

PAPER 120 – SHORT-TERM LOAD FORECASTING FOR MICROGRID SYSTEM BASED ON ARTIFICIAL INTELLIGENCE TECHNIQUES

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ABSTRACT

Microgrids are becoming increasingly popular as a means of providing localized and reliable electricity supply, particularly in remote or isolated areas. Accurately forecasting short-term electricity load demand is essential for effective microgrid management and optimal resource allocation. In this study, we present a short-term electricity load demand forecast for a microgrid system with an 11 kV dedicated feeder of the University of Jos, Plateau State, using three machine learning techniques: Adaptive Neuro-Fuzzy Inference System (ANFIS), Particle Swarm Optimization-ANFIS (PSO-ANFIS), and Support Vector Machine (SVM). The study utilizes five years of historical load demand data obtained from the Jos Electricity Distribution Company (JEDC) and weather data, including temperature, humidity, wind speed, and solar radiation, obtained from NASA for January 2018 to January 2022, with data distribution of 80%, 10%, and 10% for training, testing, and validation. The results show that PSO-ANFIS outperforms, ANFIS and SVM, with RMSE, MSE, and MAPE of 3.0372, 8.2478, and 1.7868 for PSO-ANFIS, 3.1663, 10.0254, and 3.1511 for ANFIS, while SVM yields an RMSE, MSE, and MAPE of 6.9721, 24.4407, and 4.6789 respectively. This study demonstrates the effectiveness of PSO-ANFIS in forecasting short-term electricity load demand for microgrid systems, providing valuable insights for energy management and decision-making.

KEYWORDS: Energy, Forecasting, Load demand, Management, Microgrid, and Optimal

1. INTRODUCTION

1.1 Background of the Study

Microgrids are becoming increasingly popular as a means of providing localized and reliable electricity supply, particularly in remote or isolated areas. These systems, which operate independently and sometimes in parallel with the main grid, can enhance energy security, reduce power outages, and optimizes the utilization of renewable energy sources. However, effective microgrid management requires accurate prediction by optimizing the allocation of resources, reducing operational costs, and ensuring grid stability of the short-term electricity load demand.

To this end, various machine learning techniques have been developed to forecast electricity load demand, including Expert systems, Fuzzy systems, and Adaptive Neuro-Fuzzy Inference Systems (ANFISs). ANFIS and PSO-ANFIS, have shown promise in accurately predicting load demand for microgrid systems among these techniques. ANFIS integrates the merits of fuzzy logic and neural networks to provide a hybrid modeling approach that can handle complex and uncertain systems. The incorporation of Particle Swarm Optimization (PSO) into ANFIS results in the enhancement of its performance, leading to improved model accuracy as PSO optimizes the learning process.

1.2 Aim and Objectives

In this study short-term electricity load demand prediction for a microgrid system with an 11 kV dedicated feeder of the University of Jos, Plateau State, using three machine learning techniques is the aim.

The objectives of the study can be inferred from the methodology described in the abstract and include:

- i. To apply three machine learning techniques, which include; Adaptive Neuro-Fuzzy Inference System (ANFIS), Particle Swarm Optimization-ANFIS (PSO-ANFIS), and Support Vector Machine (SVM) regression, to predict short-term electricity load demand.
- ii. To contrast the key performance index of the three machine learning techniques in terms of their prediction ability of short-term electricity load demand.
- iii. To provide valuable insights for energy management and decision-making regarding microgrid systems.

1.3 Literature Review

Khantach *et al.* (2019), in their study, proposed a load forecast model by decomposing the historical period and analyzing the historical evolution of 24 hours. PSO-trained ANFIS is expected to give a better result. Park *et al.* (2020), in their proposal, suggest an algorithm that uses a back propagation neural network (BPNN) as well as a reinforcement learning-based load demand forecasting model to select similar days. Butt *et al.* (2020), in their

study, utilized load data from a feeder to predict short-term and medium-term load demands for the next one day, three days, seven days, fourteen days, and thirty days.

Adegunmi *et al.* (2021), in their study, using the Neuro-fuzzy model for load forecasting and compared three models (ANFIS, ANN, and MLR) using RMSE and MAE as metrics.

Agboola *et al.* (2021), in their study, presented an ANN-based approach for LTLF of the Trans-Amadi industrial feeder under the PHEDC network from 2020 to 2029.

Niu *et al.* (2021), in their research, developed a machine-learning model to improve short-term electricity load forecasting accuracy.

Omitaomu and Niu (2021) presented a survey of existing research on the application of artificial intelligence techniques to load forecasting, power grid stability assessment, faults detection, and security problems in smart grid and electrical power utility systems.

Thomas and Okafor (2021) explored the use of stochastic/probabilistic extrapolation to forecast Nigeria's electricity demand from 2020-2040, using MATLAB for computation. The authors suggest that the use of artificial intelligence techniques would lead to even better results.

Ul Islam, *et al.* (2022) provided a review of hybrid deep learning models for short-term load forecasting (STLF) in smart power grids based on nature-inspired metaheuristic techniques. STLF is essential for load scheduling, unit commitment, and cost-effective operation of smart power grids.

Atanasovski *et al.* (2022) in their work compared different practical procedures for short-term load prediction and their application on primary load demand and temperature data for the Republic of North Macedonia

Stamatellos and Stamatellos (2023) discussed the significance of short-term load prediction in electrical power system planning, operation, and control.

2.0 THEORETICAL ANALYSIS

2.1 Factors Affecting Electrical Load Demand Forecasting

Weather is one of the crucial factors that can affect electricity load demand forecasting. Here are some of the major weather factors that can impact electricity demand:

(i) Temperature (ii) Humidity (iii) Precipitation (iv) Wind (v) Storms (vi) Solar Radiation (vii) Extreme Weather Events (viii) Economic Conditions.

2.2 ANFIS Model

The mathematical depiction of an Adaptive Neuro-Fuzzy Inference System (ANFIS) is presented below:

i. To start, the input signals (x_1, x_2, \dots, x_n) are converted into fuzzy values utilizing fuzzy membership functions ($\mu_{A1}(x_1), \mu_{A2}(x_2), \dots, \mu_{An}(x_n)$) for each input variable. These membership functions decide the extent to which each input signal is associated with each fuzzy set.

ii. The rule in the ANFIS model can be represented as follows: "IF x_1 is A_1 AND x_2 is A_2 AND ... AND x_n is A_n THEN y is $f(x_1, x_2, \dots, x_n)$ ", where A_1, A_2, \dots, A_n are the fuzzy sets associated with the input signals x_1, x_2, \dots, x_n , and f is the consequent of the rule that represents the output variable y .

iii. The ANFIS algorithm calculates the firing strength of each rule by multiplying the degree of membership of each input signal to its corresponding fuzzy set. Specifically, the firing strength of rule i is denoted as w_i and computed as follows:

$$w_i = \mu_{A1i}(x_1) * \mu_{A2i}(x_2) * \dots * \mu_{Ani}(x_n)$$

iv. The calculation of the normalized firing strength of each rule can be expressed as follows: $w_{i'} = w_i / (w_1 + w_2 + \dots + w_k)$

where k is the total number of rules and w_i is the firing strength of the i th rule.

v. The ANFIS system computes the output as a weighted sum of the consequents of all the rules, where the weight of each consequent is its normalized firing strength. Mathematically, it can be expressed as:

$$y = (w_{1'} * f_1 + w_{2'} * f_2 + \dots + w_{k'} * f_k) / (w_{1'} + w_{2'} + \dots + w_{k'})$$

Here, f_i represents the consequent of rule i , and $w_{i'}$ is the normalized firing strength of rule i , calculated as:

$$w_{i'} = w_i / (w_1 + w_2 + \dots + w_k)$$

The value of k is the total number of rules.

2.3 PSO-ANFIS Model

Salisu *et al.* (2019) The PSO-ANFIS algorithm combines the capabilities of Particle Swarm Optimization (PSO) and Adaptive Neuro-Fuzzy Inference System (ANFIS) to optimize ANFIS parameters.

One can express the mathematical formulation of PSO-ANFIS as follow:

$$y = f(x) = G * (a_1 x_1 + a_2 x_2 + \dots + a_n x_n + b)$$

Here is the given information:

- The output variable is represented by y .
- The input variables are x_1, x_2, \dots, x_n .

- The optimized parameters obtained from the PSO algorithm are a_1, a_2, \dots, a_n .
- The constant bias term is denoted by b .
- G is the scaling factor that ANFIS calculates.
- ANFIS model function is represented by $f(x)$.

By utilizing the PSO algorithm, the optimal values of a_1, a_2, \dots, a_n are determined so as to minimize the discrepancy between the predicted output of the ANFIS model function and the actual output. The ANFIS network is used to calculate the scaling factor G based on the input variables. The output y is determined by summing the input variables and optimized parameters, each of which is multiplied by a specific weight, and then adding the bias term to the result.

2.4 SVM Regression Model

The SVM regression model makes predictions based on the following equation:

$$f(x) = \sum_i \alpha_i K(x_i, x) + b,$$

where $f(x)$ represents the predicted output for input vector x , α_i denotes the Lagrange multipliers, x_i represents the support vectors, $K(x_i, x)$ is the kernel function that measures the similarity between x_i and x , and b is the bias term. During training, the Lagrange multipliers and bias term are determined by minimizing the cost function:

minimize:

$$\frac{1}{2} \sum_i \sum_j \alpha_i \alpha_j y_i y_j K(x_i, x_j) - \sum_i \alpha_i$$

subject to:

$$\sum_i \alpha_i y_i = 0 \text{ and } 0 \leq \alpha_i \leq C$$

Here, y_i represents the output value of the i -th training example, C is the regularization parameter that determines the trade-off between maximizing the margin and minimizing the training error. The Lagrange multipliers, α_i , are optimized subject to the constraint that the sum of their products with the corresponding output values is zero, and their values are limited to be between zero and C .

2.5 Data Normalization.

Data normalization is important because some of the data were not available or recorded as zero because of power outages due to faults online, load shedding system collapse, and maintenance to mention a few. The normalization formula is:

$$x' = \{x - \min(x)\} / \{max(x) - \min(x)\}$$

Here, x represents the original value that needs to be normalized. $\min(x)$ is the smallest value present in the range of x , $\max(x)$ is the largest value present in the range of x , and x' represents the normalized value.

By applying this formula, the original values are transformed to a new scale that ranges from 0 to 1, where 0 corresponds to the minimum value in the range of the original values, and 1 corresponds to the maximum value.

2.6 Model Statistical Evaluators

There are several statistical evaluators that could be used to assess the performance of a normalized 6-year historical load data and weather data made up of temperature, humidity, solar irradiation, precipitation, and wind speed, for training, testing, and validation.

In this study, the following statistical evaluators for the model were utilized.

(i) Root-mean-square error (RMSE)

The equation for RMSE is:

$$RMSE = \sqrt{\frac{1}{n} * \sum (y_i - x_i)^2}$$

In this context, " y_i " represents the estimated value and " x_i " represents the observed value, given that " n " refers to the total number of samples.

(ii) Mean Square Error (MSE)

The equation for MSE is:

$$MSE = \frac{1}{n} * \sum (y_i - x_i)^2$$

Assuming " n " represents the total number of instances, " y_i " is the projected value, and " x_i " is the factual value.

(iii) Mean Absolute Percentage Error (MAPE)

The equation for MAPE is:

$$MAPE = \frac{1}{n} * \sum \left(\frac{|y_i - x_i|}{x_i} \right) * 100\%$$

In the given context, " n " denotes the total number of examples, " y_i " represents the anticipated value, and " x_i " signifies the factual value.

Typically, reduced values of RMSE, MSE, and MAPE imply superior performance since they indicate that the model is generating more precise predictions.

3.0 MATERIALS AND METHODS

3.1 Materials

The components employed in predicting the load demand are:

- i. Load demand data: Load demand data is the 6-year historical primary input data from the Jos Electricity Distribution Company (JEDC) .
- ii. Weather data: temperature, humidity, solar insolation, wind speed, and precipitation from the NASA website.
- iii. ANFIS, PSO-ANFIS, and SVMR software: ANFIS, PSO-ANFIS, a software package which was developed by Yapiz *et al* (2015) and SVM Regression in MATLAB

3.2 Method

The methods used for load demand forecasting using ANFIS, PSO-ANFIS, and SVMR were as follows:

- (a) Data collection and pre-processing
- (b) Model development
- (c) Model evaluation
- (d) Model selection.

3.3 Implementation of Short-term Load Forecasting based on PSO-ANFIS

The execution of PSO-ANFIS for Short-term Load Forecasting

3.3.1 Data Collection and Pre-processing

Data collection

Primary data on the load demand on the 11kV dedicated feeder was collected using the digital logger for 6 years (January 2014 - January 2019) from the 11kv JEDC substation is situated at the Naraguta campus of the University of Jos.

The temperature, humidity, solar insolation, wind speed, and precipitation records for the designated duration were acquired from NASA as weather data.

Data pre-processing

The gathered data underwent pre-processing via the subsequent procedures:

Data cleaning

The following steps were carried out to clean the load demand and weather data:

- i. Removal of duplicates
- ii. Checked for missing values
- iii. Checked for formatting errors
- iv. Checked for consistency
- v. Checked for accuracy.

3.4 PSO-ANFIS Short-Term Implementation

In order to execute short-term load forecasting using PSO-ANFIS, the following steps were followed:

(i)Collect and pre-process the data (ii) Design the PSO algorithm(iii)Develop the ANFIS model(iv)Train the PSO-ANFIS model(v) Validate the model(vi)Forecast the load demand(vii) Evaluate the performance(viii) Refine the model.

3.5 SVM Regression Short-Term Implementation

In order to execute short-term load forecasting using SVM regression, use the following procedure:

Data collection (ii) Data pre-processing(iii). Feature selection (iv) Model training (v) Model evaluation(vi) Hyperparameter tuning(vii) Model deployment.

4.0 RESULTS AND DISCUSSION

The results obtained for PSO-ANFIS were compared with ANFIS and SVM. Tables and Graphs for the 24-hour ahead prediction are also presented from the analysis carried out.

4.1 Simulation Results of the ANFIS Model

The data collected were simulated using, ANFIS for MATLAB

The data was split into three groups, with 70% of it allocated for training, 20% for testing, and 10% for validation purposes.

The outcomes of the load demand using ANFIS-trained data, test data, and load demand are illustrated in Figures 1,2 and 3.

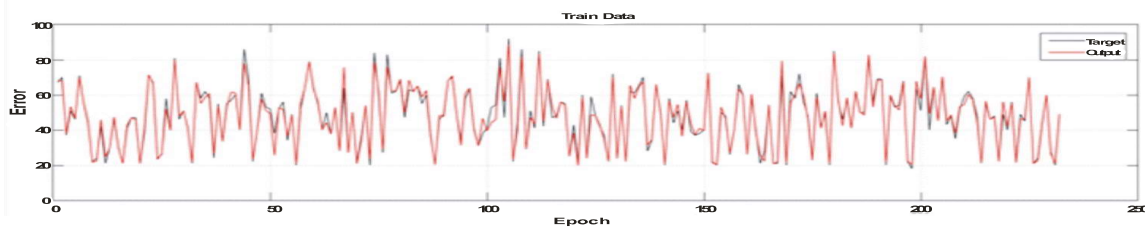


Fig 1: ANFIS Trained Data for Load Demand

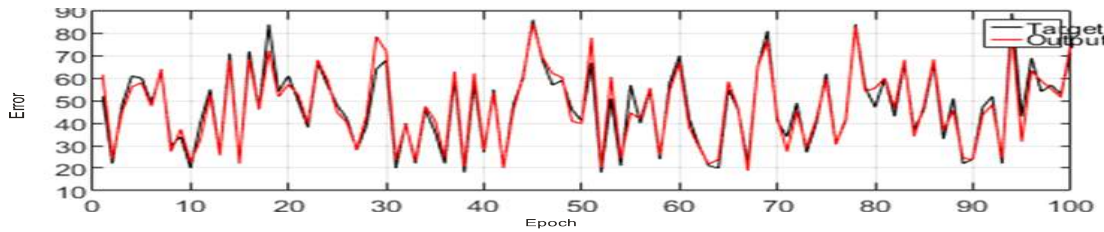


Fig 2.: ANFIS Test Data for Load Demand

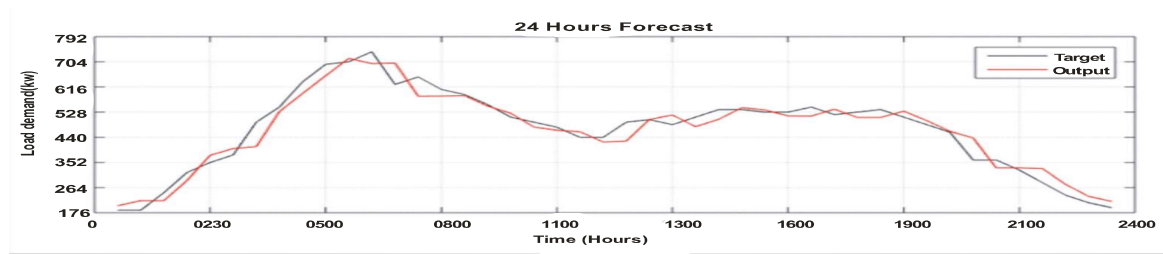


Fig 3: Load Demand Curve for 24Hours 11kV dedicated Feeder using ANFIS.

The ANFIS KPI for the 24-hour load demand was MSE of 10.0254, RMSE of 3.16663, and MAPE of 1.8627.

4.3 Simulation Results of PSO enhanced ANFIS model.

The data collected were simulated using, PSO enhanced ANFIS on the MATLAB platform. The data was split into three groups, with 70% of it allocated for training, 20% for testing, and 10% for validation purposes. Figure 4, 5, and 6 shows the simulation of PSO enhance ANFIS(PSO-ANFIS) train, test, and load demand forecast for the next 24 hours.

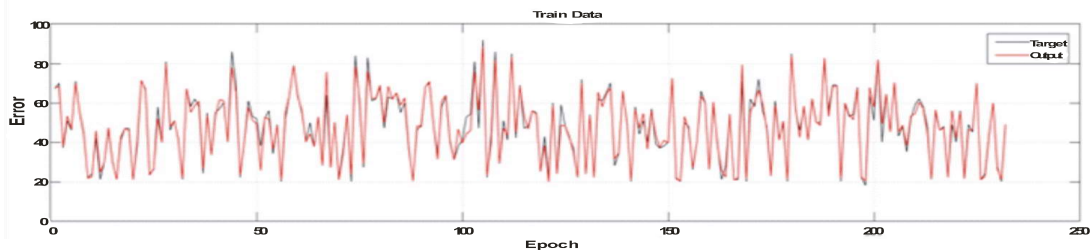


Fig 4: Trained Data for PSO-ANFIS

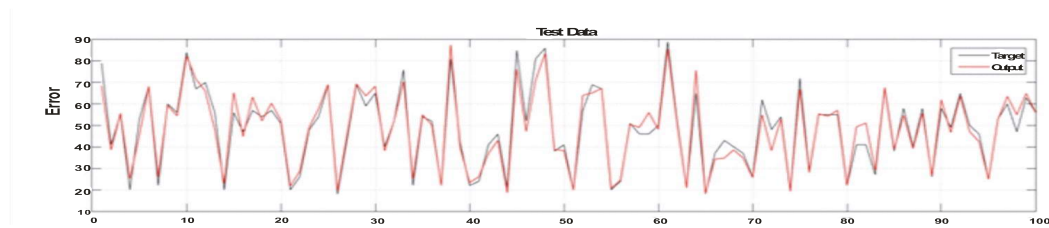


Fig 5: Test Data PSO-ANFIS

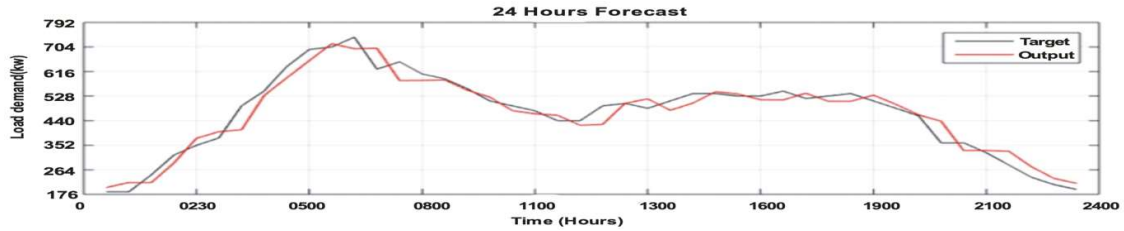


Fig 6: Load Demand Curve for 24 Hours Load Demand Forecast for the 11kV Dedicated Feeder using PSO-ANFIS

By employing PSO-ANFIS, the load demand data was examined, and a 24-hour forecast was conducted. As depicted in Figure 6, the forecast resulted in an MSE of 8.2478, RMSE of 3.0372, and MAPE of 1,7868. Table 1 indicates that the forecasting performance of PSO-ANFIS is superior to that of ANFIS.

4.3 Simulation Results using SVMR.

Support vector machine regression simulation was carried out and the Predicted versus actual load demand forecast was plotted as shown in Figure 7. With an RSME of 6.9721; MSE of 24.4407, and MAPE of 4.7623.

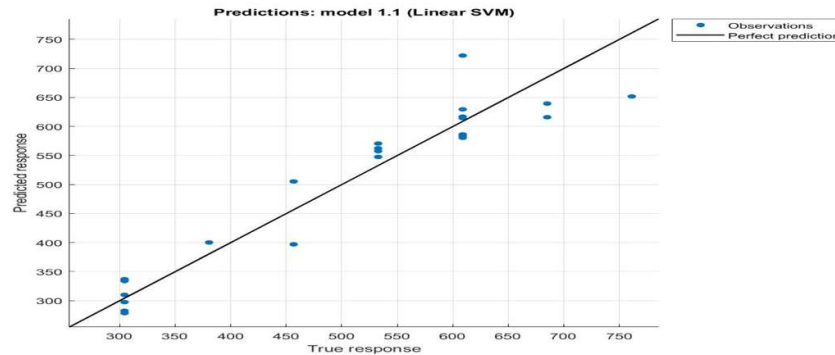


Fig 7: 24 Hours Load Demand Forecast for the 11kV Dedicated Feeder using SVMR.

4.4 Analysis of the Results

According to Table 1 analysis, the PSO-ANFIS model outperformed the other models in terms of forecasting performance. Specifically, at a 24-hour forecast, From the results, PSO-ANFIS is seen to be a better Forecasting Model compared to ANFIS and SVMR in this study It has an RMSE of 3.0372, MSE of 8.2478, and MAPE of 1.7868 as compared to ANFIS; 3.1663,10.0254, 1.8627 and SVMR of 6.9721, 24.4407 and 4.7623 respectively. Therefore, based on this analysis, it can be concluded that the PSO-ANFIS model is more effective and accurate than the ANFIS and SVMR models for short-term load forecasting.

Table 1: Comparison of ANFIS, PSO-ANFIS, and SVMR Performance Index

Method	RMSE	MSE	MAPE
ANFIS	3.1663	10.0254	1.8627
PAO-ANFIS	3.0372	8.2478	1.7868
SVMR	6.9721	24.4407	4.7623

5.0 CONCLUSION

The study utilized three machine learning methods, namely Adaptive Neuro-Fuzzy Inference System (ANFIS), Particle Swarm Optimization-ANFIS (PSO-ANFIS), and Support Vector Machine (SVM) regression, to forecast short-term electricity load demand. The study evaluated and compared the prediction capabilities of three machine learning techniques for short-term electricity load demand forecasting, namely Adaptive Neuro-Fuzzy Inference System (ANFIS), Particle Swarm Optimization-ANFIS (PSO-ANFIS), and Support Vector Machine (SVM) regression. The study's results provide valuable insights for microgrid system energy management and decision-making. The PSO-ANFIS model was identified as the most efficient and accurate technique for short-term load forecasting based on the findings. The study enhances the field of energy management by offering a dependable and efficient approach for forecasting short-term load demand.

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