

APPLICATION OF COMBINING DATA PREPROCESSING WITH WAVELET FILTERING FOR GCN-LSTM NETWORK WITH HHO OPTIMIZATION ALGORITHM IN LOAD FORECASTING MODEL

Duong Ngoc Hung^{1,2*}, Nguyen Minh Tam¹, Nguyen Tung Linh³,
Nguyen Thanh Hoan⁴, Nguyen Thanh Duy²

¹HCM University of Technology and Education, ²Tien Giang University, ³Electric Power University

⁴Department of Information Technology - Ho Chi Minh Power Corporation (EVNHCMC)

ARTICLE INFO	ABSTRACT
Received: 12/3/2024	Accurate daily load forecasting is critical for effective energy management planning. In this study, the article proposes a new method for daily load forecasting that takes advantage of load data and weather data over time in Tien Giang. The forecast model is improved by incorporating a data preprocessing Wavelet filter to the graph convolutional network to combine input data across time points, days of the year, and other input features. The output of the graph convolution network is then fed into the Long Short Term Memory network with an optimization algorithm in the load forecasting model. The forecasting model is evaluated based on load data from the mini-grid model in Tien Giang province's power grid, comparing it with other deep learning-based forecasting models. The results show that the proposed model outperforms other models in terms of root mean square error and average absolute percentage error, proving the effectiveness of the method in terms of reliability and accuracy.
Revised: 23/5/2024	
Published: 24/5/2024	

KEYWORDS

Graph Convolution Network
Long Short-Term Memory
Load Forecasting
Wavelet filter
Harris hawks optimization

ỨNG DỤNG KẾT HỢP LỌC WAVELET TIỀN XỬ LÝ DỮ LIỆU CHO MẠNG GCN-LSTM VỚI GIẢI THUẬT TỐI ƯU HÓA HHO TRONG MÔ HÌNH DỰ BÁO PHỤ TẢI

Duong Ngoc Hung^{1,2*}, Nguyễn Minh Tâm¹, Nguyễn Tùng Linh³,
Nguyễn Thanh Hoan⁴, Nguyễn Thanh Duy²

¹Trường Đại học Sư phạm Kỹ thuật Thành phố Hồ Chí Minh, ²Trường Đại học Tiền Giang, ³Trường Đại học Điện lực

⁴Công ty Công nghệ thông tin – Tổng Công ty điện lực Thành phố Hồ Chí Minh

THÔNG TIN BÀI BÁO	TÓM TẮT
Ngày nhận bài: 12/3/2024	Dự báo chính xác tải hàng ngày là rất quan trọng để lập kế hoạch quản lý năng lượng. Trong nghiên cứu này đề xuất phương pháp mới để dự báo phụ tải hàng ngày tận dụng dữ liệu phụ tải và dữ liệu thời tiết theo thời gian ở Tiền Giang. Mô hình dự báo được cải thiện bằng cách kết hợp bộ lọc Wavelet tiền xử lý dữ liệu cho mạng chuyển đổi đồ thị để kết hợp dữ liệu đầu vào theo các điểm thời gian, ngày trong năm và các tính năng đầu vào khác. Đầu ra của mạng chuyển đổi đồ thị sau đó được đưa vào mạng Bộ nhớ ngắn hạn dài với giải thuật tối ưu hoá trong mô hình dự báo phụ tải. Mô hình dự báo được đánh giá dựa trên dữ liệu phụ tải từ mô hình lưới điện nhỏ trong lưới điện tỉnh Tiền Giang, so sánh nó với các mô hình dự báo dựa trên deep learning khác. Kết quả cho thấy mô hình đề xuất vượt trội hơn về sai số bình phương trung bình gốc và sai số phần trăm tuyệt đối trung bình, cho thấy hiệu quả của phương pháp là tin cậy và chính xác.
Ngày hoàn thiện: 23/5/2024	
Ngày đăng: 24/5/2024	

TỪ KHÓA

Mạng tích chập đồ thị
Bộ nhớ dài – ngắn hạn
Dự báo phụ tải
Bộ lọc Wavelet
Tối ưu hoá HHO

DOI: <https://doi.org/10.34238/tnu-jst.9875>

* Corresponding author. Email: 1726001@student.hcmute.edu.vn

1. Introduction

Technology is becoming increasingly pervasive in our lives, leading to a corresponding surge in the demand for electricity. A novel modeling approach is proposed in this paper for inverter-dominated microgrids using dynamic phasors in small-scale grids known as microgrids (MGs) [1]. Advanced techniques and tools have been developed for optimal energy operation in microgrid (MG) models, which are small-scale grids [2]. The significance of consumer load forecasting is increasingly being highlighted, with load forecasting being considered a more intricate issue than other forecasting challenges. Precise short-term forecasts can enhance the efficiency and convenience of power system operations in each area. If the prediction indicates that storage capacity is insufficient to support future loads, utilities can alert users, prompting them to reduce their energy consumption. This is crucial since users not only wish to avoid paying more for conventional energy but also desire to receive preferential treatment from authorities.

The study [3] adopts a hybrid approach for short-term forecasting of load demand in a typical microgrid (MG) proposed, leveraging the superior capabilities of deep learning. The approach combines a static wavelet packet transform and a feedforward neural network, which is optimized using the Harris Hawks Optimization (HHO) Algorithm depicted in the figure. Harris Hawks Optimization is employed as an alternative training algorithm to optimize the weighted average and basis of neurons. In the study [4], the next approach was to use the Harris Hawks Optimization (HHO) algorithm to forecast hourly load demand. To increase the accuracy of the prediction model, this study used the HHO algorithm to compute in the Wavenet network. In paper [5], the study investigates the relevance and combination of two deep neural network architectures: Feed-forward Deep Neural Network (FF-DNN) and Recurrent Deep Neural Network (R-DNN). Additionally, the study explores the WaveNet approach proposed in [6], which employs dilating causal complexes and connection skipping to incorporate long-term information. This innovative machine learning architecture offers several advantages over other statistical algorithms.

Numerous methods for load forecasting have been proposed by researchers. One such approach, discussed in [7], involves utilizing a linear approach combined with support vector machines for robust regression specifically in the application domain of load forecasting. The SVRCCS model, as proposed in paper [8], utilizes a tent chaotic mapping function to expand the search space of the cuckoo search algorithm and prevent getting stuck in local optima. Moreover, to address the cyclic patterns observed in electric loads, the model incorporates a seasonal mechanism along with the SVRCCS. Furthermore, in paper [9], a new model for short-term load forecasting is introduced, which relies on the weighted k-nearest neighbor algorithm to achieve higher accuracy. The model's performance is also compared against the back-propagation neural network and autoregressive moving average models by examining the forecasting errors.

In order to further advance from ANN, the model proposed in [10] employs an ensemble model using a novel learning technology known as extreme learning machine (ELM) to enhance the quality of short-term load forecasting in the Australian National Electricity Market (NEM). The study [11] applied a Bayesian neural network (BNN) to predict the load. To select the inputs for the individual BNNs, the sub-series with Euclidean norms closest to the minimum norm were chosen. In [12], the issue of short-term load forecasting is addressed by utilizing a deep learning approach called Correlation Sorting-LSTM. This method involves analyzing the correlation between sub and master tables of smart meters to improve the accuracy of the forecast. Experiments were conducted in [13] to evaluate the practicality and stability of the proposed model in a real-world scenario. The forecast accuracy of the model was also compared against the LSTM and CNN models.

Short-term load forecasting can also be performed using models such as Autoregressive Integrated Moving Average (ARIMA) [14], seasonal ARIMA (SARIMA) [15], Seasonal

Autoregressive Moving Average with Exogenous (SARIMAX) [16] and Modified Autoregressive Moving Averages (ARMA) [17]. However, these methods are not suitable for handling the non-linear properties of loads and tend to be inaccurate, limiting their applicability and presenting significant drawbacks.

Researchers regard machine learning and compositing techniques as powerful methods for addressing the non-linear properties of loads. Among machine learning approaches, Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) are commonly used. Both SVM and a seasonally adjusted SVM-based association model (SSA-SVM) were employed for STLF in studies [18] – [20]. The authors compared the performance of SSA-SVM against other methods, such as ANN and seasonally integrated wavelet-based ANN and found that SSA-SVM outperformed them. Additionally, several combined approaches have also been used for load forecasting.

Several methods have been used for load forecasting, such as Grasshopper Optimization Algorithm (GOA) based on SVM [21], Genetic Algorithm (GA) combined with SVM [22], Firefly Algorithm (FFA) SVM [23], [24], Particle Swarm Optimization (PSO) based on Support Vector Machines (SVM) [25], improved Fruit Fly Optimization Algorithm based on SVM [26], horizontal migration algorithm (GTA) based on hybrid PSO and SVM [27], experimental decomposition mode (EMD) [28], and Wavelet Transform (WT) [29] with PSO-SVM.

The machine learning and matching methods, as mentioned in the references, have some drawbacks, such as the difficulty in selecting parameters and the unclear choice of input variables. To overcome these challenges, this paper proposes an improved approach for load forecasting, which combines the Graph Convolutional Network Model (GCN) with LSTM. To demonstrate the effectiveness of this technique, the proposed method is compared with other competing models, such as ANN, LSTM, CNN-LSTM, and Wavenet. The rest of the article is organized as follows: Section 2 provides a detailed description of the GCN combined with LSTM approach used in the Tensorflow library, while section 3 presents numerical results and images. Finally, conclusions are provided in the last section.

2. Proposed algorithm and experiments

2.1. Proposed algorithm

2.1.1. Identify problem

In this paper, the forecasting objective is to forecast daily capacity based on historical load data, weather data in Tien Giang area.

Definition 1: network of data types over time (days) as G . To represent the topological structure of the data network over time points in a year, we use an unweighted graph $G = (V, E)$ treating each time point as a node in the graph. V represents the set of time point nodes, $V = \{v_1, v_2, \dots, v_N\}$, E represents the set of edges and N denotes the number of nodes. The adjacency matrix A is used to represent the connection between the lines, $A \in R_{N \times N}$. In the adjacency matrix, the elements can only be 0 or 1. An element with a value of 0 indicates that there is no association between the time points, while a value of 1 indicates a connection.

Definition 2: feature matrix $X_{N \times P}$. In our analysis, we view the data information of a time point network as an attribute of the network's node. This attribute is denoted as $X \in R_{N \times P}$, where P represents the number of node attribute characteristics (length of the history time series) and $X_t \in R_{N \times i}$ is used to represent the load quantities and time-varying factors at time point i . Once again, the node attribute characteristics can be any type of data information, such as daily load and weather conditions.

2.1.2. Harris hawks optimization (HHO)

Developed from research results [4] and Figure 1, after configuring the structure of the GCN-LSTM Network, the weight set of the GCN-LSTM will be adjusted by a training algorithm to

minimize errors. Therefore, HHO is applied to train GCN-LSTM to achieve high accuracy with minimal error. The representation of the search agent in the HHO and the appropriate selection of the objective function are important factors. In HHO-GCN-LSTM, each search agent is formed by three parts: a set of weight connections between the input layer and the hidden layer, a set of weights, and a set of weight connections between the hidden layer and the output layer, along with bias weights. In this work, HHO search agents are encoded as vectors in the interval [-1, 1].

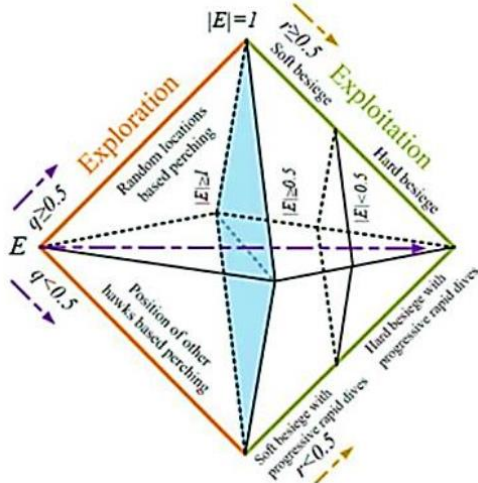


Figure 1. General diagram of HHO method [4]

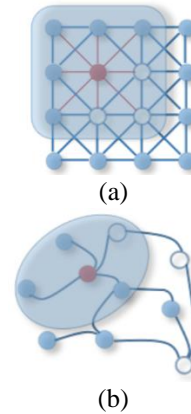


Figure 2. 2D Graph Convolutional: (a) Graph Convolutional; (b) Topological relationship node

2.1.3. Modeling spatial dependence

Acquiring complex spatial dependencies is a significant challenge in load forecasting. Traditional convolutional neural networks (CNNs) can capture local spatial features, but they are only effective in Euclidean space, such as images, regular meshes, and so on. However, the day-of-year point network is graph-based, not a two-dimensional grid. This means that the CNN model cannot effectively represent the complex topological structure of the time point network and thus cannot accurately capture the spatial dependencies. Recently, there has been significant interest in integrating CNNs into graph convolutional networks (GCNs), which can process data with arbitrary graph structures. The GCN model has been successfully applied in many areas, including document classification [18], unsupervised learning [30], and image classification [31]. The GCN model constructs a filter in the Fourier domain that operates on the nodes of the graph and their first-order neighborhood to capture the spatial features between nodes. The GCN model can then be constructed by stacking multiple layers of complexity. As shown in Figure 2, the GCN model can obtain the topological relationship between the centerline and the surrounding paths, encode the topological structure of the time point network and the data attributes, and then capture the spatial dependencies. In summary, we use the GCN model [31] to learn spatial features from the data over time.

The 2-layer GCN model can be expressed as follows:

$$f(X, A) = \sigma(\hat{A}Relu(\hat{A}XW_0))W_1 \tag{1}$$

X represents the feature matrix, A represents the adjacency matrix, $\hat{A} = \tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}$ represents the preprocessing step, $A_e = A + I_N$ is the self-connecting structure matrix, D_e is the order matrix, $D_e = P_j A_{eij}$. W_0 and W_1 represents the weight matrix in the first layer, and second, and $\sigma()$, $Relu()$ represents the activation function.

2.1.5. Time graph transformation network

We introduce a time graph convolutional network (T-GCN) model that combines a graph convolutional network and periodic units to capture both spatial and temporal dependencies in load data. The load prediction process and the specific structure of a T-GCN cell are illustrated in Figure 3, h_{t-1} represents the output at time $t - 1$, the GC is graph convolution, and u_t, r_t are the update and reset gates at time t , and ht represents the output at time t .

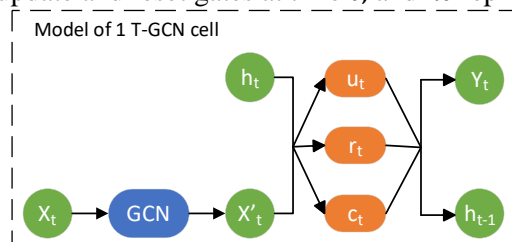


Figure 3. The specific architecture of a T-GCN unit

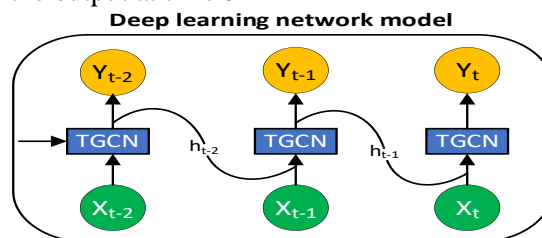


Figure 4. The specific architecture of deep learning network model with the convolution of the graph [32]

The overall network layer structure is GCN-LSTM, within which the filtered data is reconstructed into data arrays comprising power output data, temperature data, and time encoding codes. In Figure 4, each time series data array is fed into each symbolic network layer X_{t-2}, X_{t-1}, X_t . Input data X_t undergoes graph convolution to produce X'_t , and the result X'_t is combine with h_{t-1} (the results obtained from the previous network layer). In this phase, the program determines the full structure of the GCN-LSTM network model and initial initialization parameters for training.

Therefore, the problem of load forecasting based on non-time characteristics can be viewed as learning the mapping function f based on the network structure G and feature matrix.

X is computed by using the inputs of historical load data, weather data for the next T time points, as shown in Equation 2:

$$[X_{t+1}, \dots, X_{t+T}] = f(G; (X_{t-n}, \dots, X_{t-1}, X_t)) \tag{2}$$

where n is the length of the historical time series and T is the length of the time series to be predicted.

2.1.6. Data filter based on Wavelet transform

Through electricity load surveys in the Tien Giang area, sudden changes often appear and create disturbances when observing the past database. Therefore, assessing the reliability of this data set will be essential in the data processing stage before entering load forecasting models to produce forecasting results. In this paper, the author uses a data filter application that considers the reliability of the data source by analyzing many different levels of reliability and using the HHO-GCN-LSTM model.

2.1.7. Wavelet Filter Model – HHO – GCN – LSTM

Raw data including power output data collected in Tien Giang after passing through the filter and temperature data are fed into the training network using the HHO-GCN-LSTM model. Through Figure 5, to perform the network training phase according to the HHO-GCN-LSTM model, follow the following steps:

Step 1: First, the program initializes the structure of the GCN-LSTM network layers. Each GCN-LSTM (TGCN) element is built as shown in Figure 5.

Step 2: The training process is performed with computational loops to update the parameters of the GCN-LSTM network model. In this study, the calculation to achieve convergence of parameters in each iteration uses the HHO optimization algorithm. This process is symbolically shown in the diagram figure 5 including:

- The weight set w is initialized and updated through calculation iterations of the HHO algorithm, with the use of the objective function to evaluate convergence according to the target fit $< \epsilon$ or after n iterations limited by HHO optimization. When convergence is achieved, the set of weights considered optimal will be applied to the network model in k iterations of that network model.

- At the end of the training process, the GCN-LSTM network model with weight sets has been optimized through HHO.

Step 3: The trained GCN-LSTM network model will be included in the data to perform experimental prediction. The load curve forecast results are calculated with errors with actual data according to the RMSE and MAPE equations to evaluate the model.

After evaluating the load curve forecasting models, researchers should use these models to run experimental forecasts for different time points.

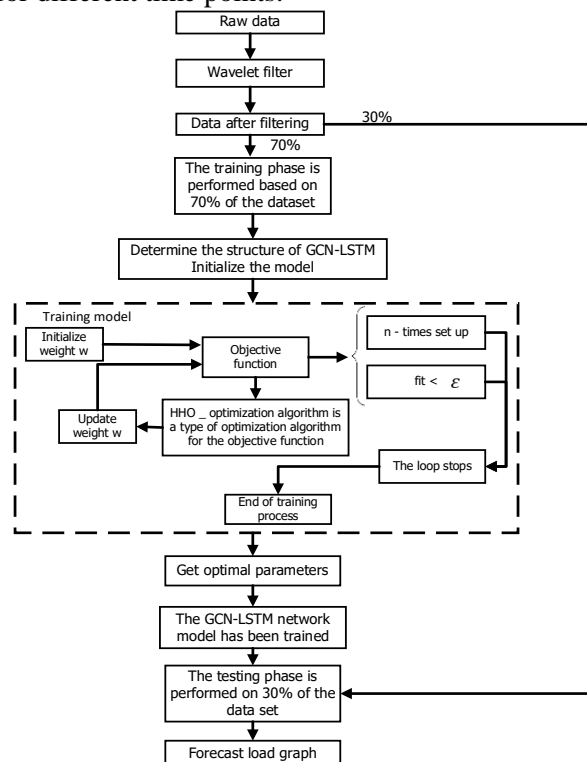


Figure 5. The proposed algorithm integrates Wavelet Filter – HHO – GCN – LSTM

2.2. Experimentation

2.2.1. Datasets

To conduct the simulation for the proposed approach, the dataset used is related to the electrical load in Tien Giang. In order to address the load forecasting problem, factors that affect power consumption, in addition to demand periodicity, are also taken into consideration. These factors include weather parameters such as outdoor temperature, humidity, solar irradiance, speed, and wind throughout the day, as well as time-related variables such as festivals or economic conditions, which can significantly impact load prediction accuracy. However, collecting the external factors is a complex process, and the collected data is usually in the form of continuous and cyclic time series throughout the day. As a result, this study evaluates the data based on the timeline and encodes time using various formats such as day, week, month, and holidays, along with outdoor temperature data in Tien Giang for the corresponding time periods.

Temperature data is shown in the Figure 6 below, including: electrical load (MWh, blue), outdoor temperature in Tien Giang province according to the respective timelines (°C, orange). It can be seen

that the load profile is significantly influenced by the temperature data variation. Therefore, the included outdoor temperature acts as a highly correlated factor with the electrical load data.

During the tests, the input data is normalized to the interval [-1,1]. In addition, 70% of the data is used as the training set and the remaining 30% is used as the test set. We have predicted load for the next 15 minutes, 30 minutes, 45 minutes and 60 minutes.

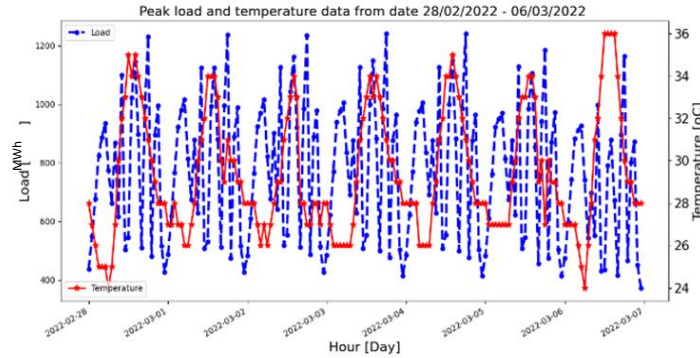


Figure 6. Week electricity and temperature data in Tien Giang

2.2.2. Evaluation indicators

To evaluate the predictive performance of the T-GCN model, we use five indicators to evaluate the differences between real load information Y_t, \hat{Y}_t and predicted, including:

- Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_t - \hat{Y}_t)^2} \tag{3}$$

- Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{\hat{y}_i - y_i}{y_i} \right| \tag{4}$$

Specifically, RMSE and MAPE are used to measure prediction error: the smaller the value, the better the predictive effect. Accuracy is used to detect prediction accuracy, which is the higher the value, the better the prediction efficiency.

3. Results and Discussion

3.1. Error evaluation results

The table below shows the performance of the models mentioned above. The proposed model performs better than other models in most criteria, in which the RMSE and MAPE coefficients clearly show the superiority of the proposed method. In which, the proposed model gives much lower figures than the compared methods (at least % compared to the next method).

Table 1. Forecast results

MODEL	RMSE	MAPE (%)
LSTM	20.4574	4.6159
CNN-LSTM	29.8788	3.75
Wavelet	5.2657	0.8749
HHO-GCN-LSTM	2.521	0.58
Wavelet filter-HHO-GCN-LSTM (Saturday)	3.2636	0.73
Wavelet filter-HHO-GCN-LSTM (Sunday)	4.56	1.21
Wavelet filter-HHO-GCN-LSTM (Monday- Friday)	2.834	0.54

According to the results shown in Table 1, the prediction model using LSTM gives the highest error results (RMSE: 20.4574; MAPE: 4.6159). The CNN-LSTM integrated model gives an improved MAPE error of 3.75%, but the RMSE is not good at 29.8788%. The results when applying the Wavenet model have a clear improvement in both indicators. Specifically, for the basic Wavenet model, the MAPE has dropped below 1 at 0.8749. But the underlying Wavenet is still quite high with an RMSE of 5.2657. The proposed algorithm optimizes HHO for the GCN-LSTM network (HHO-GCN-LSTM), resulting in a clear improvement with a MAPE of 0.58% and RMSE of 2.521. At the same time, the model uses the Wavelet filter for the HHO-GCN-LSTM model. In the results of Weekdays (Monday-Friday), Saturday, and Sunday, the error on Saturday and Sunday is not good, while Weekday shows better improvement. Thereby, when applying the Wavelet filter, it is necessary to evaluate the data to ensure group separation and appropriate use.

3.2. Forecast graph results

The forecast results shown in the graph are shown in Figure 7.a – 7.e. Each figure shows actual data (solid blue line) and forecast data (dashed red line). The proposed method (Wavelet -HHO-GCN-LSTM) shows better accuracy when shown on the graph, the forecast results and the actual data almost coincide. Other methods have large errors, the graph shows the difference between two large data.

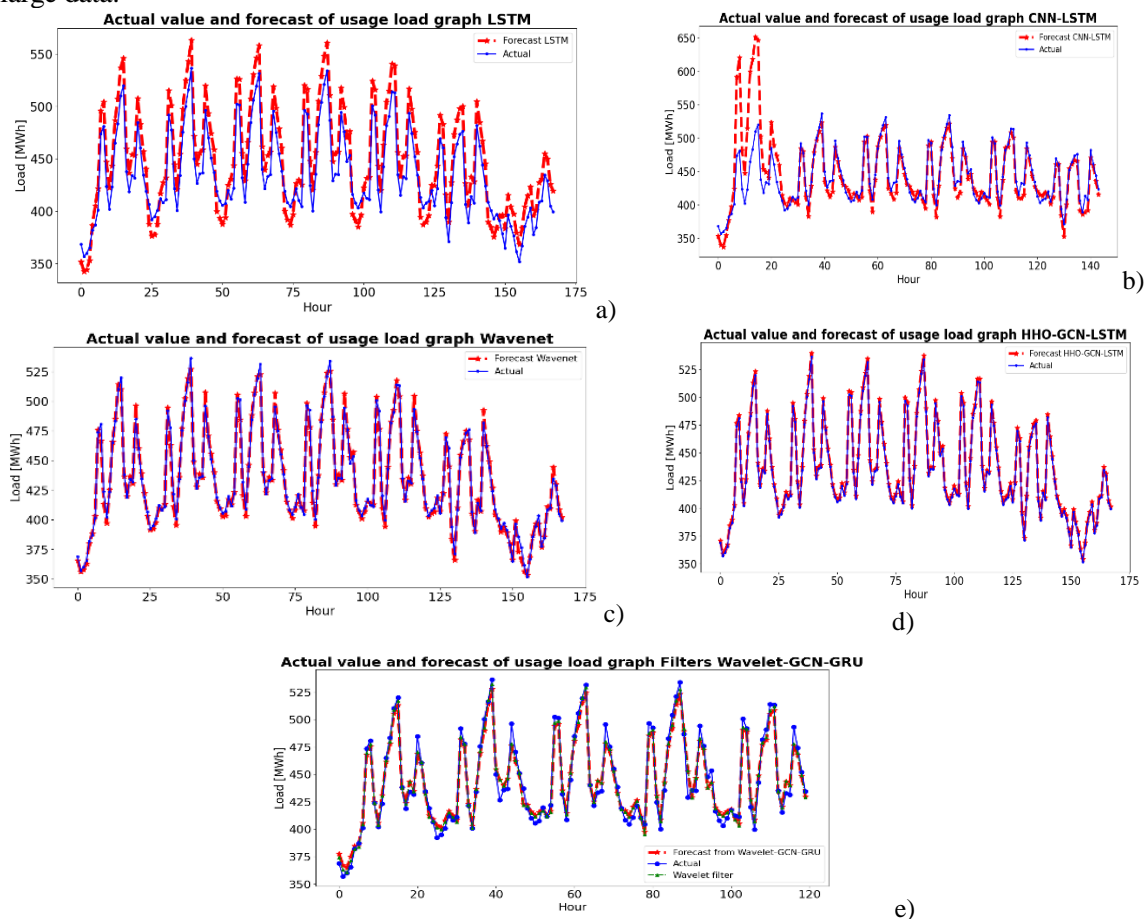


Figure 7. a) Graph showing actual value and LSTM network method on March 6, 2023 – March 12, 2023; b) Graph showing actual value with CNN-LSTM network method from March 6, 2023 – March 12, 2023; c) Graph showing actual value with the proposed method combining Wavenet network on March 6, 2023 – March 12, 2023; d) HHO-GCN-LSTM forecast results March 6, 2023 – March 12, 2023; e) Wavelet-HHO-GCN-LSTM Filter forecast results Monday, March 6, 2023 – Friday, March 10, 2023

Figure 7a shows that the LSTM method gives forecast results that do not closely match actual data, especially at peak points with large errors. Therefore, the calculated results in table 1 accurately demonstrate the high level of error for weekly forecasts.

Through Figure 7b, it is shown that the CNN-LSTM method demonstrates relatively good performance in predicting actual data on the following days. However, there is a significant deviation on the first day, especially in the period from 0 to 24 hours. Therefore, table 1 shows an unusually high level of RMSE error, while the MAPE error indicates better performance than the LSTM method.

Through Figure 7c, it is shown that the Wavenet method shows good performance in predicting real data, however, there exists a peak with higher error. Therefore, table 1 shows that the calculated error level is quite accurate according to the forecasted weekdays.

Based on Figure 7d, it can be seen that the HHO-GCN-LSTM method gives better prediction results than Wavenet when applied to real data. However, there are some bottom points on March 6, 2023 and March 12, 2023 with higher deviations.

Based on Figure 7e, it can be seen that the Wavelet-HHO-GCN-LSTM method gives quite good prediction results when applied to real data. However, larger errors appear at the bottom load of the days, leading to the calculation of RMSE results with a higher degree of error.

4. Conclusion

It can be seen from the above results that when using the HHO algorithm as an optimization function for the GCN-LSTM network (HHO-GCN-LSTM), the network performance is significantly improved, with MAPE and RMSE parameters are superior (Table 1). At the same time, the research also offers the ability to apply Wavelet filters to groups of data separated by PCA, Dendrogram and probability distribution density evaluation methods. However, a current drawback of the study is that the algorithm consumes a lot of computational resources and takes more time than the compared methods when used. A limitation of only one numerical value can be optimized when the falcon algorithm is used in its current form. In the future, research will focus on expanding the algorithm to be able to handle optimization of multiple values at the same time as well as minimize the consumption of computational resources of the method, while still maintaining the or improve program performance.

REFERENCES

- [1] K. Yu, Q. Ai, S. Wang, J. Ni, and T. Lv, "Dynamic Phasors-Based Modeling and Stability Analysis of Droop-Controlled Inverters for Microgrid Applications," *IEEE Transactions on Smart Grid*, vol. 5, no. 6, pp. 2980-2987, 2014, doi: 10.1109/TSG.2014.2331280.
- [2] U. B. Tayab and Q. M. Humayun, "Enhanced droop controller for operating parallel connected distributed-generation inverters in a microgrid," *J. Renew Sustain Energy*, vol. 10, no. 4, 2018, Art. no. 045303.
- [3] U. B. Tayab, A. Zia, F. Yang, J. Lu, and M. Kashif. "Short-term load forecasting for microgrid energy management system using hybrid HHO-FNN model with best-basis stationary wavelet packet transform," *Journal Elsevier Energy*, vol. 203, 2020, doi: 10.1016/j.energy.2020.117857.
- [4] T.-H. Nguyen, Q.-H. Pham, V.-T. Nguyen, V.-A. Truong, H.-V. Nguyen, and D. N. Truong. "Hybrid HHO-Wavenet Model Applies in Short-term Load Forecasting for Microgrid System," *2022 6th International Conference on Green Technology and Sustainable Development (GTSD), IEEE*, 2022, pp. 1177-1183.
- [5] N. H. Duong, T. H. Nguyen, and M. T. Nguyen, "Short term load forecast using deep learning," *2019 Innovations in Power and Advanced Computing Technologies (i-PACT)*, 2019, doi: 10.1109/i-PACT44901.2019.8690036
- [6] F. D. Rueda, J. D. Suárez, and A. D. R. Torres, "Short-Term Load Forecasting Using Encoder-Decoder Wave Net: Application to the French Grid," *Energies*, vol. 14, 2021, Art. no. 2524, doi: 1996-1073/14/9/2524.
- [7] S. D. Cosmis, R. D. Leone, *et al.*, "Electric Load Forecasting using Support Vector Machines for Robust Regression," *Proceedings of Conference on the Emerging M&S Applications in Industry & Academia, Modeling and Humanities Symposium*, vol. 9, pp. 1-8, April 2013.
- [8] Y. Dong, Z. Zhang, and W.-C. Hong, "A hybrid seasonal mechanism with a chaotic cuckoo search algorithm with a support vector regression model for electric load forecasting," *Energies*, vol. 11, 2018, Art. no. 1009.

- [9] G.-F. Fan, Y.-H. Guo, J.-M. Zheng, and W.-C. Hong, "Application of the Weighted K-Nearest Neighbor Algorithm for Short-Term Load Forecasting," *Energies*, vol. 12, 2019, Art. no. 916.
- [10] R. Zhang, Z. Y. Dong, Y. Xu, K. Meng, and K. P. Wong, "Short-term load forecasting of Australian National Electricity Market by an ensemble model of extreme learning machine," *IET Gener. Transm. Distrib.*, vol. 7, pp. 391–397, 2013.
- [11] M. Ghofrani, M. Ghayekhloo, A. Arabali, and A. Ghayekhloo, "A hybrid short-term load forecasting with a new input selection framework," *Energy*, vol. 81, pp. 777–786, 2015.
- [12] C. Xu, W. Li, M. Yu, J. Xu, J. Liu, Y. Wang, and L. Zhu, "A Correlation Sorting-LSTM Method for High Accuracy Short-term Load Forecasting based on Smart Meter Data," *IEEE, 2020 7th International Conference on Information, Cybernetics, and Computational Social Systems (ICCSS)*, Feb. 03, 2021, doi: 10.1109/ICCSS52145.2020.9336912.
- [13] C. Bo-Juen, C. Ming-Wei, and L. Chih-Jen, "Load forecasting using support vector Machines: a study on EUNITE competition 2001," *IEEE Trans Power Syst.*, vol. 19, no. 4, 2004, Art. no. 1821e30.
- [14] B. Nepal, M. Yamaha, A. Yokoe, and T. Yamaji, "Electricity load forecasting using clustering and ARIMA model for energy management in buildings," *Japan Architectural Review*, vol. 3, no. 1, pp. 62-76, Nov. 22, 2019, doi: 10.1002/2475-8876.121.
- [15] C. Bo-Juen, C. Ming-Wei, and L. Chih-Jen, "SARIMA Model Forecasting of Short-Term Electrical Load Data Augmented by Fast Fourier Transform Seasonality Detection," *2019 IEEE Canadian Conference of Electrical and Computer Engineering (CCECE)*, Oct. 11, 2019, doi: 10.1109/CCECE.2019.8861542.
- [16] F. R. Alharbi and D. Csala, "A Seasonal Autoregressive Integrated Moving Average with Exogenous Factors (SARIMAX) Forecasting Model-Based Time Series Approach," *Inventions and Innovation in Electrical Engineering/ Energy/ Communications*, vol. 7, no. 4, 2022, Art. no. 94, doi: 10.3390/inventions7040094.
- [17] J. Che and J. Wang, "Short-term load forecasting using a kernel-based support vector regression combination model," *Appl. Energy*, vol. 132, 2014, Art. no. 602e9.
- [18] W.-C. Hong, "Electric load forecasting by support vector model," *Appl. Math Model*, vol. 33, no. 5, 2009, Art. no. 2444e54.
- [19] E. Ceperic, V. Ceperic, and A. Baric, "A strategy for short-term load forecasting by support vector regression machines," *IEEE Trans Power Syst.*, vol. 28, no. 4, 2013, Art. no. 46e64.
- [20] A. Selakov, D. Cvijetinovic, L. Milovic, S. Mellon, and D. Bekut, "Hybrid PSOeSVM method for short-term load forecasting during periods with significant temperature variations in city of Burbank," *Appl. Soft Comput.*, vol. 16, 2014, Art. no. 80e8.
- [21] H. Lu, M. Azimi, and T. Iseley, "Short-term load forecasting of urban gas using a hybrid model based on improved fruit fly optimization algorithm and support vector machine," *Energy Rep.*, vol. 5, pp. 666-677, 2019.
- [22] A. Kavousi-Fard, H. Samet, and F. Marzbani, "A new hybrid modified firefly algorithm and support vector regression model for accurate short-term load forecasting," *Expert Syst. Appl.*, vol. 41, no. 13, pp. 6047-6056, 2014.
- [23] M. Barman and N. B. D. Choudhury, "Season specific approach for short-term load forecasting based on hybrid FA-SVM and similarity concept," *Energy*, vol. 174, 2019, Art. no. 886e96.
- [24] M. Barman, N. B. D. Choudhury, and S. Sutradhar, "A regional hybrid Goa-SVM model based on similar day approach for short-term load forecasting in Assam, India," *Energy*, vol. 145, 2018, Art. no. 710e20.
- [25] W. Sun, "A novel hybrid GA based SVM short term load forecasting model," *2009 Second International Symposium on Knowledge Acquisition and Modeling*, vol.2, pp. 227-229, 2009.
- [26] H. Jiang, Y. Zhang, E. Muljadi, J. J. Zhang, and D. W. Gao, "A short-term and high-resolution distribution system load forecasting approach using support vector regression with hybrid parameters optimization," *IEEE Transactions on Smart Grid*, vol. 9, no. 4, 2018, Art. no. 3341e50.
- [27] X. Wang and Y. Wang, "A hybrid model of EMD and PSO-SVR for short-term load forecasting in residential quarters," *Journal of Mathematical Problems in Engineering*, vol. 2016, 2016, Art. no. 9895639.
- [28] Q. Chen, Y. Wu, X. Zhang, and X. Chen, "Forecasting system based on wavelet transform and PSO-SVM. 2nd international conference on anti-counterfeiting," *Security and Identification*, vol. 2008, pp. 305-309, 2008.
- [29] S. Qiang and Y. Pu, "Short-term power load forecasting based on support vector machine and particle swarm optimization," *J. Algorithm Comput. Technol.*, vol. 13, pp. 1-8, 2018.
- [30] L. Zhao, Y. Song, C. Zhang, Y. Liu, P. Wang, T. Lin, M. Deng, and H. Li, "T-GCN: A Temporal Graph Convolutional Network for Traffic Prediction," *IEEE Transactions on Intelligent Transportation Systems*, 2019, doi: 10.48550/arXiv.1811.05320.
- [31] J. Bruna, W. Zaremba, A. Szlam, and Y. Lecun, "Spectral networks and locally connected networks on graphs" *International Conference on Learning Representations (ICLR2014)*, CBLS, April 2014, arxiv: abs/1312.6203.
- [32] T. N. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks," *International Conference on Learning Representations*, Sep. 2016, doi: 10.48550/arXiv.1609.02907.