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Enhancing Urban Intelligence Energy Management: Innovative Load Forecasting Techniques for Electrical Networks

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Abstract

Energy sustains the world, yet fossil fuels, a finite resource, are dwindling. This necessitates a shift towards more sustainable energy sources, such as electricity. Accurate load forecasting is crucial in today's global energy landscape, as it helps predict various aspects such as production, revenue, consumption, economic conditions, weather impacts, power system utilization, customer demand, and economic growth. For instance, an increase in electricity demand within a country often signifies a boost in industry and production, leading to economic progress and reduced unemployment. This project aims to enhance prediction accuracy through meticulous input filtering, taking into account factors like population growth, planned loads, inflation, and competitive pricing pressures from producers. Despite inherent prediction errors, efforts are made to minimize these discrepancies. This paper introduces a novel combined method for mid-term energy forecasting. To demonstrate its efficacy, real data from the past ten months, collected from subscribers of the Kerman distribution company, was used to forecast energy consumption over the next ten days. The innovative method, which integrates multiple forecasting techniques and robust filters, significantly improves forecasting precision. The following error metrics were recorded for the proposed method: MSE: 0.009, MAE: 0.083, MAPE: 0.776, RMSE: 0.095, AE: 0.013.

Keywords

Energy Prediction, Forecasting, Regression, Neural Network, MTLF

1. Introduction

Load forecasting is an invaluable tool for manufacturers aiming to minimize forecasting errors and reduce cost penalties. Electrical loads vary over time due to fluctuating factors such as population growth and economic conditions. This research introduces a combined method that utilizes a sophisticated algorithm and efficient filtering for improved load prediction, which is crucial for cost savings in production and strategic planning in power plant and electrical network development. Various methods for future energy prediction are discussed in references [1]-[9]. [1] highlights the effectiveness of input filters, enhancing the strength of our input collection, yet lacks precise techniques like robust algorithms, which our proposed method addresses. Reference [2] introduces a new feature selection technique for load and price forecasting; however, it falls short due to insufficient filtering of initial inputs, rendering it incomplete. Short-term load forecasting methods, discussed in references [3]-[5], also share this incompleteness. In reference [6], a method combining wavelet transform and partial least squares regression is proposed; though it has a robust core, it neglects suitable input and output filters, leading to significant errors. Artificial Neural Networks (ANNs) are renowned for pattern recognition in load prediction, as detailed in references [7]-[8]. ANNs are adept at modeling complex tasks but are not sufficiently robust on their own. Reference [9] discusses a kernel-based modeling approach using Support Vector Machines (SVM) for Short-Term Load Forecasting (STLF), yet it too lacks output filtering, leading to larger errors. Additionally, a variety of algorithms have been utilized for load forecasting [10]-[14], including fuzzy logic inference [15]-[17], time series [18]-[20], and mathematical regressions [21] [22]. Despite extensive research in the field of load forecasting, the need for more precise methods continues to grow, especially with rapid population increases that exacerbate errors in existing methods. For example, an error of 1% in a population of 8 billion represents a significantly larger absolute error than the same percentage in a population of 2 billion. To address this, we propose a refined method using suitable filters, a potent Genetic Algorithm (GA) to enhance the ANN, and a feature selection technique MRMRMS. This research focuses on Mid-Term Load Forecasting (MTLF), employing a combination of ANN, GA, and curve fitting with appropriate filters. We also consider scheduled loads, incorporating detailed programs from municipalities and ministries to further enhance accuracy and significantly improve predictive values. The main steps and contributions of this research are outlined in **Figure 1**.

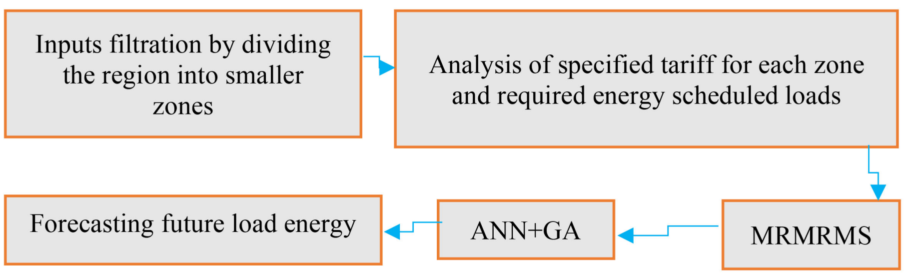

Figure 1. General Schematic of the proposed method.

2. Duration of Energy Forecasting

The time duration for energy forecasting can be categorized into four distinct classes, as detailed in references [23] [24]:

1) Long-term energy forecasting: This type is utilized for planning several years to several decades into the future. **2)** Mid-term energy forecasting: Employed for making predictions spanning several days to a few months. **3)** Short-term energy forecasting: Used for forecasting from the next few hours up to the next few days. **4)** Very short-term energy forecasting: Applicable for predictions ranging from the next few minutes to one hour. This paper primarily focuses on the mid-term type of energy forecasting.

3. Area Classification

In energy, predicting the whole region is not studied together; we should divide the area into some smaller zones. There are two main types of area classifications: regular and irregular.

3.1. Regular Classification

In the regular format, we divided the area into smaller regions of equal size, as illustrated in **Figure 2**.

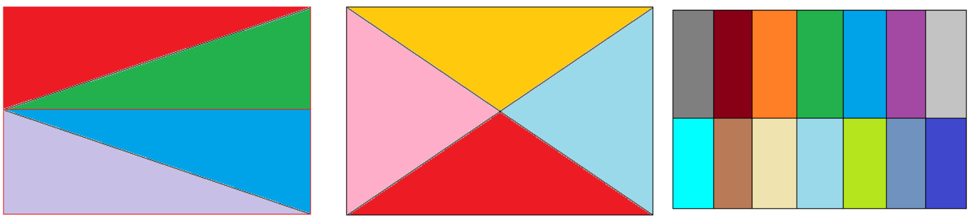

Figure 2. Samples of regular classification for electrical load consumption.

3.2. Irregular Classification

In irregular classification **Figure 3**, the area is divided into zones based on load consumption. This means that areas with similar load consumption are grouped, enhancing the accuracy of the calculation process.

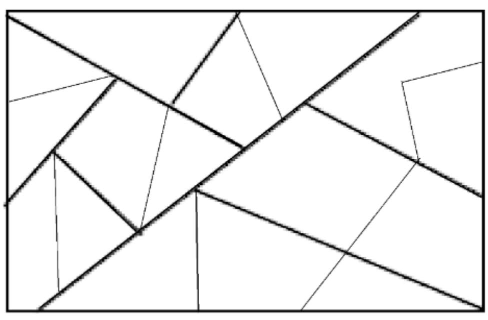

Figure 3. Example of irregular classification for electrical load consumption.

We used irregular classification in this paper, which it divided Kerman city to 11 zones like **Figure 4**:

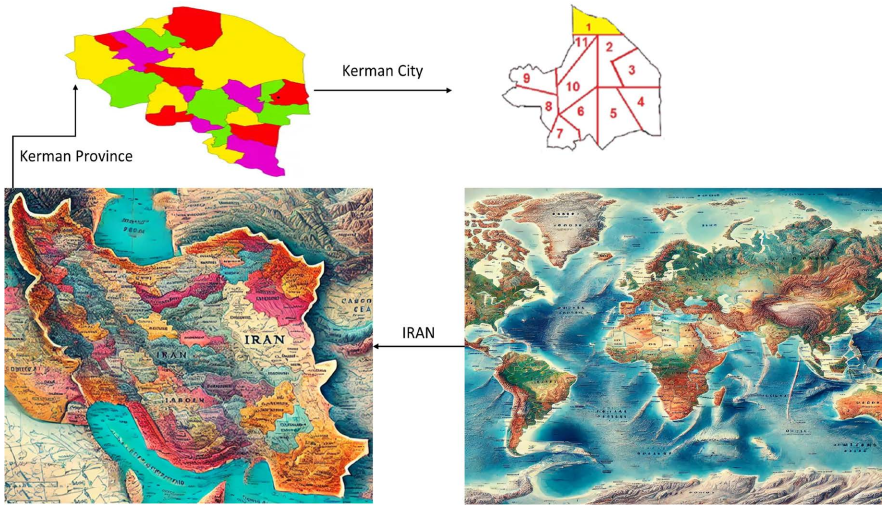

Figure 4. Irregular classification for electrical load consumption uses in this paper.

4. Proposed Method

This paper introduces a combined method for mid-term load forecasting (MTLF) that integrates Artificial Neural Networks (ANN), Genetic Algorithms (GA), and curve fitting. This method employs scheduled loads and detailed programs from municipalities and ministries as inputs, enhancing accuracy compared to solely relying on historical data. Demand varies with the time of day, typically increasing on weekends [25]. Additionally, load fluctuations are influenced by monthly temperature variations [26]. Temperature is a critical weather parameter affecting load consumption, with a direct relationship between temperature changes and demand levels.

As shown in **Figure 5**, the load increases as temperatures drop. Similarly, during summer, the load also rises as temperatures become warmer. The multiple linear regression models for load are described as follows:

Equation (1) is

$$\begin{aligned} P(t) = {} & K_1 + K_2 * t + K_3 * \left(T(t) - T_s\right) + K_4 \left(T(t) - T_C\right)^2 \\ & + K_5 \left(T(t) - T_C\right)^3 + K_6 (T(t) - T(t-1) + K_7 (T(t-1) \\ & - T(t-2) + K_8 (T(t-2) - T(t-3) + K_9 WP_1(t) + K_{10} WP_2 \end{aligned}$$

where:

$P(t)$: daily load, $K_i s$: constants, $T(t)$: dry bulb temperature at time t (This is the average temperature for the forecast load), $T(t - i)$: the daily temperature of time t-i., WP_i: i-the weather parameter, besides the temperature.

4.1. Filtration

The filtration stage of inputs involves two primary steps.

4.1.1. Curve Fitting with Appropriate Regression

Various regression models are employed, including logistic, nearest neighbor, linear, and among others [1]. An example of the logistic regression method can be described by the general form shown below:

$$y = \frac{y_{\infty}}{1 + a\epsilon^{-bx}} \tag{2}$$

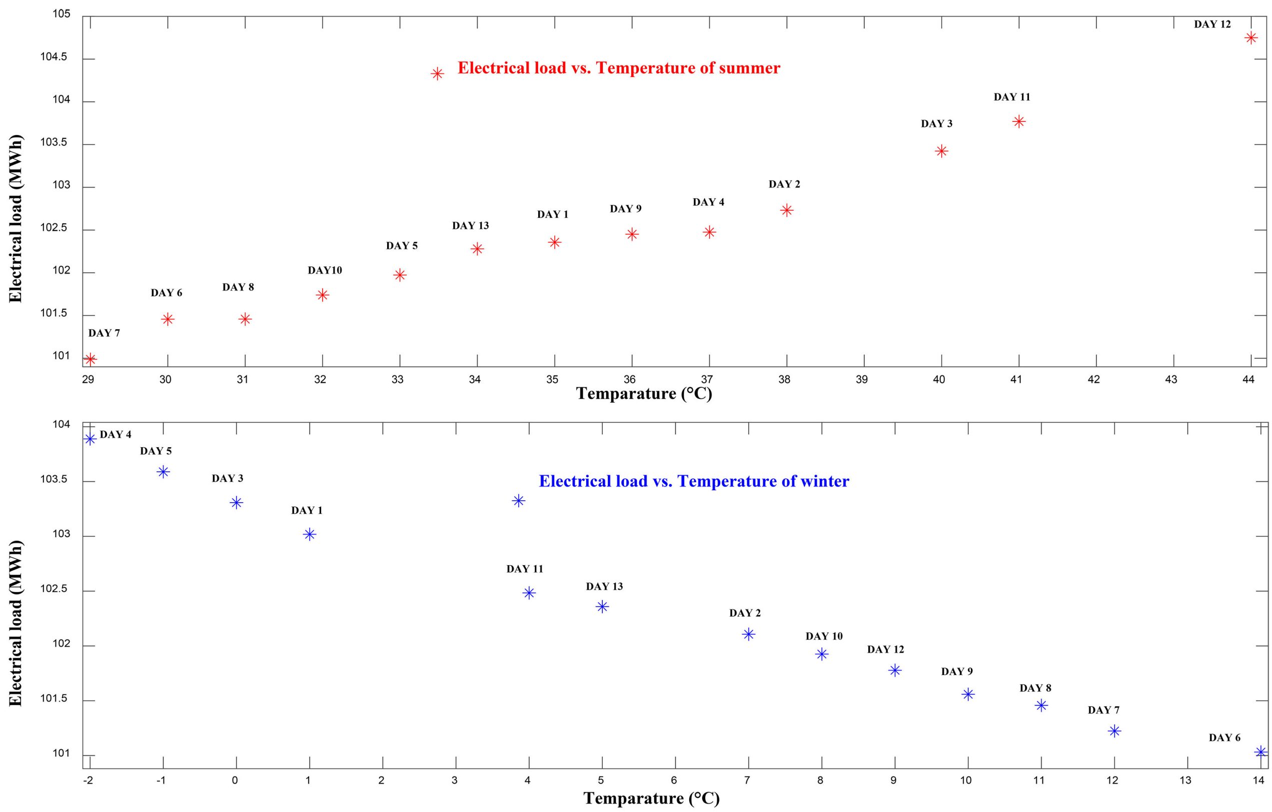

Figure 5. Weather-sensitive load model for 13 different days in summer temperature and winter temperature for Kerman city.

4.1.2. MRMRMS

MRMRMS is a filtering approach that selects a minimal subset of the most informative inputs for the forecasting process by maximizing relevancy, minimizing redundancy, and maximizing the synergy of the candidate features. This method, referred to as MRMRMS, is discussed next, with relevancy, redundancy, and interaction measures based on information-theoretic criteria [2].

4.2. Artificial Neural Network Description

Artificial Neural Networks (ANN) are computational models inspired by the human brain, designed to analyze and process data. ANNs are particularly adept at modeling the relationships between inputs and outputs, making them highly suitable for nonlinear tasks such as load forecasting. An ANN is composed of three main parts: Input Layer, Hidden Layer, and Output Layer as shown in Figure 6.

ANNs can effectively model the relationship between inputs and outputs, especially for nonlinear tasks such as load forecasting. Training an ANN is highly sensitive to data quality, necessitating the elimination of unsuitable data through effective filtering methods. Additionally, we employ a genetic algorithm (GA) to calculate optimal weights due to its strong accuracy. Numerous methods and algorithms are available for load forecasting, including GA, Ant Colony Optimization (ACO), and Artificial Bee Colony (ABC), among others [27]-[46]. The remaining aspect of the MRMRMS algorithm involves the fine-tuning of its adjustable parameters, including α, β, and the threshold TH. α is an adjustable parameter within the MRMRMS algorithm that requires fine-tuning specific to the problem, while β and TH are similar adjustable parameters needing precise calibration [1] [2]

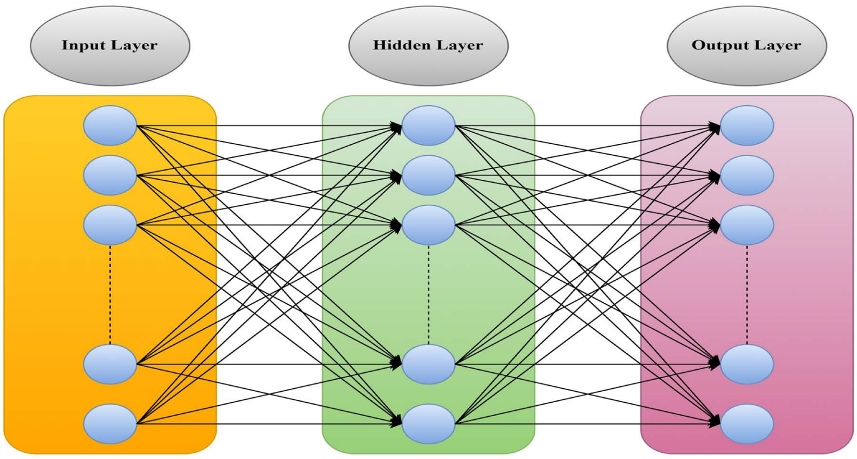

Figure 6. Artificial neural network structure including input, hidden layer, output layer, and output.

4.3. Numerical Results

In this section, we demonstrate the accuracy of the proposed method using real load consumption data from the Iranian electricity market in Kerman city. Initially, we collected data from June 22, 2023, to July 4, 2023, spanning 13 days. We then utilized data from June 22, 2023, to June 28, 2023 (7 days) to forecast load consumption from June 29, 2023, to July 4, 2023 (6 days) using various methods including land consumption curve fitting, ANN + GA, ANN + GA + MRMRMS, and the proposed method. Subsequently, we compared the forecasting results with the actual data and calculated errors to demonstrate the effectiveness of the proposed method. The actual data for our 13-day period is presented in **Table 1**, while the errors calculated using a 5-system metric are shown in **Table 1** and **Figures 7-12**.

Also, the results for the last day (13) are 100.621, 100.731. 101.031, 101.989, 102.280 respectively.

To demonstrate the accuracy of our methods, we calculate errors using five different metrics: Mean Square Error (MSE), Mean Average Error (MAE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE).

Table 1. Comparison of the proposed with the common methods for load forecasting with real data.

Method	Energy Consumption (MWh)					
	Day1	Day2	Day3	Day4	Day5	Day6
Land consumption + Curve fitting	102.357	102.732	103.424	102.476	101.974	101.457
ANN + GA	102.357	102.732	103.424	102.476	101.974	101.457
ANN + GA + MRMRMS	102.357	102.732	103.424	102.476	101.974	101.457
Proposed method	102.357	102.732	103.424	102.476	101.974	101.457
Actual data	102.357	102.732	103.424	102.476	101.974	101.457
Method	Day7	Day8	Day9	Day10	Day11	Day12
Land consumption + Curve fitting	100.987	100.021	100.745	99.023	101.247	101.953
ANN + GA	100.987	100.447	100.925	100.221	101.557	102.024
ANN + GA + MRMRMS	100.987	100.835	101.124	100.783	103.907	102.983
Proposed method	100.987	101.203	102.252	101.795	103.423	104.782
Actual data	100.987	101.458	102.451	101.740	103.770	104.750

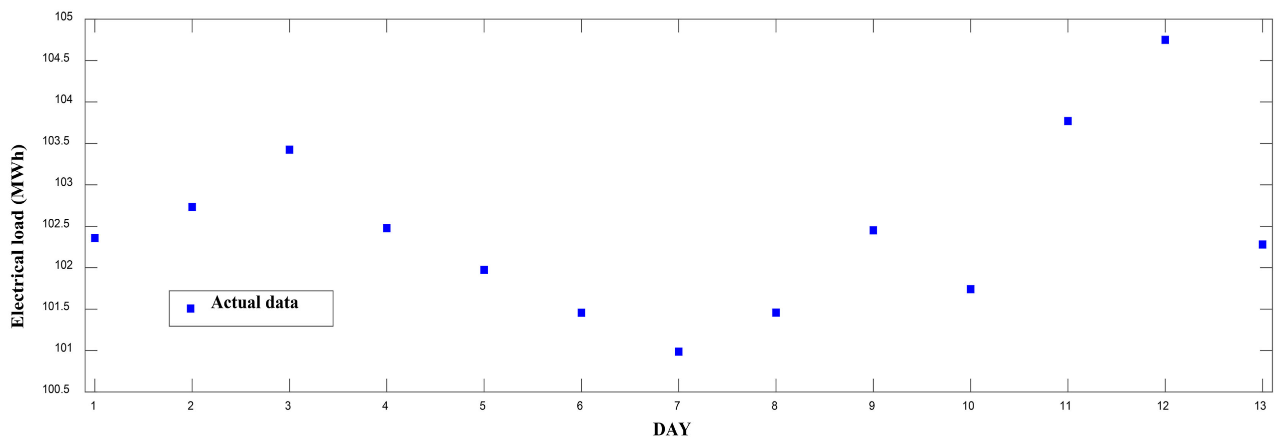

Figure 7. Actual data for 13 days of load forecasting.

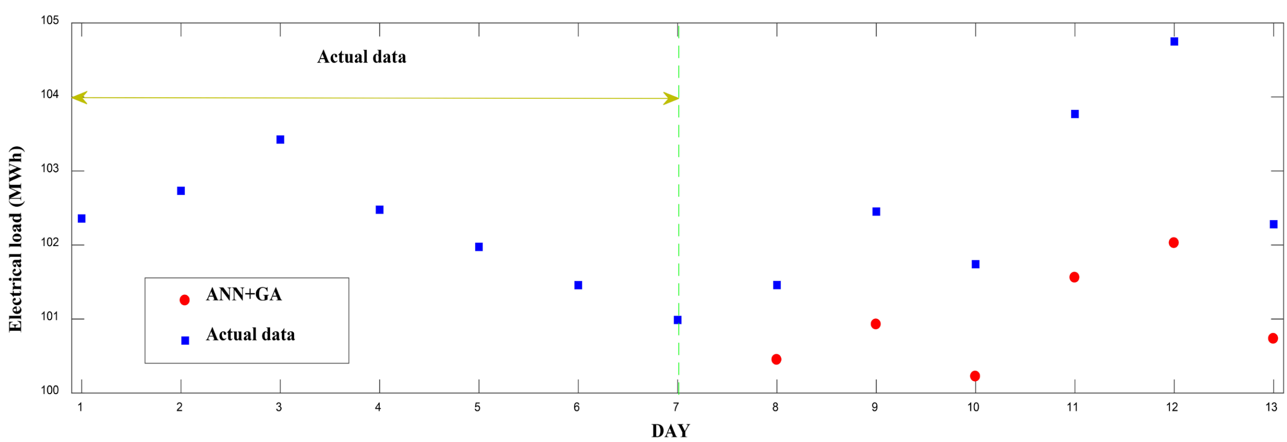

Figure 8. Load forecasting with ANN + GA.

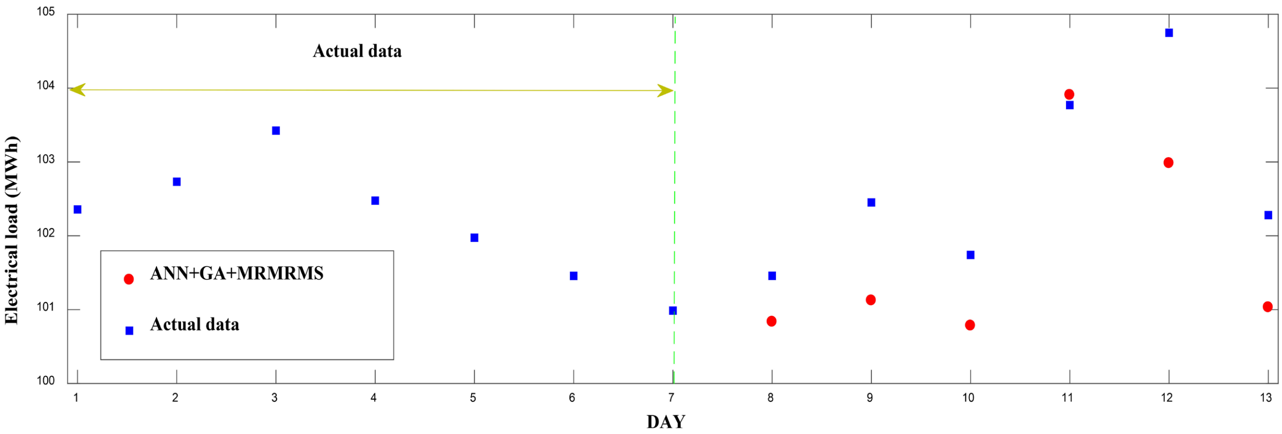

Figure 9. Load forecasting with ANN + GA + MRMRMS.

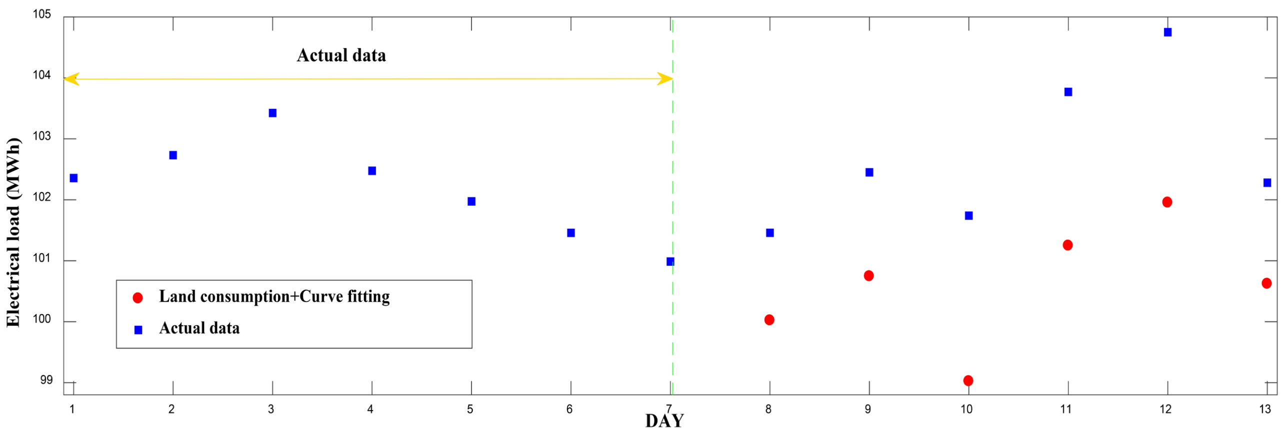

Figure 10. Load forecasting with land consumption+ curve fitting.

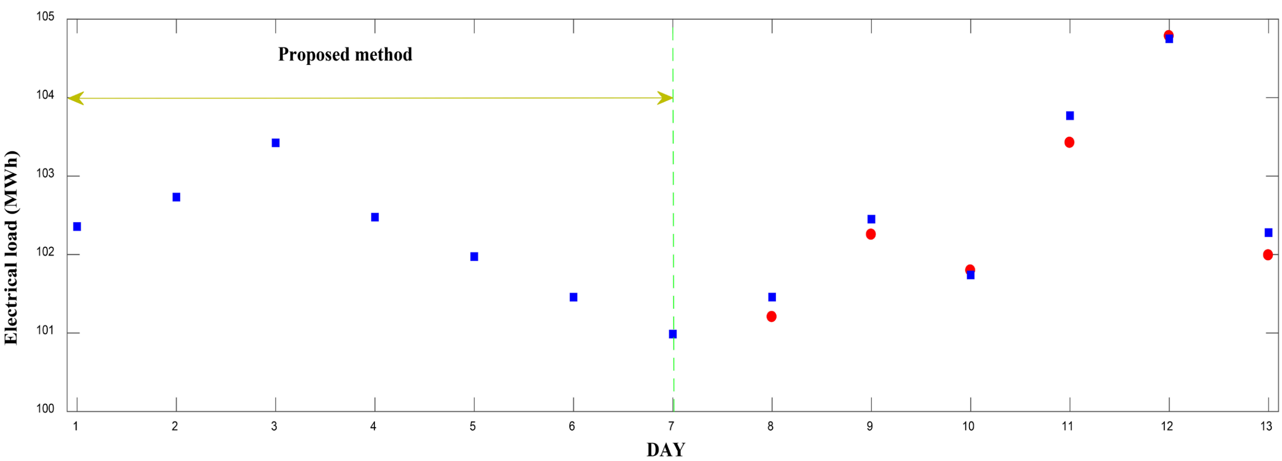

Figure 11. Load forecasting with proposed method.

The formulas used to calculate the errors are presented in Table 2. For a clearer comparison of results, refer to Table 3 and Figure 13.

As shown in Table 3 and Figure 13, the land consumption plus curve fitting method resulted in the highest values of MSE, MAE, MAPE, RMSE, and AE. In contrast, the proposed method exhibited the lowest values for these error metrics. Further comparison between the ANN + GA + MRMRMS and ANN + GA methods in Table 3 reveals that the ANN + GA + MRMRMS method has lower values of MSE, MAE, MAPE, RMSE, and AE, demonstrating the effectiveness of the MRMRMS enhancement. Moreover, when comparing the results for the ANN + GA + MRMRMS method with the proposed method, we observe higher error metrics for the former. This suggests that the filtering techniques employed in the proposed method significantly enhance its accuracy. Additionally, to better understand the impact of the proposed method on forecasting accuracy, we conducted the same analysis in Zone 1.

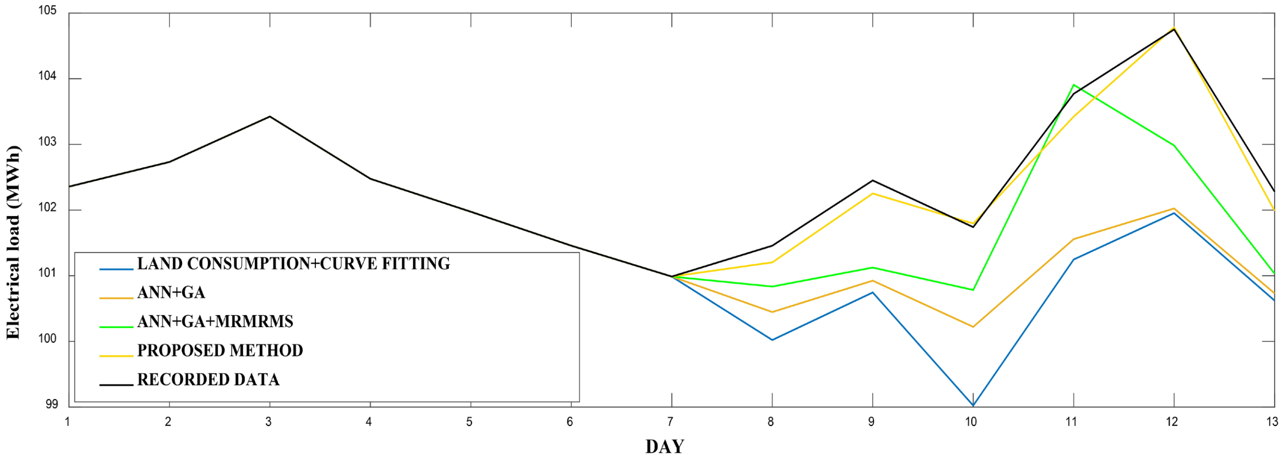

Figure 12. Comparison of the load forecasting with different methods.

Table 2. Performance metric rules.

Metric	Equation
Mean square error	$MSE = \frac{1}{N}\sum_{i=1}^{N}(A_i - F_i)^2$
Mean absolute error	$MAE = \frac{1}{N}\sum_{i=1}^{N}\lvert F_i - A_i\rvert$
Mean absolute percentage error	$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left\lvert\frac{A_i - F_i}{A_i}\right\rvert \times 100\%$
Root mean square error	$RMSE = \sqrt{\frac{1}{N}\times\sum_{i=1}^{N}(F_i - A_i)^2}$
Mean average error	$AE = \frac{1}{N}\sum_{i=1}^{N}(A_i - F_i)$

Also, results for the last day (13) are, 9.27, 9.34, 10.02, 10.47, 10.39 respectively.

As shown in Table 4, the values closest to the actual data are ranked from the most accurate to least as follows: the proposed method, ANN + GA + MRMRMS, ANN + GA, and land consumption plus curve fitting. For a clearer visualization, refer to Figures 12-18.

Table 3. The comparison results of MTLF provided models considering various error criteria.

Metric	Land consumption + curve fitting	ANN + GA
MSE	4.882	3.397
MAE	2.139	1.757
MAPE	2.078	1.704
RMSE	2.209	1.843
AE	2.139	1.757
Metric	**ANN + GA + MRMRMS**	**Proposed method**
MSE	1.294	0.052
MAE	1.009	0.196
MAPE	0.981	0.191
RMSE	1.137	0.228
AE	0.964	0.167

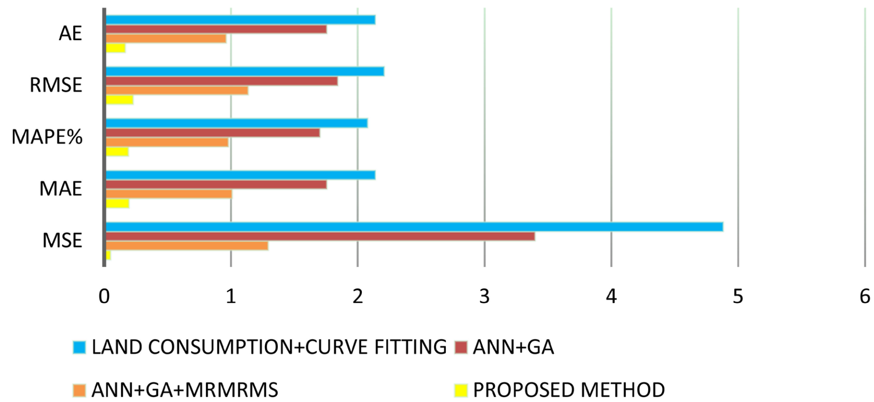

Figure 13. The comparison results of MTLF provided models considering various error criteria (RMSE, MAE, MAPE, AE and MSE).

Table 4. Comparison of the proposed with the common methods for load forecasting with real data in zone1 (MWh).

Method	Energy Consumption (MWh)					
	Day1	Day2	Day3	Day4	Day5	Day6
Land consumption + Curve fitting	10.22	10.81	11.24	10.53	9.82	9.41
ANN + GA	10.22	10.81	11.24	10.53	9.82	9.41
ANN + GA + MRMRMS	10.22	10.81	11.24	10.53	9.82	9.41
Proposed method	10.22	10.81	11.24	10.53	9.82	9.41
Actual data	10.22	10.81	11.24	10.53	9.82	9.41
Method	Day7	Day8	Day9	Day10	Day11	Day12
Land consumption + Curve fitting	8.87	8.91	9.43	9.14	9.91	10.45
ANN + GA	8.87	9.03	9.64	9.17	10.13	10.75
ANN + GA + MRMRMS	8.87	9.61	9.92	9.37	11.11	12.34
Proposed method	8.87	9.47	10.3	9.79	11.52	12.77
Actual data	8.87	9.53	10.47	9.77	11.41	12.83

Figure 14. Actual data for 13 days of load forecasting in zone1.

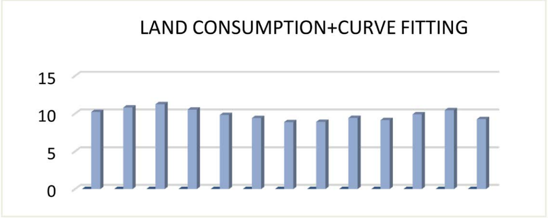

Figure 15. Load forecasting with land consumption + curve fitting in zone1.

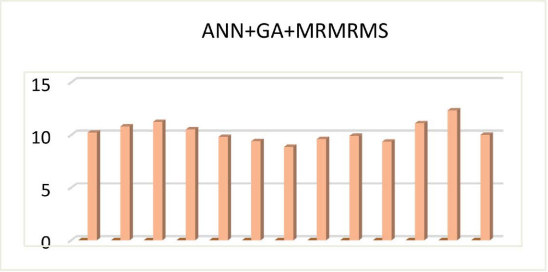

Figure 16. Load forecasting with ANN + GA + MRM-RMS in zone1.

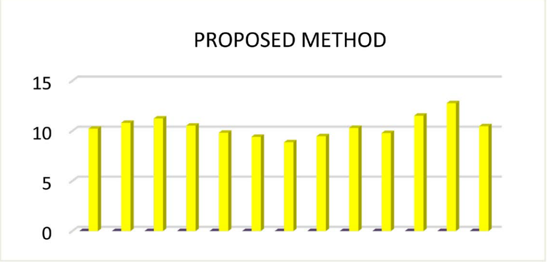

Figure 17. Load forecasting with proposed method in zone1.

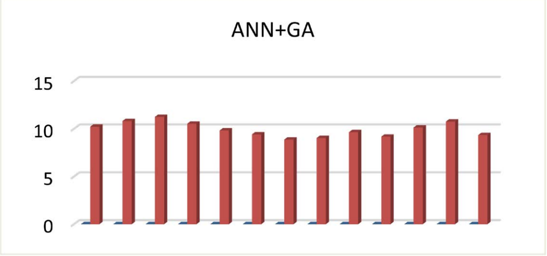

Figure 18. Load forecasting with ann + ga in zone1.

In **Figure 19**, a comparison of different methods illustrates that the proposed method demonstrates greater accuracy than the others. Additionally, a detailed comparison of error rates and accuracy is presented in **Figure 20** and **Table 5**.

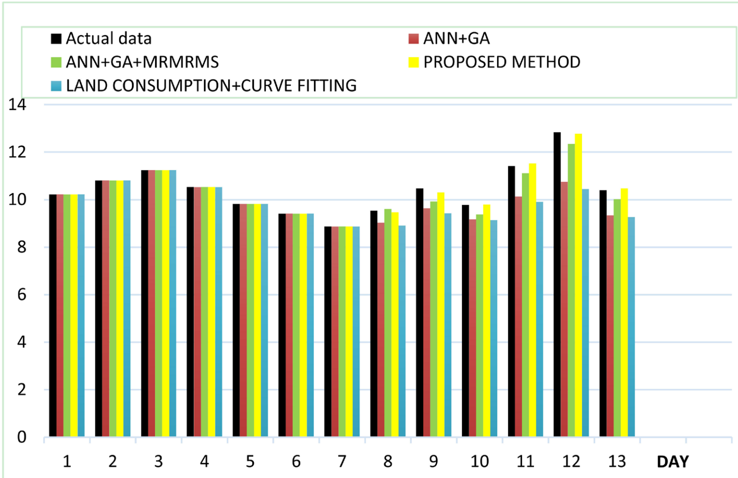

Figure 19. Comparison of the load forecasting with different methods in zone1.

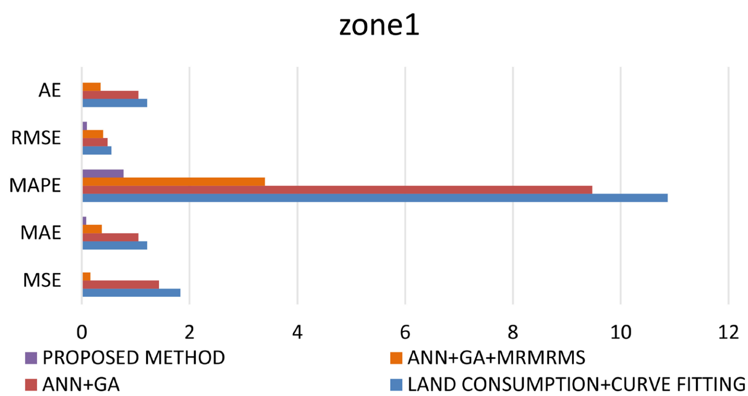

Figure 20. The comparison results of MTLF provided models considering various error criteria in zone1 (RMSE, MAE, MAPE, AE and MSE).

Table 5. The comparison results of MTLF provided models considering various error criteria in zone1.

Metric	Land consumption + curve fitting	ANN + GA
MSE	1.83	1.43
MAE	1.21	1.05
MAPE	10.87	9.47
RMSE	0.55	0.48
AE	1.21	1.05
Metric	**ANN + GA + MRMRMS**	**Proposed method**
MSE	0.161	0.009
MAE	0.37	0.083
MAPE	3.4	0.776
RMSE	0.4	0.095
AE	0.35	0.013

5. Conclusions

In this study, we introduced a novel mid-term load forecasting technique for electrical networks, utilizing robust filters. The effectiveness of this method was validated by comparing it against four alternative approaches using real-world data. The proposed method demonstrated superior performance, consistently exhibiting lower error rates across all metrics:

- **Proposed Method:** MSE: 0.009, MAE: 0.083, MAPE: 0.776, RMSE: 0.095, AE: 0.013.
- **Land Consumption + Curve Fitting:** MSE: 1.83, MAE: 1.21, MAPE: 10.87, RMSE: 0.55, AE: 1.21.
- **ANN + GA:** MSE: 1.43, MAE: 1.05, MAPE: 9.47, RMSE: 0.48, AE: 1.05.
- **ANN + GA + MRMRMS:** MSE: 0.161, MAE: 0.37, MAPE: 3.4, RMSE: 0.4, AE: 0.35.

Future research should focus on exploring additional algorithms and filters to further enhance the accuracy and applicability of load forecasting techniques. Investigating the integration of renewable energy sources and advanced machine learning techniques, such as deep learning and reinforcement learning, could provide significant improvements. Additionally, real-time data processing, integration of geographical information systems (GIS), and the development of hybrid models that incorporate economic, weather and social data are promising areas for further study. The impact of consumer behavior on energy usage and adaptive algorithms that respond to data changes also merit exploration. Establishing benchmarks and standards for load forecasting methods could facilitate industry-wide improvements, enhancing the reliability and efficiency of energy management systems. Collectively, these avenues offer significant potential for advancing the field of load forecasting.

Acknowledgements

All Authors contributed equally.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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