PREDICTION OF MICROGRID ELECTRICITY DEMAND USING ANN OPTIMIZED BY MFO

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ABSTRACT

In this paper, a neural network (ANN) optimized by Moth Flame Optimization (MFO) Algorithm is used for prediction of micro grid electricity demand. The forecasting tool was created using historical data on actual electricity usage, weather variables, daily and weekly variations and indicators for working and non-working days. The results of the forecast are shown for upcoming days with an hourly time duration. The validation findings showed that the proposed method can anticipate micro grid electricity consumption with a tolerable small error and a reasonable calculation time.

Keywords: Microgrid Electricity Demand, Neural Networks, MFO (Moth Flame Optimization)

1. INTRODUCTION

Small day-ahead electricity demand forecasts are crucial for providing the necessary data for the proper management of energy in micro-grids. It helps micro-grid operators and users to make better choices about the flexibility, stability as well as control of the microgrid. Power demand forecasting in microgrids cannot be accurately predicted using the current standard forecasting techniques for electricity demand at regional level. This is because electricity consumption in microgrids is extremely erratic and far lower than regional or national demands. Electric load prediction is a challenging operation because of many important dominant elements that must be considered. Several methods have been used to manage this complex process. Based on the information considered, prediction methods are either based on time-series or regression. Depending on the characteristics of the past and present time series, the time-series techniques describe the future power demand [1]. Regression (causal) techniques define the electricity demand in terms of extrinsic (natural or social) factors [2].

Predictions of the demand for electricity have been made using Artificial intelligence methods, like Expert systems, fuzzy logic and Neuro-fuzzy systems. For the purpose of forecasting power demand, a methodical Type-2 fuzzy logic structure was created utilising the extreme learning approach [3]. For the problem of predicting the demand for electricity in smart grids, expert system, which are based AI solutions have been examined [3]. A method based on fuzzy logic and factorised meteorological factors is suggested for estimating short-term electric load. For the purpose of predicting electric load, a Neuro-fuzzy based time series regression algorithm is developed.

The majority of the aforementioned techniques, however, were designed for high-scale load demands As contrast to national/regional electric consumption, the micro-grid load demand data is significantly smaller and very variable, hence these methods are ineffective for analysing micro-grid energy demand. For the forecasting of micro-grid electric power demand ,another systematic method is therefore required. Furthermore, for a potential accuracy enhancement, the majority of the earlier approaches did not incorporate the actual power output of the wind generator with external predictor variables like weather parameters.

Electricity demand forecasting techniques based on Artificial intelligence based methods have been found to have higher forecasting accuracy than traditional techniques [4-5]. For predicting electricity demand, artificial neural networks (ANNs), one of the well-known AI techniques, have been used extensively in a variety of forms [3]. With stronger results than the competition, AI-based methods based on ANNs have recently emerged as the most popular strategies for anticipating electric load demand. The majority of models for forecasting energy demand predict electric demands at the national or regional levels. There are however, surprisingly few research on estimating load demand at scales smaller than a microgrid, a single building, a commercial district, an industrial unit, or a household.

For increased forecasting efficiency and accuracy, this study considers a number of predictor variables, including overall microgrid load data and/or variables based on meteorological data. In this study, the demand for microgrid electricity is predicted using a neural network that has been tuned by the MFO algorithm. The forecasting tool was created using historical data on actual electricity usage, weather variables, daily and/or weekly variations, and indicators for working and non-working days. According to the validation results, the developed technique can anticipate the micro grid's electricity demand with a tolerable small margin of error and a manageably quick calculation time.

2. ARTIFICIAL NEURAL NETWORK (ANN)

An effective data processing model called an artificial neural network (ANN) can capture a complicated and existing relationship inside a dataset. ANN can quickly pick up information and learn how the data behaves. The way in which the brain and other biological nervous systems of humans process information served as inspiration for the development of the ANN model. The ANN model's distinctive setup for manipulating information is one of its key features.I It is made up of numerous information-processing neurons arranged in different hierarchical layers. Input, hidden, and output layers make up the layers. Input, hidden, and output neurons, respectively, are the neurons that make up these levels. Through specific scaled connections, these neurons are linked. Weights are the neuronal connections between the scales. The ANN's neurons work together to solve a specific true problem.

2.1 Feed Forward Artificial Neural Network

Information moves directly forward from inputs to outputs in FFANN. Using feed forward connection weights, the output of the model is generated directly from the input. Although in recurrent neural network (RNN), output is dependent not only on the model's current inputs but also on its past or potential future inputs, outputs, or states. RNNs are difficult to construct in terms of computing complexity, despite the fact that they are useful for large dimension and extremely complex situations.

However, for situations involving the processing of reduced-dimension data, like forecasting, FFANNs are simple to use, quick, and very effective. The amount of hidden layer neurons should indeed be carefully chosen when creating an FFANN model to solve a particular problem. However, there is no established method for choosing the right number of neurons for the hidden layer.

Figure 1 schematically depicts the structure of the FFANN model used in this work's objective of forecasting power demand. Figure 2 shows the mathematical representation of ith neuron. In Figure 2, w_{ij} is a connecting weight, x is the input to the ith neuron, y_i is the output, bi is a bias quantity (often constant), and fi is the activation function. A significant role is performed by the activation function during the training of the FFANN model. It regulates how the neurons' output behaves. Equation 1 can be used to get the FFANN neuron output based on Figure 2.

Normally, Back Propagation (BP) algorithm is used to develop FFANN. In the BP learning, the input-output dataset is used to alter the neuron connection weights using the BP algorithm. This considerably facilitates the FFANN model's ability to quickly understand the behaviour of the data. The BP runs a gradient descent in direction of the global minimum value to determine FFANN weight parameters during training phase. In spite of the fact that BP training techniques need less computation time, they may be unable to attain a global optimal solution. Consequently, the BP training does not ensure consistent, accurate electricity demand predictions throughout time.

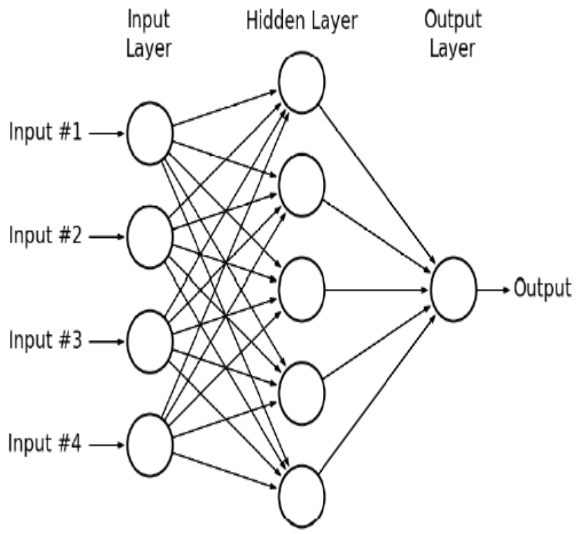


Figure 1: Structure of FFANN

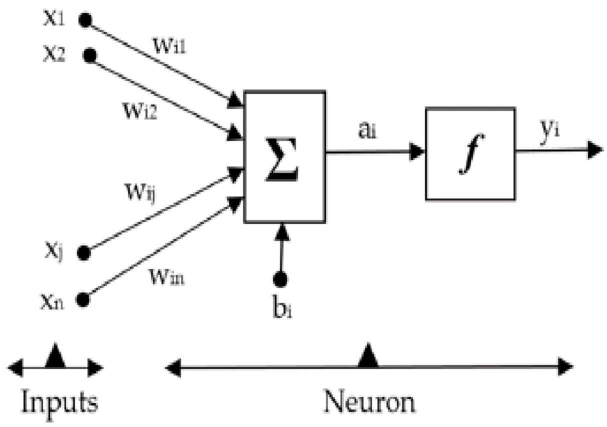


Figure 2: Mathematical model of a neuron of FFANN.

$$y_i = f_i\left(\sum_{j=1}^{n} w_{ij}.x_j + b_i\right) \qquad (1)$$

3. MFO algorithm

Mirjalili put forth the Moth-Flame Optimization (MFO) algorithm [6]. It is covered by algorithms for population-based metaheuristics. MFO begins by creating moths at random in the solution space, determining each moth's fitness values (i.e., position), and then labelling the ideal position with a flame. The next step is to update the moths' positions using a spiral movement function to obtain better positions that are tagged by a flame, update the new best positions, and then repeat the previous steps till the termination criteria are satisfied.

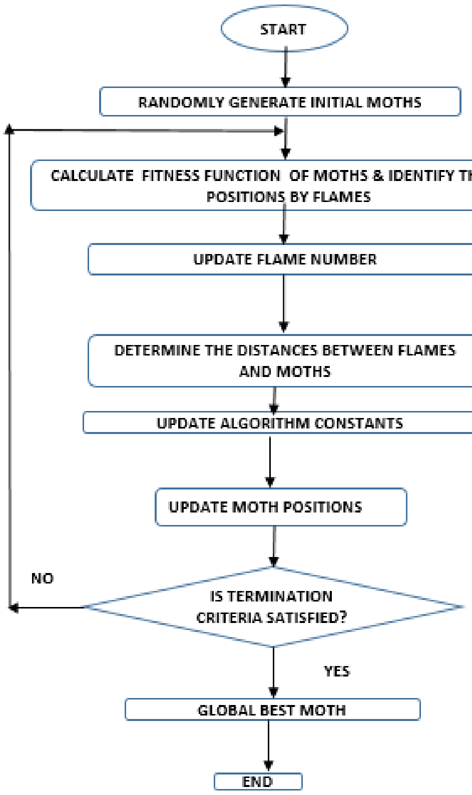


Figure 2: Flow-Chart of MFO Algorithm.

4. Simulation Results

In this paper, the forecast performance of the created forecast model is validated across a one-year testing window duration. The suggested algorithm is implemented by means of a MATLAB script. The 4 GB of RAM and an i-5 processor operating at 2.50 GHz are utilised. The input variables used to construct the forecast model are the outside temperature, air humidity, and number of daylight hours. The electricity demand dataset (Figure 3) and a year's worth of predictor data are utilised to train this FFANN model. Several independent experimental experiments have been carried out to determine the best FFANN model setup. The training data is divided into four divisions that stand in for the four distinct seasons: summer, winter, fall, and spring. Table 1 lists the parameters needed for FFANN.

Table 1
Parameter Values of FFANN

Parameter	Value
Structure	Feed forward type
Hidden layer	1
Neurons in hidden layer	20
Activation function (for hidden neurons)	Tansig
Neurons in output layer	1
Activation function (for output neurons)	purelin
Training Ratio	0.01
No. of Epochs	1000

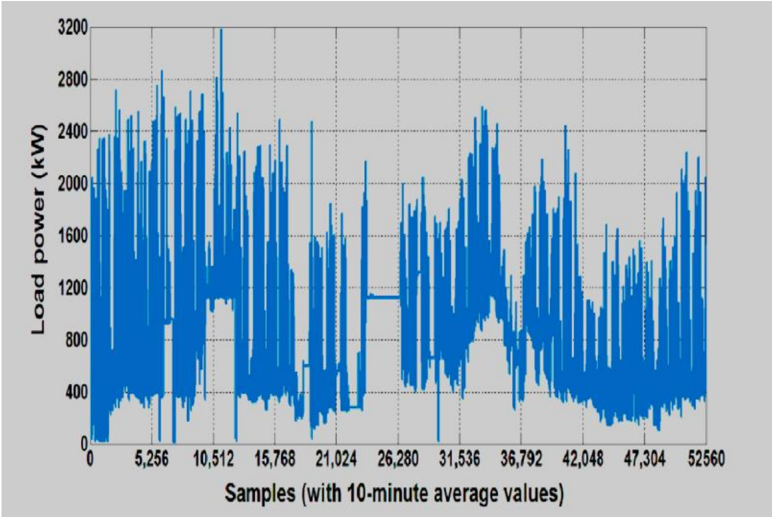
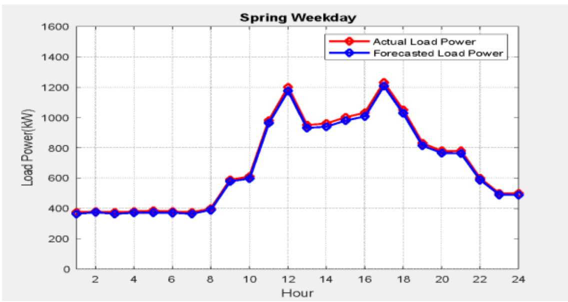


Figure 3: Load Demand Curve

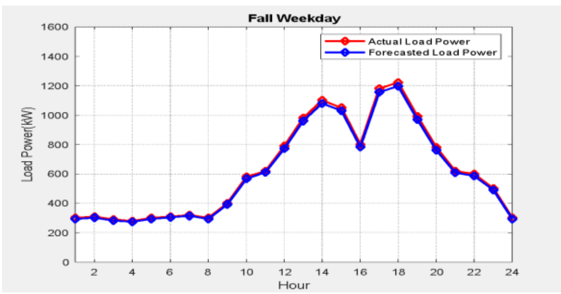
The weight and biases of the FFANN are further modified by the Moth flame optimization technique in this study using the parameter values listed in Table 2 and a one-year testing window length. It is selected to use RMSE as the objective function. The fitness value of the proposed approach (RMSE) is reduced as iteration is increased during the training process.

Table 2
Parameters of MFO

Parameter	Value
Search agents	30
Population Size	20
Maximum iterations	1000



(a)



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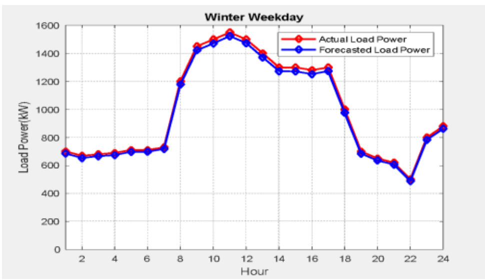

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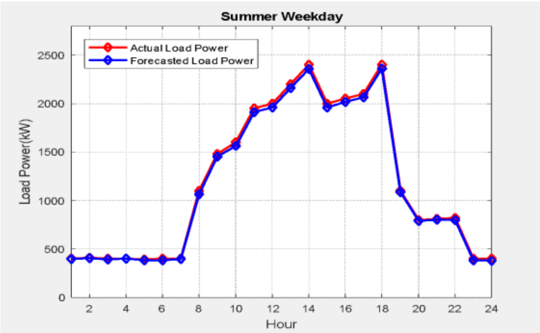


(d)

Figure 4 (a-d) Real (red) versus forecasted (blue) load for weekdays of four seasons

Table 3
Forecasting Accuracy Assessment Values for Fall weekday

Parameter	[7]	Proposed
'RMSE(kW)'	34.44	14.149
'MAPE(%)'	3.3	2.0542
'NMAE(%)'	1.43	1.0368
'SDE(kW)'	32.17	12.122

Table 4
Forecasting Accuracy Assessment Values for Spring weekday

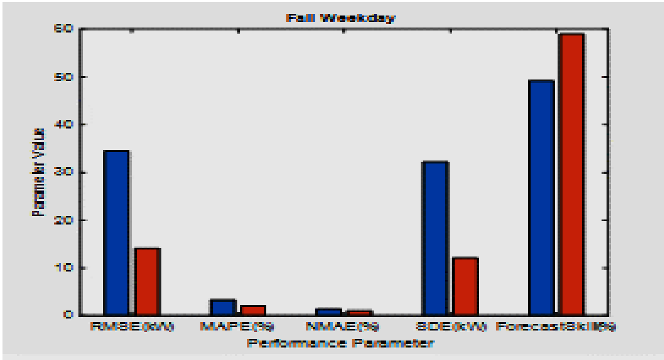
Parameter	[7]	Proposed
'RMSE(kW)'	34.44	15.218
'MAPE(%)'	3.3	2.1236
'NMAE(%)'	1.43	1.1583
'SDE(kW)'	32.17	13.654

Table 5
Forecasting Accuracy Assessment Values for Winter weekday

Parameter	[7]	Proposed
'RMSE(kW)'	34.44	21.294
'MAPE(%)'	3.3	2.063
'NMAE(%)'	1.43	1.3059
'SDE(kW)'	32.17	19.398

Table 6
Forecasting Accuracy Assessment Values for Summer weekday

Parameter	[7]	Proposed
'RMSE(kW)'	34.44	26.294
'MAPE(%)'	3.3	2.0232
'NMAE(%)'	1.43	0.92925
'SDE(kW)'	32.17	21.438



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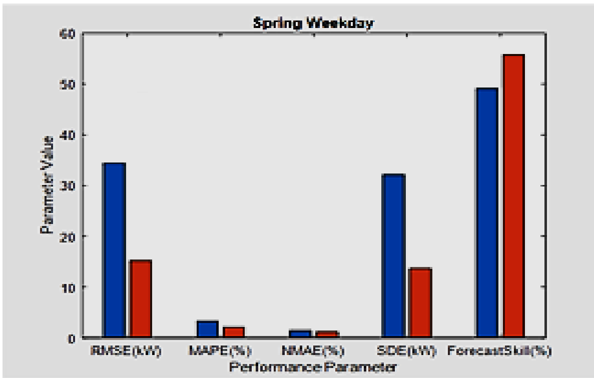

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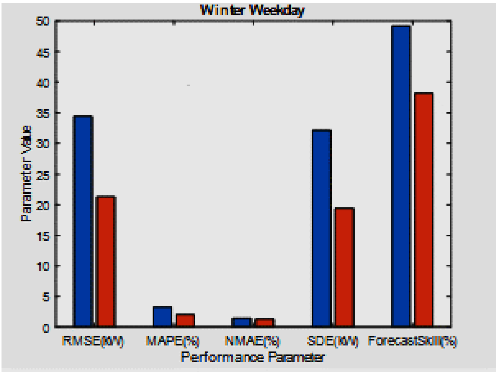

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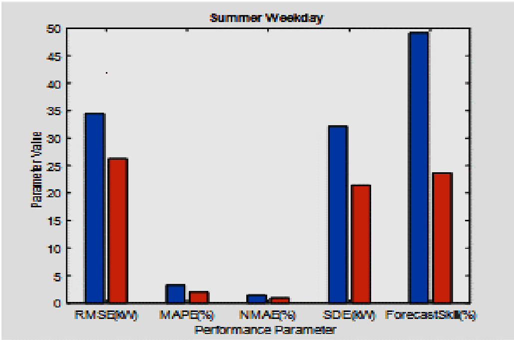

(d)

Figure 5 (a-d) Forecasting Accuracy Assessment for four seasons (blue: [7], orange: Proposed)

TABLE 5.7
Overall Prediction Performance Analysis of proposed model

Day Type	MAPE (%)	RMSE (kw)	NMAE (%)	SDE (kw)
Winter weekdays	2.063	21.294	1.3059	19.398
Spring weekdays	2.1236	15.218	1.1583	13.659
Summer weekdays	2.0232	26.294	0.9292	21.438
Fall weekdays	2.0542	14.149	1.0368	12.122
Average	2.066	19.23875	1.107	16.654

With a one-year testing window, the developed forecast model's prediction performance is evaluated. Figures 4 (a-d) show the predicted electricity consumption using the suggested method. This method had the lowest RMSE. The graphs (Figures 5(a-d)) compare the actual electricity demand to the demand that was predicted using the method based.

5. Conclusion

The proposed scheme has produced improved prediction outcomes as compared to those published in the literature. Research on energy management systems, control of demand response scheduling tasks, dispatching centres, and other control units of the microgrid can use the results of the microgrid electricity demand prediction which have been obtained. In future, the performance of the Moth flame optimization algorithm's forecasts may be enhanced by its hybridization with chaotic maps.

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