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Research Article

Comparison of Different Forecasting Techniques for Microgrid Load Based on Historical Load and Meteorological Data

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Abstract:

Microgrids (MGs) are decentralized energy systems that integrate Distributed Energy Resources (DERs), energy storage units, and advanced control mechanisms to ensure reliable power supply. Due to the intermittent nature of renewable energy sources, accurate load forecasting is crucial for the stable operation of MGs, particularly in both grid-tied and islanded modes. This study explores the performance of multiple forecasting techniques, including Linear Regression (LR), Regression Tree (RT), Support Vector Regression (SVR), Gaussian Process Regression (GPR), and Artificial Neural Networks (ANN), to predict MG load using historical load and meteorological data. The models were evaluated using comprehensive datasets that include calendar parameters and detailed weather metrics such as temperature, humidity, wind speed, and felt temperature. Performance was assessed through error metrics including Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Among the tested models, the ANN model incorporating a full set of meteorological parameters achieved the best performance, with a MAPE value of 2.58%. These findings highlight the importance of integrating detailed meteorological data for load forecasting in MGs, providing a framework for more reliable energy planning and enhanced operational efficiency.

1. Introduction

For power systems, Short-Term Load Forecasting (STLF) is of great importance. A large amount of the energy produced cannot be stored due to reasons such as high cost, inefficiency and physical size in energy storage systems. Therefore, the energy produced is mostly transferred to the loads through power distribution lines after undergoing some energy transformation [1]. In this situation generation-consumption imbalance can lead to voltage instability, blackouts or other disruptions, making it vital to effectively manage this balance in power systems. Since MG loads are mostly fed from renewable energy sources with high dependence on weather conditions, maintaining this balance is even more critical for MGs. STLF is important for a stable grid control by determining the operation of generation units and ensuring this balance. Furthermore, load forecasting offers many additional advantages in the long-term, such as the ability to include or remove power units from the system and define the characteristics of power purchase agreements [2].

Electricity load, or electrical demand, is influenced by a wide range of factors. Although factors such as population density, economic development and geographical location reveal the electrical load pattern of the region, calendar parameters and meteorological factors have a greater impact in defining instantaneous load fluctuations [1,3]. The calendar effect is basically the pattern created by the date-based load model. More specifically, the effects of temporal differences affecting social life and industry, such as day-night, weekday-weekend, summer-winter, etc., are reflected in the electrical load profile [4]. Another important factor affecting the electrical load is meteorological parameters. Many studies in the literature indicate that weather effects are among the factors that have the greatest impact on the load profile. The increased use of heating and cooling systems, especially in difficult temperature conditions, directly affects electricity consumption [4,5,6].

There are various techniques based on statistical methods and machine learning for load prediction in the literature. In [1], the hybrid forecasting model utilizes the SVR method for the weather-sensitive component of the load, while the Holt-Winters method is employed for the base part. The achieved success rate is 2.73% MAPE. In [7], STLF for MGs is made using Group Method of Data Handling (GMDH) and Artificial Neural Networks (ANN) methods, and the advantages, disadvantages and success rates of the models are given. As a result of the study, it was stated that ANN made more successful effective predictions than GMDH. In [8], the deep recurrent neural network with long short-term memory model they developed reached a MAPE value of 7.43% in the prediction they made using historical load and weather data at 1 hour resolution. In [9], the load was forecasted using Seasonal Autoregressive Integrated Moving Average (SARIMA) and Multiple Linear Regression (MLR) methods with half-hourly load and weather data resolution. In the study showing that the SARIMA method makes more successful forecasts than MLR, it is also mentioned that prediction successes vary seasonally, so more accurate predictions can be made by using a specific forecasting method to each season. In [10], a hybrid machine learning technique with SVR and Long Short-Term Memory (LSTM) methods was developed to load forecasting for a MG without using meteorological data. MAPE values for SVR, LSTM and hybrid model were calculated as 12.83, 10.48 and 3.74, respectively. In [11], Autoregressive Integrated Moving Average Exogenous (ARIMAX), Neural Networks (NN) and Wavelength Neural Networks (WNN) methods were compared for MG load estimation and WNN was determined as the most successful method for the study.

This study bridges the gap by combining calendar and weather data, evaluating multiple forecasting techniques, and providing a detailed comparison of their performance using metrics such as MAPE, MSE, and RMSE. Our results demonstrate the superiority of the ANN model with enhanced meteorological inputs, achieving a MAPE below 3%, showcasing its potential for reliable MG load forecasting.

2. Material and Methods

2.1 Data Preparation

In this paper, electrical load data of the city of Duquesne, USA, was obtained through the open access data sharing management tool called Data Miner. Calendar factors have been created with historical parameters such as year, month, day and hour, as well as the parameters resulting from their derivation. Some of these derived factors are:

- The hour index provides a better definition of the model by dividing the day into time intervals where consumption intensity varies.
- The week index defines the situation between weekdays and weekends where consumption varies.
- DST index determines the dates when daylight saving time is active in the USA.

The meteorological dataset for the same region was obtained through the web service OpenWeather. Along with temperature and humidity data, which are frequently used in load forecasting models, wind speed, dew point, felt temperature and weather condition index are presented as parameters in this study. The sampling period for each data type was set to one hour and standardized to the UTC (Universal Time Coordinate).

2.2 Correlation Analysis

In this study, correlation analysis was used to investigate the relationship between meteorological data and electrical load. Correlation analysis is a statistical method that measures the strength and direction of the relationship between two variables. The Pearson correlation coefficient, denoted as R, quantifies the magnitude and direction of this relationship. The formula for calculating the Pearson correlation coefficient is presented in equation 1.

$$R = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sum_{i=1}^{n}(x_i - \overline{x})^2 (y_i - y)^2} \qquad (1)$$

Where, x_i is the value of the independent variable, $\overline{x}$ is the average of the independent variables, y_i is the value of the dependent variable $\overline{y}$ is the average of the dependent variables and n is the number of variables.

In this study, meteorological data serves as the independent variable, while electrical load data is the dependent variable. Upon examining the scatter plot of electrical load versus air temperature shown in Fig. 1, a negative correlation is observed for temperatures below 15°C, whereas a positive correlation is observed for temperatures above 15°C. Table 1 presents the correlation coefficients between electrical load and various parameters, including temperature, perceived (feels-like) temperature, dew point, humidity, and wind speed. As a result of the analysis, it is seen that temperature and perceived temperature have a strong linear relationship with the load, especially in summer months. In summer, temperature, perceived temperature, dew point, and wind speed are positively correlated with load and negatively correlated with humidity. In winter months, while the load is negatively correlated with other parameters except wind speed, it is seen that the linear relationship between load and the wind is almost non-existent. Apart from these parameters, different weather conditions (clear, cloudy, rainy, snowy, foggy, etc.) are expressed numerically and included in the dataset.

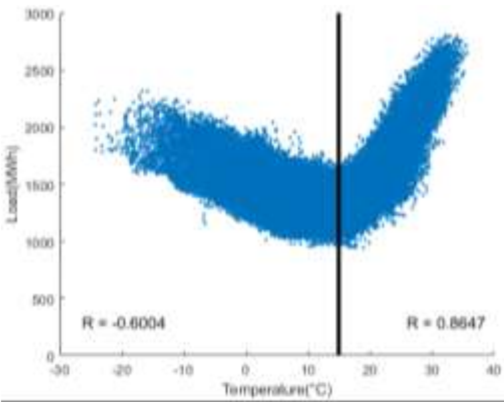

Figure 1. *Load-temperature scatter plot.*

Table 1. *Correlation coefficient of some meteoritical parameters.*

Parameters	Summer	Winter
Temperature	0.8940	-0.5390
Feels like	0.8903	-0.5466
Dew point	0.4716	-0.5839
Humidity	-0.4670	-0.2438
Wind speed	0.2744	0.0384

2.3 Load Forecasting Models

In this study, Short-Term Load Forecasting (STLF) was performed using Linear Regression (LR), Regression Tree (RT), Support Vector Regression (SVR), Gaussian Process Regression (GPR), and Artificial Neural Network (ANN) techniques within the MATLAB environment. Table 2 presents the detailed configurations of the models used for load forecasting, including various LR models (Linear, Interactions, Robust, and Stepwise), RT models (Fine, Medium, and Coarse), SVR models with different kernels (Linear, Quadratic, Cubic, and Gaussian at varying scales), GPR models with diverse kernels (Rational Quadratic, Squared Exponential, Matern 5/2, and Exponential), and a fully configured ANN model optimized with Bayesian Regulation and 22 hidden layers using a sigmoid activation function.

Linear Regression (LR): One of the most basic ways to model the linear relationship between independent variables and dependent variables. In cases where the number of variables is single, the model is called simple LR, and models in which the relationship of more than one parameter with the response variable is examined, such as in load forecasting, are called multiple LR [12].

Regression Tree (RT): RT is a machine learning algorithm that helps predict the dependent variable based on one or more independent variables. RT use a tree structure similar to decision trees, but the branches of these trees are based on partitioning of the independent variables, with a regression (prediction) value given at the end of each branch [13].

Support Vector Regression (SVR): SVR aims to classify predictions in the most accurate way by aiming to find the most appropriate separating hyperplane between two or more classes. Using customizable kernel functions, it is suitable for both linear and nonlinear regression applications [14].

Gauss Process Regression (GPR): GPR is a regression method used to make data predictions that often contain uncertainty. Similar to SVR, GPR can be customized for different datasets with its kernel-based structure [15].

Artificial Neural Network (ANN): ANN is a machine learning model inspired by biological neurons. ANN usually consists of an input layer, one or more hidden layers, and an output layer. Transfer functions that produce outputs according to hidden layer inputs realize the train through the interaction of neurons. Some transfer functions are: Linear, sigmoid, hyperbolic tangent and gaussian. As a result of the experiments, ANN with 22 hidden layers and sigmoid activation function was trained with Bayesian Regulation (BR) optimization for this study [16]. Four models were developed to assess the impact of forecast parameters on various techniques in load forecasting and to identify which parameters exert influence. These models, in which calendar effects and meteorological effects are used individually or together, are listed below. The success of the models used as input in each prediction technique was compared based on the evaluation criteria of MAPE, MSE, and RMSE.

M1: Includes calendar parameters and historical load data only.

M2: Includes temperature parameters and historical load data only.

M3: Combines calendar parameters, temperature, humidity parameters, and historical load data.

M4: Integrates calendar parameters, temperature, humidity, feels-like temperature, dew point, wind speed, weather condition parameters, and historical load data.

2.3 Evaluation Metrics

To evaluate the accuracy of the forecasting models, this study employs three commonly used error metrics: Mean Absolute Percentage Error (MAPE),

Table 2. *Detailed forecast models with model parameters.*

Forecast Model	Detailed Forecast Model	Model Parameters
Linear Regression	Linear Regression	Preset: Linear Terms: Linear
	Interactions LR	Preset: Interactions linear Terms: Interactions
	Robust LR	Tuning constant for robustness: 4.6850
	Stepwise LR	Maximum number of steps: 1000
Regression Tree	Fine RT	Maximum splits: 71207 Minimum leaf size: Minimum parents: 10
	Medium RT	Maximum splits: 71207 Minimum leaf size: 12 Minimum parents: 24
	Coarse RT	Maximum splits: 71207 Minimum leaf size: 36 Minimum parents: 72
Support Vector Regression	Linear SVR	Kernel: Linear Epsilon: 30.9118 Regularization par. (C): 309.1179 Kernel scale (Gamma): Auto
	Quadratic SVR	Kernel: Quadratic Epsilon: 30.9118 Regularization par. (C): 309.1179 Kernel scale (Gamma): Auto
	Cubic SVR	Kernel: Cubic Epsilon: 30.9118 Regularization par. (C): 309.1179 Kernel scale (Gamma): Auto
	Fine Gaussian SVR	Kernel: Gaussian Epsilon: 30.9118 Regularization par. (C): 309.1179 Kernel scale (Gamma): 1.3
	Medium Gaussian SVR	Kernel: Gaussian Epsilon: 30.9118 Regularization par. (C): 309.1179 Kernel scale (Gamma): 1.3
	Coarse Gaussian DVR	Kernel: Gaussian Epsilon: 30.9118 Regularization par. (C): 309.1179 Kernel scale (Gamma): 20
Gauss Process Regression	Rational Quadratic GPR	Kernel: Rational Quadratic Beta: 1987.24 Sigma: 50.82 Active set size: 2000
	Squared Exponential GPR	Kernel: Squared Exponential Beta: 1751.76 Sigma: 60.67 Active set size: 2000
	Matern 5/2 GPR	Kernel: Matern 5/2 Beta: 1945.80 Sigma: 52.98 Active set size: 2000
	Exponential GPR	Kernel: Exponential Beta: 2185.63 Sigma: 3.11 Active set size: 2000
Artificial Neural Network	Artificial Neural Network	Number of hidden layers: 22 Activation function: Sigmoid Optimization method: Bayesian Regulation

Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). These metrics provide complementary insights into the forecasting performance.
Mean Absolute Percentage Error (MAPE): MAPE is widely used in load forecasting as it provides a scale-independent measure of prediction accuracy by expressing errors as a percentage of the actual values. The formula for MAPE is given in equation 2.

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t-\overline{y}_t}{y_t}\right| \times 100 \qquad (2)$$

Where, y_t is the metered value, $\overline{y}_t$ is the forecasted value and n denotes the number of samples.

Mean Squared Error (MSE): MSE measures the average squared difference between actual and predicted values, penalizing larger errors more significantly than smaller ones. The formula for MSE is given in equation 3.

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}\left(y_t - \overline{y}_t\right)^2 \qquad (3)$$

Where, y_t is the metered value, $\overline{y}_t$ is the forecasted value and n denotes the number of samples.

Root Mean Squared Error (RMSE): RMSE is the square root of MSE, offering a measure of error in the same units as the target variable. It is defined as in equation 4.

$$\text{RMSE} = \sqrt{\text{MSE}} \qquad (4)$$

This RMSE metric provides a clearer interpretation of average prediction errors in the context of the dataset, as it reflects the magnitude of errors in the same scale as the forecasted values (e.g., in megawatts for load forecasting).

3. Results and Discussions

In this study, the load forecasting performance of various models, including Linear Regression (LR), Regression Tree (RT), Support Vector Regression (SVR), Gaussian Process Regression (GPR), and Artificial Neural Network (ANN), was evaluated using historical load and meteorological data. The models were assessed based on MAPE, MSE, and RMSE metrics to provide a comprehensive comparison of their accuracy and reliability.

3.1 Model Performance Across Metrics

Table 3 presents the MAPE values for different forecasting techniques across all models (M1 to M4). The ANN model consistently outperformed other methods, particularly in the M4 configuration, where it achieved a MAPE of 2.58%, highlighting its superior ability to capture complex, nonlinear relationships in the dataset.
Similarly, as shown in tables 4 and 5, the ANN model exhibited the lowest MSE and RMSE values under the M4 configuration. Specifically, the RMSE value of 46.06 MWh indicates that the ANN model's average prediction error is significantly lower than other techniques, making it the most reliable model for practical applications.

Table 3. *MAPE (%) values of different forecast techniques. The bold values represent the best performance on the data set*

Techniques	M1	M2	M3	M4
LR	8.0551	7.5112	5.4327	4.8904
RT	6.7217	7.8659	3.8531	3.7183
SVR	6.8766	7.3702	3.8443	3.1848
GPR	**3.9325**	7.9294	3.6035	3.3999
ANN	5.2533	**7.2061**	**2.6465**	**2.5813**

Table 4. *MSE (MWh e+03) values of different forecast techniques. The bold values represent the best performance on the data set*

Techniques	M1	M2	M3	M4
LR	18.212	16.775	14.011	8.2117
RT	13.287	18.301	5.4476	4.2469
SVR	11.846	15.977	4.1296	2.9334
GPR	**4.8197**	18.155	3.6026	3.1877
ANN	7.4067	**14.843**	**2.2229**	**2.1218**

Table 5. *RMSE (MWh) values of different forecast techniques. The bold values represent the best performance on the data set*

Techniques	M1	M2	M3	M4
LR	134.95	129.52	118.37	90.618
RT	115.27	135.28	73.808	65.168
SVR	108.84	126.40	64.262	54.160
GPR	**69.424**	134.74	60.022	56.460
ANN	86.062	**121.83**	**47.147**	**46.063**

3.2 Comparative Analysis of Models

The results reveal several key insights:

- Linear Regression (LR) models struggled to capture the underlying complexity of the data, as evidenced by their higher MAPE, MSE, and RMSE values, particularly in the M1 and M2 configurations.
- Regression Tree (RT) and Support Vector Regression (SVR) models showed improved performance when additional meteorological

data were included (M4), but their accuracy remained inferior to that of the ANN model.

- Gauss Process Regression (GPR) model has the best performance in the M1 configuration among all the models. However, it still cannot outperform the ANN model in the other configurations.

3.3 Practical Implications

The ANN model's strong performance, particularly in terms of low RMSE, demonstrates its potential for real-world applications. The ability to accurately forecast hourly load fluctuations is crucial for optimizing energy resource allocation and maintaining grid stability. As illustrated in Fig. 2, the M4-ANN model closely tracks the actual metered load, providing reliable predictions even during periods of significant load variation.

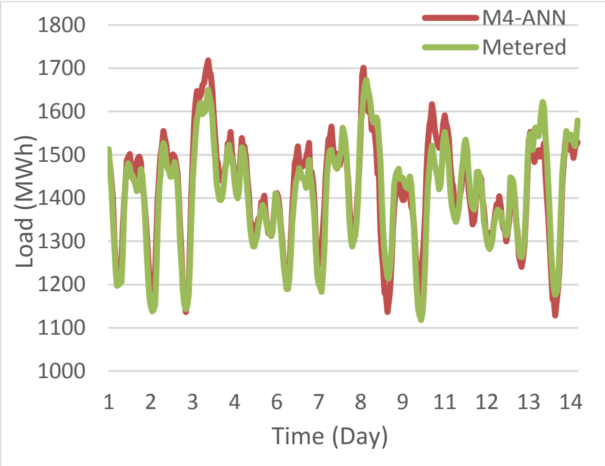

Figure 2. *Hourly load consumption using the M4-ANN model and actual metered load data.*

3.4 Comparison with Literature

The findings of this study align with existing literature, which emphasizes the effectiveness of ANN-based models for load forecasting tasks. For instance, studies such as [7] and [8] highlight similar advantages of ANN in capturing nonlinear patterns, particularly when combined with diverse input parameters. However, the improved accuracy achieved in this study, with a MAPE below 3%, demonstrates the added value of incorporating a wider range of meteorological data. The subject is applied in different fields as reported in literature [17-26].

4. Conclusions

In this study, in addition to calendar effects and air temperature effects, which are frequently used as input in load forecasting algorithms, felt temperature, dew point, humidity and wind speed effects are included in the model. These extra parameters increased the prediction success and reduced the MAPE value to 2.5813% for the data set used. In addition, it has been observed that the Squared Exponential GPR model is at a level that can be considered successful for forecasts made using only calendar effects and historical data of the load. Finally, it has been observed that using only temperature data in load prediction does not provide a sufficient success rate.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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