or exploding gradient issues during training on lengthy data sequences and can handle input data of varying lengths, including missing or incomplete data. This makes LSTMs particularly suitable for analyzing data over several months to a year. This study used 75% of the dataset from 2016 to 2018 for training and validation and used the remaining 25% from 2019 to evaluate the model's performance. At each time step t, the LSTM network receives an input vector (x_t), the cell state (c_{t-1}), the preceding hidden state (h_{t-1}), and an input vector. We next use (1)-(6) to calculate the new hidden state (h_t), cell state (c_t) and input gate (i_t).

$$Forgetgate(f_t) = \sigma(Wfx_t + Ufh_{(t-1)} + bf) \tag{1}$$

$$Inputgate(i_t) = \sigma(Wix_t + Uih_{(t-1)} + bi) \tag{2}$$

$$candidatecellstate(c_{t\_tilde}) = tanh(\,Wcx_{x\_t} + Uch_{(t-1)} + bc) \tag{3}$$

$$outputgate(o_t) = \sigma(Wox_t + Uoh_{(t-1)} + bo) \tag{4}$$

$$cellstate(c_t) = f_t \otimes c_{t-1} + i_t \otimes c_{t\_tilde} \tag{5}$$

$$hiddenstate(h_t) = o_t \otimes tanh\, c_t \tag{6}$$

In an LSTM network, the sigmoid function (σ) and ⊗ element-wise multiplication are key operations. The input vector at time step t is x_t while h_{t-1} and c_{t-1} represent the previous hidden and cell states. The forget, input, and output gates are under the controlled by weight matrices and bias vectors (Wf, Uf, bf, Wi, Ui, bi, Wc, Uc, bc, Wo, Uo, and bo), which determine the amount of information retained or discarded. How much of the prior cell state should be remembered is decided by the forget gate f_t. How much of the candidate cell state $c_{t-tilde}$ should be added to the cell state c_t is determined by the input gate. The output gate o_t determines how much of the current cell state should be output as the hidden state h_t. Backpropagation through time trains the network to minimize loss functions such as MSE, RMSE, or MAPE. Hyperparameters, which define the network's architecture and behavior, are crucial for accurate load forecasting. To prevent underfitting or overfitting and ensure optimal performance, we must tune those utilizing techniques such as PSO, GWO, HPO, and opposition-based HPO.

3.4. Opposition based hunter prey optimization

HPO, a population-based method for optimizing hyperparameters, benefits from integrating OBL to enhance exploration, exploitation, convergence speed, and robustness. OBL generates a variety of solutions, assisting in escaping local optima and accelerating convergence while reducing sensitivity to initial conditions and noise. The iterative OHPO process optimizes prey locations with OBL, allowing the hunter to adjust based on the optimal prey location, making it effective for LSTM models. Figure 1 illustrates the OHPO process. Initially, the population is randomly set as to ($\vec{x}$)={$\overrightarrow{x_1}$, $\overrightarrow{x_2}$, …, $\overrightarrow{x_n}$}, A proposed algorithm revises individual positions in each iteration, evaluates them using an objective function, and generates a random population to apply an opposition-based strategy, which is beneficial for complex, nonlinear solution spaces with numerous local optima. $H_{i,G}^{j}$ denotes the current solution.

$$OH_{i,G}^{j} = x_i + y_i - H_{i,G}^{j} \tag{7}$$

Equation (7) combines opposition-based and random solutions within defined bounds to evaluate fitness, guided by algorithmic rules and strategies. Positions of population members are iteratively adjusted to enhance solutions, evaluated by the objective function. Equation (8) randomly assigns positions within the search space.

$$x_i = rand(1, d) \bullet * (upb - lowb) + lowb \tag{8}$$

In this case, x_i represents the location of the hunter or prey, $rand$ is a random value between 0 and 1, $lowb$ denotes the problem variables' lowest value (lower boundary), upb denotes their highest value (upper boundary), and d denotes the problem's total number of variables (dimensions). Calculating the fitness function determines which solution holds the optimal hyperparameters for effective long-term electrical load forecasting.

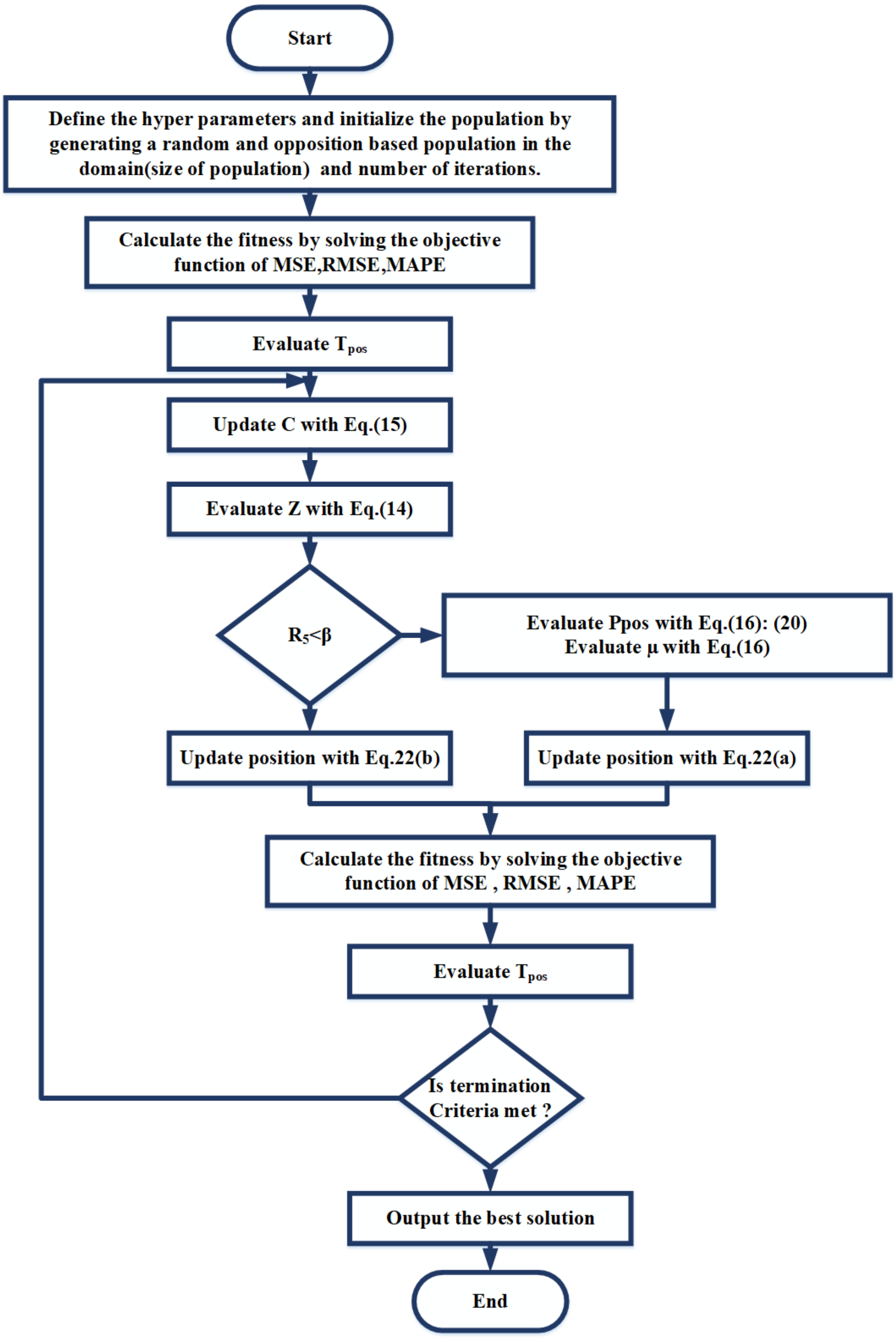


Figure 1. Flow chart of opposition-based hunter prey optimization

Equations (9)-(12) calculate the fitness of each solution once the initial population is created and the positions of each agent are determined.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y_i}\right)^2 \tag{9}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y_i}\right)^2}{n}} \tag{10}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y_i}}{Y_i}\right| \tag{11}$$

$$Fitness(F_i) = \frac{MSE+RMSE+MAPE}{3} \tag{12}$$

The proposed search mechanism optimizes hyperparameters by directing agents towards optimal positions through two steps: exploration and exploitation. Exploration involves random behaviors, revealing promising areas, while exploitation minimizes these behaviors to facilitate searching around these identified areas.

$$x_{i,j}(t+1) = x_{i,j}(t) + 0.5\left[\left(2CZP_{pos(j)} - x_{i,j}(t)\right) + \left(2(1-C)Z\mu_{(j)} - x_{i,j}(t)\right)\right] \tag{13}$$

Equation (13) is responsible for updating the hunter's current position represented by $x(t)$ based on the next position ($x(t-1)$), the prey's position (P_{pos}), the mean of all positions (*l*), and an adaptive parameter (Z) calculated using (14).

$$P = \vec{R}1 < \mathrm{C};\ \mathrm{IDX} = (\mathrm{p} == 0); Z = R_2 \otimes IDX + \vec{R}_3 \otimes (\sim \mathrm{IDX}) \tag{14}$$

In this scenario, $\vec{R}_1$ and $\vec{R}_3$ are random vectors (0-1), P is a binary vector (0 or 1) indicating the number of problem variables, R_2 is a random number (0-1), and IDX indexes $\vec{R}_1$ where P == 0. Parameter C governs exploration versus exploitation, reducing gradually from 1 to 0.02 across iterations using (15).

$$C = 1 - iter\left(\frac{0.98}{MaxIt}\right) \tag{15}$$

$MaxIt$ is the maximum number of iterations, and iter refers to the current iteration value. Where the first step is to calculate the average position of all search agents using (16) and denote it as μ. Finding each search agent's distance from the mean position is the second stage.

$$\mu = \frac{1}{n}\sum_{i=1}^{n}\vec{x}_i \tag{16}$$

Using (17) to calculate the distance based on the Euclidean distance (D_{euc}),

$$D_{euc(i)} = \left(\sum_{i=1}^{d}\left(x_{i,j} - \mu_j\right)^2\right)^{\frac{1}{2}} \tag{17}$$

Equation (18) states that the prey (P_{pos}) is the search agent with the largest distance from the mean position.

$$\vec{P}_{pos} = \vec{x}_i / i\ i \rightleftarrows sindexofMax(end)sort(D_{euc}) \tag{18}$$

The convergence of the algorithm will be delayed if we continuously select the search agent that has the greatest distance from the mean position (μ) at the end of each iteration. In the hunting context, the prey dies when it is caught, forcing the hunter to move on to a new target. Equation (19) describes the decreasing method we employ to address this problem.

$$kbest = round(C \times N) \tag{19}$$

where *N* represents the quantity of search agents. We now adjust (18) and utilize (20) to determine the prey position.

$$\vec{P}_{pos} = \vec{x}_i / i\ i \rightleftarrows ssortedD_{euc}(kbest) \quad (20)$$

Initially, *kbest* equals N, the count of search agents. The hunter targets the farthest search agent from the average position (μ) for attack. Each iteration sorts of agents by distance from μ. The optimal global position offers a safe area for selecting prey, increasing prey survival chances. Equation (21) updates the prey's position.

$$x_{i,j}(t+1) = T_{pos(j)} + CZ(2\pi R_4) \times \left(T_{pos(j)} - x_{i,j}(t)\right) \quad (21)$$

The formula describes a dynamic prey position $x(t)$ and its future $x(t+1)$, optimized at T_{pos} with adaptively determined Z (14), and adjusted by random R_4. Parameter C, balancing exploration and exploitation, decreases iteratively (15). The method uses COS for exploitation, positioning prey at varying angles from T_{pos}. Equation (22), integrating (13) and (21), includes β = 0.1 and random R_5 (0-1): if $R_5 < \beta$, the agent hunts, updating via (22a); if $R_5 > \beta$, it preys, updating via (22b).

$$x_i(t+1) = \begin{cases} x_i(t) + o.5\left[\left(2CZP_{pos} - x_i(t)\right) + \begin{pmatrix} 2(1-c) \\ Z\mu - x_i(t) \end{pmatrix}\right] if R_5 \beta \quad (22a) \\ T_{pos} + CZ\cos(2\pi R_4) \times \left(T_{pos} - x_i(t)\right) else \quad (22b) \end{cases} \quad (22)$$

Opposition-based strategies enhance the performance of HPO techniques by introducing a complementary search direction. In traditional HPO, prey (optimal solutions) is sought by predators (search agents) in a competitive manner. OHPO introduces a parallel search for solutions that are opposite (complement) to the current best solutions found. This dual-direction search increases the exploration of the search space, potentially discovering better solutions faster and more robustly. In LTLF, this approach aims to improve the identification of optimal hyperparameters, enhancing the model's predictive accuracy and efficiency.

4. RESULTS AND DISCUSSION

The study utilized electrical load data from the 230/110 kV auto substation in Coimbatore, Tamil Nadu, India, recorded at 10-minute intervals from 2016 to 2019, alongside climate data. Eight independent variables, including temperature, wind speed, and humidity, were analyzed. We utilized the OHPO technique to optimize hyperparameters for an LSTM model to forecast long-term electrical load. OHPO, a metaheuristic algorithm, mimics predator-prey dynamics to enhance search efficiency. OHPO-configured LSTM did better than other methods in long-term load forecasting, as shown by MSE, RMSE, and MAPE tests. This was because it used an opposition-based strategy. Figures 2 to 7 illustrate these findings.

The study evaluated various LTLF approaches using LSTM models by comparing their MSE, RMSE, and MAPE. The OHPO-configured LSTM model demonstrated the best performance with the lowest MSE (0.25), RMSE (0.5), and MAPE (0.27), indicating the highest accuracy. The HPO-configured LSTM was the second best, with an RMSE of 1 and a higher MAPE value. GWO and PSO-configured LSTM techniques had higher RMSE and MAPE values, while traditional LSTM showed significant improvement through hyperparameter optimization, which is established in Figures 8(a) to 8(c).

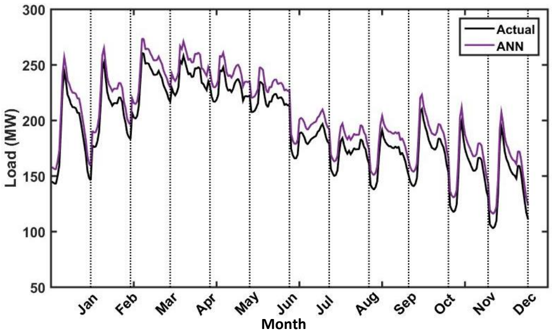


Figure 2. Comparison of the actual and traditional ANN model predicted values for LTLF

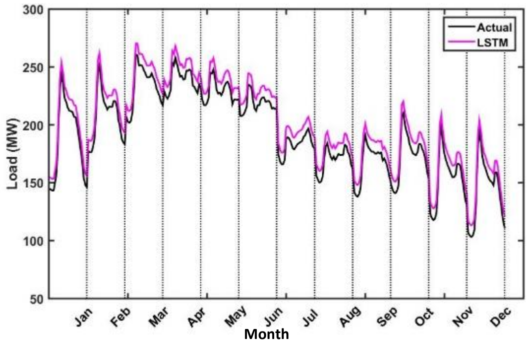


Figure 3. Comparison of real values vs conventional LSTM model predicted values for LTLF

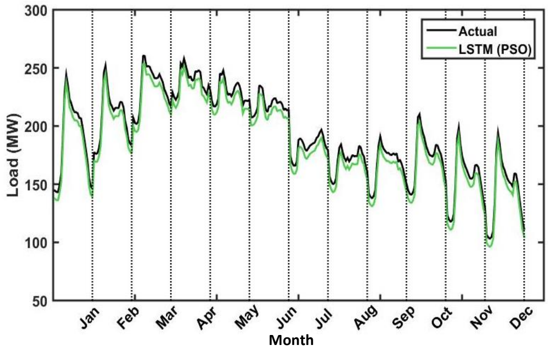


Figure 4. Comparison between the PSO-configured LSTM model predicted values for LTLF and the actual values

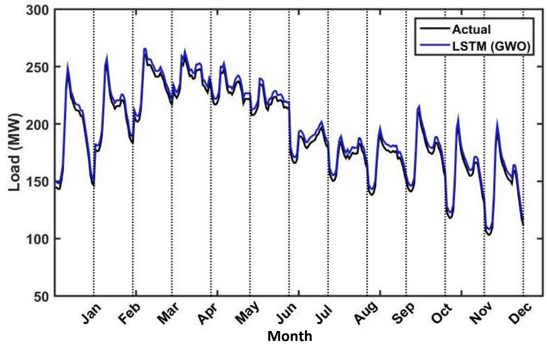


Figure 5. Comparison of the GWO-configured LSTM model's predicted values for LTLF with the actual values

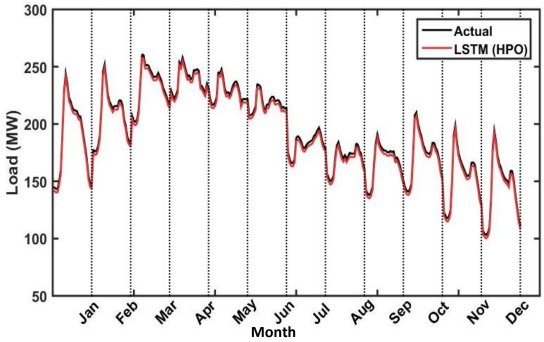


Figure 6. Comparison of HPO-configured LSTM model predicted values for LTLF with actual values

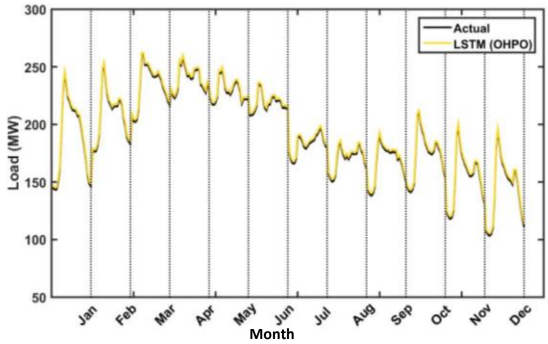
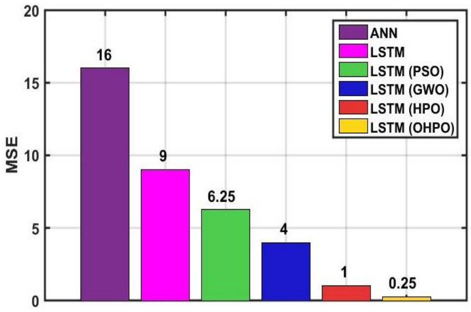
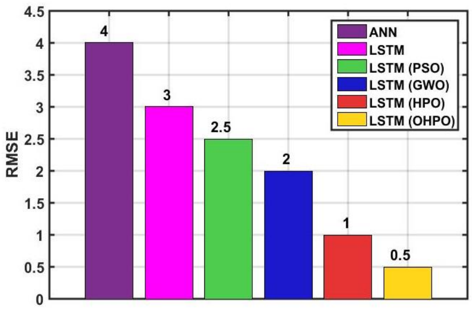


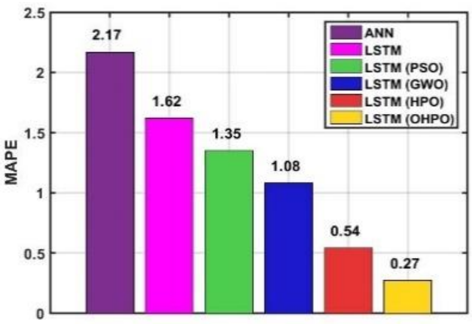
Figure 7. Comparison of actual values vs OHPO configured LSTM model predicted values for LTLF



(a)



(b)



(c)

Figure 8. Comparison of (a) MSE, (b) RMSE, (c) MAPE for different techniques in LTLF

5. CONCLUSION

This study proposes an approach to developing an LTLF model for the Coimbatore region in Tamil Nadu, India. Using LSTM networks and opposition-based learning in the hunter-prey optimization technique to tune hyperparameters significantly improved the model's accuracy. The results demonstrate that the proposed approach outperforms comparative techniques in terms of various error measures for LTLF, achieving an MSE of 0.25, RMSE of 0.5, and MAPE of 0.27. These findings are crucial for the power system industry, as accurate LTLF is essential for planning and managing future energy demands. Moreover, the approach shows potential for enhancing LTLF not only in Coimbatore but also in other regions. While this study makes important contributions to the field of LTLF, there are limitations that future research could address. For instance, expanding the study scope to include additional regions or exploring alternative optimization techniques could yield further insights. Overall, this research offers a promising approach to addressing the challenge of LTLF and holds significant implications for the power system industry.

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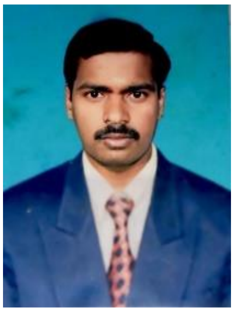

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