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DEPARTMENT OF ELECTRICAL AND INFORMATION ENGINEERING

INTEGRATED LOAD AND RENEWABLE ENERGY FORECASTING

IN MICRO-GRID POWER SUPPLY

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A Thesis Submitted in Partial Fulfillment for the Degree of Master of Science (Electrical and Electronic Engineering) in the Department of Electrical and Information Engineering in the University of Nairobi.

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Declaration

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Dedication

First and foremost, I dedicate this work to the Almighty God. I'm forever grateful, your grace was more than sufficient. This work would not have been a success without divine health, your protection and financial provision, indeed you are faithful God; all the glory goes back to you.

Secondly, I dedicate this work to my Mom Florence and my Dad Boniface, thank you for moral support. You always prayed for me, encouraged and motivated me. I can't count the number of times you called to ask my progress, I can gladly say I enjoyed each time you asked and it made an impact in pushing progress. I am grateful.

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List of Symbols, Abbreviations and Nomenclature

ANN – Artificial Neural Network

PSO – Particle Swarm Optimization

GA – Genetic Algorithms

NN – Neural Network

NNS – Nearest Neighbor Search

NWP – Numeric Weather Prediction

PSO – Particle Swarm Optimization

ARMA- Auto Regressive Moving Average

STLF- Short Term Load Forecasting

PV- Photovoltaic

ABSTRACT

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Integrated Load and Renewable Energy Forecasting for Microgrid Power Supply

For power planning and operation activities, accurate forecasting of demand is very important in sustaining the load demand in the electrical power system. There has been increased use of renewable energy generation which involves nature that is beyond human control. Unlike other sources of electricity, like hydro generators there is uncertainty in estimating power from renewable sources. Therefore, proper and accurate techniques for forecasting renewable energy and load demand are of paramount importance. Several forecasting techniques have been researched on in the past and are classified into; physical, statistical and Artificial Intelligence techniques. How input variables relate to output variables has been solved using these techniques, ranging from linear to complex non- parametric relationships.

This research involves short term forecasting for integrated load and renewable energy (solar and wind) using Artificial Neural Network and Particle Swarm Optimization Techniques. The proposed models use weather variables and historical data for load, solar power and wind power forecasting. Particle Swarm Optimization is used to train the algorithm and update the weights and bias of the neural network.

Key words: Artificial Neural Network, Particle Swarm Optimization, Load Forecasting, Renewable Energy Forecasting.

CHAPTER 1

INTRODUCTION

1.1 Background Information

Forecasting is the prediction of the future happening based on present and past trends of various inputs. There are three types forecasting based on the period of prediction; Short Term Forecasting (STF) which has estimation period of minutes, hours to a day, Medium-Term Forecasting (MLF) has estimation period of several days, week to a month and Long-Term Forecasting (LTF) has estimation period of months to several years. In this paper, short term forecasting for renewable energy and load is discussed [1].

Several researches have been done on either load, solar or wind forecasting separately using different methods. Each system and forecasting technique seek to get closer to the actual values and get to reduce the error between the forecasted values and the actual values. Few researchers have done hybrid models by combining either load and wind or load and solar. Forecasting for load and renewable energy is important for planning and operation purposes in the power system, especially for generation allocation and unit dispatch for generators, marketing and security system analysis [2].

The load demand is usually non-linear and renewable energy is usually intermittent and stochastic in nature which makes the traditional method of forecasting less accurate and ineffective. Recently the Artificial intelligence and hybridized methods (optimization of AI and optimization techniques) have been used [3]. For power system operation, the forecasted load should be done accurately for the scheduling of generation and reduction of unnecessary expenditure caused by surplus production or shortage of power meant to supply the demand.

It is impossible to ignore the fact that renewable energy, recently, has substantially been introduced into power system. Renewable energy has proved to be cost effective, eco-friendly and reliable compared to the other sources of energy. Despite the advantages of renewable energy, there has been a challenge in predicting solar power and wind power due to their intermittent nature. This is a subject of interest in research since the correct forecasting for renewable energy is imperative for planning and operation of power systems purposes [5].

1.1 Problem Statement

Electric power grids and isolated power systems with high infiltration of renewable energy sources are highly faced with a challenge of predicting the expected amount of power generation from the renewable generators; this is due to the intermittent nature of weather variables that affect the power generation.

There has not been much attention given to the optimal net load forecasting for micro grid power systems that are highly infiltrated with renewable energy or that have renewable energy source as the main supply of power.

There is a need for accurate prediction of load demand and renewable energy generation in micro grid for the purposes of planning, operation and grid management of power system.

1.2 Objectives

The main objective:

Modelling integrated renewable energy (Wind and Solar power) and Load demand forecasting for micro grid.

The specific Objectives are:

- i) To model wind power, solar power and load demand forecasting separately before integration.
- ii) To model an integrated hybrid system (load, Wind and solar).
- iii) To determine the reliability of the proposed model (hybrid of solar-wind-load forecast).

1.3 Research Questions

- i) How to acquire the required data for forecasting and data set pre-processing?
- ii) How to create a forecasting models for Load, solar power and wind power using?
- iii) How to optimize ANN using PSO to get the accurate precision for load demand forecasting and renewable energy forecasting models?
- iv) How do we use solar power, wind power and load as input data set to create one forecasting model which gives optimal forecasted net load?

1.4 Justification

Recently, the penetration of renewable energy in both macro grid and micro grid has increased significantly. The intermittent nature of renewable energy source affects the management and operation of the grid, scheduling of power production by other generators and participation in electricity markets between micro grids and utility grid. The reliability and security of the electrical system is very important for its economic operation. It is imperative to factor in the effects of weather variables when forecasting for renewable energy generation and load demand. The methodology for forecasting should be selected with the aim of getting results that are close to the actual values with minimum errors. This thesis aims therefore to provide an accurate hybrid forecasting model that integrates load demand, wind power and solar power forecast.

1.5 Scope of Work

This work develops a hybrid system which integrates forecasting electric load, solar power and wind power for micro grid power system. It is assumed that the renewable energy generators (wind turbines and solar PV plants) are the only power generators supplying the load demand in the micro grid. Forecasting is done separately for load, solar and wind and results for net load compared for both models. The possibility of having the input data updated online for a real time forecasting system is explored. This involves short-term forecasting for the next one hour using of artificial neural network to forecast and particle swarm optimization to optimize the parameters. Forecasted load, wind and solar power are integrated to determine the net load for power generation and micro grid management.

Information for forecasting solar power, wind power and load are obtained from the Global energy Forecast 2014 dataset (GEFCOM2014) rather than using Numerical Weather Prediction (NWP) data to forecast. Specific details on how to forecast the speed of the wind and the irradiance of the solar which are the main inputs to wind, solar power forecasting models will not be tackled.

1.6 Contribution to knowledge

This research provides an improved forecasting methodology for a hybrid system that integrates load demand, wind power, and solar power forecast. The main objective is to model integrated renewable energy (Wind and Solar power) and Load demand forecasting for the micro grid. Here, wind power, solar power, and load demand forecasting are done separately before integration using ANN-PSO. The results from the three models are used as input for the net load forecasting model.

1.7 Thesis Organization

This thesis is structured into five chapters: Chapter 1 introduces the topic of research by giving a background of load and renewable energy forecasting. In Chapter 2, a review of literature on previous similar research work is given and the problem formulation for three forecasting models (Load, Solar, and Wind) and the formulation for net load. Chapter 3 covers the methodology. Results and analysis are discussed in Chapter 4, and the conclusion of the research is done in Chapter 5. The references and the appendix follow subsequently.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

Several research works tackling combined load and renewable energy forecasting have been reviewed.

In **Abderrezak Laouafi, et al (2017) [1]** the model proposed is used to forecast load, solar and wind power. Historical data for load demand and power generations from renewable energy sources (wind and solar), were used as input to the proposed model ignoring the weather forecasted data. The input variables, having a complex (nonlinear relationship) with the output variables, the researchers used a Feed-Forward Back Propagation Neural Network model to solve the problem. Though Artificial Neural Networks (ANN) has the advantage of being able to solve complex problems, in this research, a Feed- forward back propagation approach is useful in shrinking the size of the problem by providing a parallel approach that creates a better correlation between the input variables and the outputs. This research develops separate models for load, wind and solar for the next one hour.

Gamal Aburiyana, et al (2017) [2] discussed several forecasting techniques for load, wind and solar. For load forecasting time series analysis, fuzzy logic regression analysis, artificial analysis and hybrid methods are commonly used. Non parametric (AI) and hybridized method have been used recently to overcome the limitation of statistical methods such as auto regression, stochastic time analysis linear regression and others. For wind and solar forecasting, linear method such Auto regression moving average are applicable. Wind and solar being naturally stochastic AI techniques are most suitable for solving the nonlinearity of input data and output data relationship. Hybridization of AI techniques with optimization methods such as GA, PSO, fuzzy logic, and others have been used in pursuit of more accurate results. One of the mostly used Artificial intelligence technique is the ANN due to the ability to solve relationships that are complex. ANN has the capability to make a decision despite the uncertainty and unpredictability of the patterns. It also has the capability to denoise images.

Hao Quan, et al (2014) [3] uses ANN to forecast short term load demand and wind power. With wind power being a negative load to the power system and considering its stochastic nature, this is makes load foresting a more complex activity due to the high level of uncertainty involved. Point

forecasting is a common method for modelling load demand and wind power forecasting. However, point forecast does not have the capability of handling the uncertainties associated with the sets of data. This research introduces prediction intervals (PI) in place of point forecast. The PIs are developed by Lower Upper Bound Estimation (LUBE) method using neural network. LUBE is used to overcome the shortcoming of point forecast, multi-objective problem with many parameters is constrained to create a problem that is single-objective with less parameters. The results from Neural Network-LUBE model are then optimized using Particle Swarm Optimization. Though there is improved result compared to the traditional techniques of forecasting like ARMA, model does not integrate both wind and load.

In **Vishnu P. Menon, et al (2017) [4]** ANN was used for STLF and solar power forecasting. Solar irradiance and solar power output are intermittent and therefore there is a lot of uncertainty on the input variables. Point forecasting which has been commonly used in traditional methods of forecasting is replaced with probability distribution functions. The researchers introduce the concept of correcting the forecasted load by factoring in the effect of Solar PV power generation in the power system. The model didn't have consumer behaviors included as input whereby the consumer may choose to use solar power or utility.

Amanpreet Kaur, et al (2016) [5] developed a model that forecasts the net load for micro grid. The micro grid is considered to be highly infiltrated with solar power generation. Support vector regression method is used for forecasting solar and autoregressive model to forecast the load demand. Both models use a linear relationship of combined past outputs to forecast for the future. To forecast the net load, the author used two methods; Additive model whereby load and solar were forecasted separately and the results are added to obtain the net load. Integrated model whereby the results from solar forecasting model are used as input for the load forecasting. The result showed that integrated model was more accurate compared to additive models. However, the limitation of the proposed model is that for STLF for solar which is intermittent recourse cannot be solved accurately using linear relation, for instant at local level solar is not always readily available.

Zhen Wen et al (2015) [6] proposes a combined forecasting model which incorporates load, wind power and solar PV power. Support vector regression Method (SVR) based method was used for forecasting. GA Searching Method was used for optimization of the parameters. The model has the

ability to update the parameters online in order to achieve accuracy. The researchers compares two results from two model tradition model whereby the wind, solar and load are forecasted separately and the results from the respective models are added to get the net load, and the other model is a combine model whereby there is only one forecasting model for net load, with historical data for wind power, load and solar power being used as input for calculation of the net load. The models are able to make a decision on whether to schedule for dispatch or not.

2.2 Summary of Review on Load and Renewable Energy Forecasting

The literature review on forecasting of load and renewable energy and the existing gaps is summarized in Table 2.1

Table 2.1: Review on the Load and Renewable Energy Forecasting

Ref No	Title	Data Fore-Cast	Forecast Horizon	Forecasting Models	Contribution	Gap
[1]	One-Hour Ahead Electric Load and Wind-Solar Power Generation Forecasting using Artificial Neural Network	Load, Wind and Solar	Very Short Term (1 Hour)	Feed-forward back propagation neural network (FFBPNN)	<ul style="list-style-type: none"> • Developed separate load, wind and solar models that run parallel series of 15minutes for the next one-hour forecast. • (FFBPNN) was used to model. • Only the historical load data and power generation data from Renewable energy sources are used as input. 	<ul style="list-style-type: none"> • No integration of load, solar and wind. • Weather variables were not considered for the inputs to the models.
[2]	Overview of Forecasting Techniques for Load, Wind and Solar Powers	Load, Wind and Solar	STF MTF LTF	Review of forecasting methods and optimization techniques.	<ul style="list-style-type: none"> • The author discusses; parametric (statistical) methods used forecasting models such as ARIMA, • Non parametric Method (Artificial intelligence) Methods for forecasting models such as ANN, Support vector Machine. • Hybridized methods for modeling forecasting models. 	<ul style="list-style-type: none"> • No integration of load, solar and wind reviewed. • The research only reviews the techniques used for forecasting load, solar and wind.

Ref No	Title	Data Fore-Cast	Forecast Horizon	Forecasting Models	Contribution	Gap
[3]	Short-Term, Load and Wind Power Forecasting Using Neural Network-Based Prediction Intervals	Wind and load Forecasting	Short term	Neural Network LUBE-Prediction Interval PSO	<ul style="list-style-type: none"> • The Authors Enhanced the Neural Network Model by using Lower Upper based estimation (LUBE). • To overcome the limitation of point forecasting they used prediction intervals for training NN Model. • PSO is also integrated with LUBE to enhance the searching capability. 	<ul style="list-style-type: none"> • The proposed model is not integrated.
[4]	Correcting Forecast of Utility's Demand with Increasing Solar PV Penetration	Load and Solar	Short term	ANN	<ul style="list-style-type: none"> • The researchers consider a power system that is highly penetrated with solar power generation. • The original load demand is forecasted. • The solar power is forecasted. • Combination of forecasted load and forecasted solar power is done to get the corrected load forecast. • (ANN) based forecasting model to forecast demand and solar power and PDF to forecast the corrected load, 	<ul style="list-style-type: none"> • The model didn't have consumer behaviors included as input whereby the consumer may choose to use solar power or utility.

Ref No	Title	Data Fore-Cast	Forecast Horizon	Forecasting Models	Contribution	Gap
[5]	Netload forecasting for high renewable energy penetration grids	Solar and Load	Short Term	Support Vector Regression Autoregressive Model Autoregressive Model with exogenous input	<ul style="list-style-type: none"> • This research introduced the concept of forecasting for net load for grids that have high penetration of renewable energy. • Net load forecast is obtained by integrating load demand forecast and solar power forecasts. 	<p>The model used is linear time series regression which is not realistic for prediction of solar power which is intermittent in nature.</p> <ul style="list-style-type: none"> • The model does not include weather condition as input which is stochastic and creates a complex relationship between the input variables and output. • Since the integration model uses forecasted solar power as one of the inputs to Net load forecast, real-time forecasting for solar with reliable forecasted data is very important but lacks in this proposed model.

Ref No	Title	Data Fore-Cast	Forecast Horizon	Forecasting Models	Contribution	Gap
[6]	A Combined Forecasting Method for Renewable Generations and Loads in Power Systems	Load, Wind and Solar	Short term	Support vector machine Grid searching GA - Searching	<ul style="list-style-type: none"> • In this research, an adaptive forecasting model is developed to forecast the net load. The model uses wind, solar and load data to calculate the net load and the results as input to the forecasting model. • The proposed is model is able to update parameters online to enhance accuracy. • A comparison between the offline combined forecasting model and the online (self-adaptive) combined forecast is done. 	<ul style="list-style-type: none"> • This model involves calculation of net load from load data, solar power generated data and wind power generated data, the result is then used to forecast the net load. The model neither forecasts the load demand nor the renewable energy but net load.
	In this thesis			<ul style="list-style-type: none"> • Separate models were developed for wind power forecast, STFL and Solar power forecast using hybrid of ANN and PSO technique. • The result from each model; load forecasting, solar forecasting and wind forecasting models were integrated in another model to obtain the forecasted net load. • The reliability of the results from the models was validated by comparing the forecasted values with the actual values and calculation of errors. 		

This thesis involves three separate forecasting models for wind power, solar power and load demand. The integration is done by using forecasted solar power and forecasted wind power and forecasted load demand as input for net load forecasting as shown in Figure 2.2.

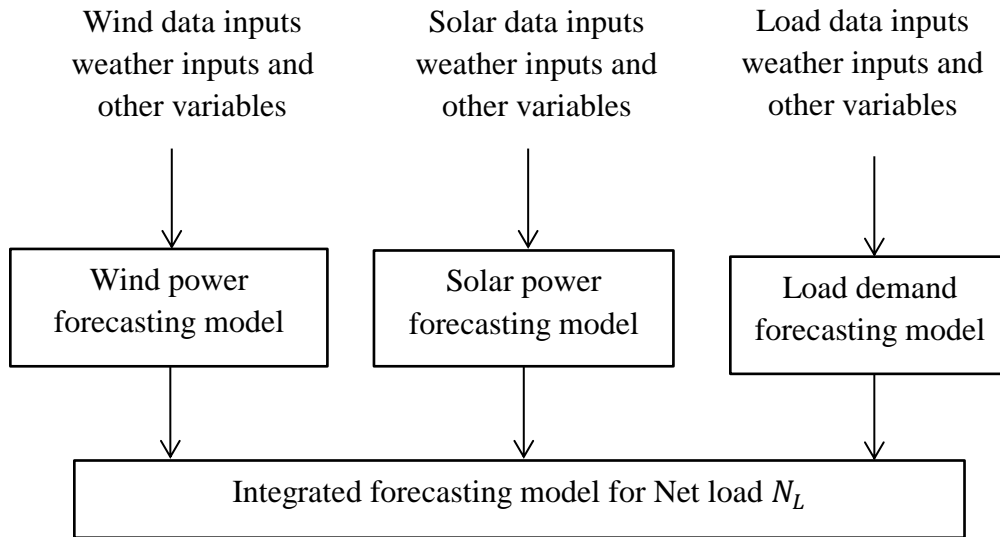


Figure 2.2: Forecasting Models

2.3 Existing Gaps

The following existing research gaps are tackled in this thesis:

- i) Integration of wind-solar and load forecasting and the effects of net load forecasting due to renewable energy.
- ii) Uncertainties in renewable energy prediction and the effect of weather parameter in solar and wind power prediction.

2.4 Problem Formulation

We assume that the only renewable energy generators incorporated to the grid are solar and wind. Weather parameters such as speed of wind and temperature to forecast wind power to be generated, in addition solar irradiance, and humidity have been used to forecast solar power generated. It's also assumed that there has been wind power and solar power generators before and therefore historical data from the previous generation is used as input. If the forecasted demand is more than the supply from the renewable energy generation then the surplus is gotten from traditional methods of power generation. For cases where the forecasted production is seen to be exceeding the demand, the surplus is sold to the utility (grid).

2.4.1 Wind power forecasting

Cut-in speed – Minimum required speed where the turbine rotor overcomes friction and begins to generate power [8].

Cut-out speed – This is achieved when the motion of the turbine blades is brought to rest. This prevents damage from strong winds [8].

The power output from wind is given by [15]:

$$P_w = \frac{1}{2} A \rho V^3 C_p \quad (2.1)$$

Where P_w is the ideal power harnessed by rotor (W), A is swept area by rotor (m^2), V is the velocity of wind (m/s) and C_p is the power coefficient, defined as the efficiency of the wind turbines, at specific wind speed the power coefficient is given by the ratio of the definite electric power actually produced by the wind turbine and the overall wind power that flows into the blades of wind turbines usually set as 0.593 as per the Betz Limit or Betz' Law [25].

Accounting for the variance in the increasing speed with height, the wind velocity V at turbine height h is given by [12]:

$$V = v_o \left(\frac{h}{h_o} \right)^\alpha \quad (2.2)$$

Where v_o the reference wind speed at a height is h_o , α is the friction coefficient based on the ground surface (rough or smooth terrain). Therefore, the effect of land terrain is taken into consideration in the wind power forecast.

To determine the output of wind characteristics, we use fitting equation illustrated by a sigmoid curve as:

$$P_W(v) = \begin{cases} 0 & 0 \leq V \leq V_{ci} \\ A + \frac{B-A}{1+\exp\left[\frac{(C-V)}{D}\right]} & V_{ci} < V < V_{co} \\ 0 & V_{co} < V \end{cases} \quad (2.3)$$

Where $P_W(v)$ is the wind power output for a speed V , v_{ci} is the cut-in speed, v_{co} the cut-out speed (cut-in and cut-out speeds are useful in addressing uncertainties in that we know the productive speeds of wind which lead to power generation). A, B denote asymptotes acting horizontally, C is the point of inflection on the curve and D represents the scale parameter.

A 24hr future wind forecasting is employed through ANN approach. Statistical features is used as inputs to the multilayer perception model by considering the cluster approach for the network output [16, 17]. The input vector I is given as function of W_{avg} , T_{avg} , W_{dir} , yd as:

$$I = [W_{avg}, T_{avg}, W_{dir}, yd] \quad (2.4)$$

Where W_{avg} is the average velocity of wind for the past 24hrs, T_{avg} denotes the mean temperature for the past 24 h, W_{dir} represents the direction of wind for the last 24hrs and yd denotes specific day of the year [16].

The parameters T_{avg} , W_{dir} and yd are used to reduce the uncertainty and improve accuracy. The output of ANN model gives the expected production of power for 24hrs ahead.

This model is assigned 15 neurons per hidden layer, 6 neurons per input layer and 24 components for output layer production for the 24hrs ahead [16].

The accuracy of the model is determined from the Mean Absolute Percentage Error (MAPE), as in Equation 2.5 [1]:

$$MAPE = \frac{1}{N} \sum_{j=1}^N \frac{|P_a^j - P_f^j|}{P_a^j} \times 100 \quad (2.5)$$

Where;

N denotes number of cases forecasted, P_a^j the actual power and P_f^j the amount of forecasted power.

2.4.2 Solar Power Forecasting

The power output for a PV module is given by [9, 10];

$$P_s = I_T \alpha \{1 - \gamma(T_{cell} - T_{ref})\} \quad (2.6)$$

Where I_T is the solar incident radiation, α is a constant which is the product of the packing factor and efficiency module estimated to be about 0.11, T_{ref} is the reference temperature set at 25°C and γ is the temperature coefficient set at -0.47%. The operating temperature T_{cell} is given by [10]:

$$T_{cell} = T_{air} + (0.0125NOCT - 0.25)S \quad (2.7)$$

Where $NOCT$ is taken to be 50°C, T_{air} is the real time data on the ambient air temperature and S is the insolation level valued at 80 mW/cm².

I_T and T_{air} are the input variables I for the artificial neural network.

$$I = [I_T, T_{air}] \quad (2.8)$$

2.4.3 Forecasting the Load Demand [11]

The load demand is predicted using ANN. PSO algorithm is used to replace the inbuilt back propagation algorithm for the training method in the ANN structure. This helps reduce the forecasting error of the ANN.

For accurate forecasting the days of the week is divided up as Monday type, Weekday type, Saturday type and Sunday type.

The input to the ANN is as follows in equation (2.9);

$$L = [P_h, T_h, X_s,] \quad (2.9)$$

Where P_h the historical is hourly load demand, T_h is the daily average temperature and X_s is the type of day. Type of day is divided up as Sunday, Saturday and Weekday types.

Load data is be taken in hourly basis, temperature in hourly basis and season input as a number from one to four. The output is the forecasted load for 24hrs.

The performance of the forecasting strategy is judged by the mean absolute percentage error (MAPE) as shown by equation (2.5).

2.4.4 Integrating the Forecasted Wind Power and Forecasted Load Power

To integrate the forecasted wind power, forecasted solar power and forecasted load demand, the forecasted power from the wind turbines and PV solar generators are treated as negative loads. The difference between the forecasted load demand and the forecasted power produced from renewable energy generators is considered the forecasted net load demand. The forecasted net load $NL(t)$ is important for management of the total hourly energy balance.

$$NL(t) = Pd(t) - (P_w(t) + P_s(t)) \quad (2.10)$$

Where $Pd(t)$ power is the forecasted load and $P_w(t)$ is the total forecasted power production by wind turbines and $P_s(t)$ is the forecasted solar power.

If $NL(t) < 0$, there is an excess production compared to demand. Surplus energy is thus sold to the grid or managed by energy management system.

If $NL(t) > 0$, the load demand exceeds production and the difference is bought from the grid (this ensures there is no loss of power supply).

Total power required to be generated is given by:

$$\sum_{i=1}^N P_w + \sum_{j=1}^M P_s + P_{grid} \geq P_D + P_{loss} \quad (2.11)$$

Where P_D is the forecasted total load power demand, P_s is the solar power forecasted, P_w is the forecasted power output of the wind turbine, P_{grid} is the total power supply from established traditional methods for example (hydropower) and P_{loss} is the transmission power losses. P_{loss} is deterministic; can be calculated and therefore it is represented by a constant.

2.4.5 Tackling Load Uncertainties

A challenge facing load, solar and wind forecasting is load uncertainties. Load uncertainties lead to sudden rise or fall in power demand which may cause system instability. The sudden rise in power demand may be due to factors such as factories starting up, special events or holidays in a year.

Taking total load to be total sum of demand from households, industries and miscellaneous, we have:

$$Total\ Load = L_T = \sum_{i=1}^N R + \sum_{j=1}^M C + M \quad (2.12)$$

Where R is demand from residential, C is demand from commercial (industries) and M is miscellaneous.

$$T_{RE} = RE \quad (2.13)$$

T_{RE} , is the total power generated from renewable energy sources.

And,

$$RE = \sum_{i=1}^N P_w + \sum_{j=1}^M P_s \quad (2.14)$$

Where RE is the total Renewable Energy generated, P_s is the power output from the solar plants, P_w is the power output of the wind turbines,

When we have a sudden rise in demand exceeding supply that was not forecasted, this is treated as uncertainties given as:

$$U < T_{RE} \quad (2.15)$$

One way to tackle this excess demand is by using conventional methods such as hydro from the grid, to supplement for the short term.

$$L_T - T_{RE} = U \quad (2.16)$$

The sudden rise in power demand can also be tackled by load shedding.

Extremely low demand that was not predicted is also an uncertainty that needs to be tackled. It means the wind turbines and solar plants are generating excess power which is difficult to be stored. Unprecedented excess power in the micro grid may lead to issues such as frequency instability [12].

This kind of uncertainty can be tackled by:

- i) Dumping the excess power to the grid

$$T_{RE} - L_T = U \quad (2.17)$$

Where U is taken to the grid.

- ii) Offering incentives to consumers during such periods to encourage power consumption.

$$\text{When } T_{RE} \gg L_T \quad (2.18)$$

Consumers is deducted some amount from their bill during such a period.

2.4.6 Overall Formulation [12]

The key objective of generation dispatch is it to meet the load demand whilst taking care of the uncertainties and losses in the power system, as stated in equation 2.18 below:

$$RE \pm P_{grid} = P_D + P_{loss} \pm U + \varepsilon \quad (2.19)$$

Where RE is the total Renewable Energy generated, P_{grid} is the power supply from the grid, $P_{loss,j}$ is the transmission power losses, P_D is the forecasted total load power demand, U is the uncertainties and ε includes other errors not captured in the forecast. The surplus power is provided for by the grid so that even when the combined solar and wind power generation falls short of the predicted value, then the power supplied is still enough to cater for the load. This is to enhance the efficiency of the power supply system while maximizing the use of the generated renewable energy [12].

$$I = [P_W, P_S, P_D] \quad (2.20)$$

2.5 Solar, Wind and Load Forecasting Methods Applied to the Problems

In the reviewed works, the following methods have been applied to hybrid of load, solar and wind forecasting: Particle Swarm Optimization (PSO), Enhanced Harmony Search (EHS), Pattern Search Algorithm, K-Nearest Neighbor Search (K-NN) and Artificial Neural Networks (ANN).

2.5.1 Enhanced Harmony Search (EHS)

This is an algorithm that is based on random searching of a population by the process of simulating the tuning of the pitches of musical instruments until the desired harmony is reached. Harmony search algorithm involves playing of a note in search of the best harmony by each musician. The best harmony is then considered as the optimum solution. In EHS, single memory is utilized to evolve and escapes from local optimal points; this distinguishes it from other optimization techniques that are population based. It has a disadvantage that it is time consuming in the optimization process. In [20] EHS algorithm has been used to estimate the parameters that are used in determination of Support Vector Regression mapping properties for modelling wind forecasting.

2.5.2 Pattern Search Algorithm (PSA)

PSA is a direct searching method that is comprised of two processes. The favorable direction of the search is determined by exploratory process and the power up process. The favorable direction is achieved by powering up the two processes in search of the optimal solution. PSA has been used in SVM models to optimize parameters for prediction [6]. It does not require a gradient hence can be used on functions that are not continuous or differentiable.

2.5.3 K-Nearest Neighbor (K-NN) Search

It is used to assign weight values to the contributions of the neighbors. In [10] they used K-NN search to find the most similar wind speed data of past neighbor and find a similarity between them. NN involves lazy learning and the approximation of the function is done locally. It is among the simplest of algorithms. Its sensitivity to the local structure of the data is one of its major limitations.

2.5.4. Neural Networks

ANN is inspired by how human brain and nerve cells work. They were designed to mimic characteristics of the biological neuron. This method is used in [4] to predict wind power generation, solar power generation and load demand due to their ability to identify complex patterns.

2.5.5 Particle Swarm Optimization (PSO)

It is an optimization technique based on population. In [21] the optimization weights and biases of ANN structure are done using PSO. It has an advantage in that it escapes local optimal solutions compared to the back-propagation algorithm, but also has a disadvantage in that it has a slow convergence rate and converges prematurely.

2.5.6 Time-Series Regression

A predictor is an independent variable relates to the target and dependent variable in a way that can be investigated by a type of modeling technique which is predictive in nature, termed regression analysis. Based on the history of response, the future response is predicted by the time series regression. In a timely order, past observations of predictors are built in a design matrix, which starts the time series. An approximate relation between the design matrix and the response is gotten through application of ordinary least squares modeling process.

Time series regression Disadvantages [4]

- i. Data must be independent.
- ii. Highly sensitive to outliers (data that is surprising).

Time series regression Advantages

- i. Shows the impact strength of multi-independent variables on the dependent ones
- ii. It is an indicator of the significant relationships in-between independent variable and dependent variable.

2.6 Machine learning in ANNs

The following are strategies used for training and learning of ANN model:

Supervised learning

There are comparisons made with the neural network outputs i.e. solutions with the correct answers, from where the ANN is able to eradicate the potential errors. The correct answers are provided by the trainer as ANN comes up with guesses meant for recognition of patterns for the comparison and rectification. Thus, the process is more scholarly with a guide.

The data is categorized into training, test and validation. The link relating input and output is matched by the activation function with the weights between the layers under consideration. Some of the layers found in artificial neural network include hidden, output and input layers. Estimation and classification problems can easily be solved by the artificial neural networks in different structures.

i) Unsupervised learning

In this learning, based on existing data sets, pattern recognition is processed. This learning is applied in cases where there are unknown answers for the data sets.

ii) Reinforcement learning

Here, the learning is based on observations by making decisions from the environment.

Considering the models mentioned above and different structures, estimation and classification of problems can be done. In ANN layers, there is bonding of the layers (weight) and activation function. This function matches the link between the input and the output.

Advantages of Neural Networks

- i) No restrictions imposed on the variables for the input variables.
- ii) Ability to learn and identify hidden patterns in complex relationships through non-linear modeling.

Disadvantages of Neural Networks

- i) Proneness to overfitting
- ii) Greater computational burden.

2.7 Chapter Conclusion

This research work involves forecasting wind power generation, solar power generation and load demand for a microgrid. The results from the three forecasting models are used to forecast the netload of a microgrid and that is where the integration comes in. From the literature review, several researches have been done on forecasting power generation from renewable energy sources and load demand. However, none of the research have tackled the integration of the three forecasting models; wind power, solar power and load demand using ANN-PSO. Also, forecasting of the netload has not been given much attention by researchers. This chapter also captures a review of several methodologies which have been used in the previous researches for forecasting. The input variables for wind power and solar power model were derived for their respective formulas for the power generation equation (2.1) and (2.6), and historic data. Input variables for load forecasting is given by equation (2.9). The formulation for the netload forecasting is given by equation (2.10). The overall formulation for netload and determining on whether to buy or sell to the grid has been discussed in this chapter.

CHAPTER 3

METHODOLOGY

3.1 Method Statement

This chapter captures the methodology of forecasting for load demand the generated wind power, generated solar power and the netload for a micro-grid power system. While literature review, identification of research gap and problem formulation were tackled in the previous chapter, this chapter detailed methodology is discussed. Figure 3.1 shows areas of discussion for methodology to begins from selection of dataset, data preprocessing, creation of models by coding and simulation using ANN and PSO techniques on Matlab 2018a software. Results and analysis are discussed in the chapter 4 of this thesis.

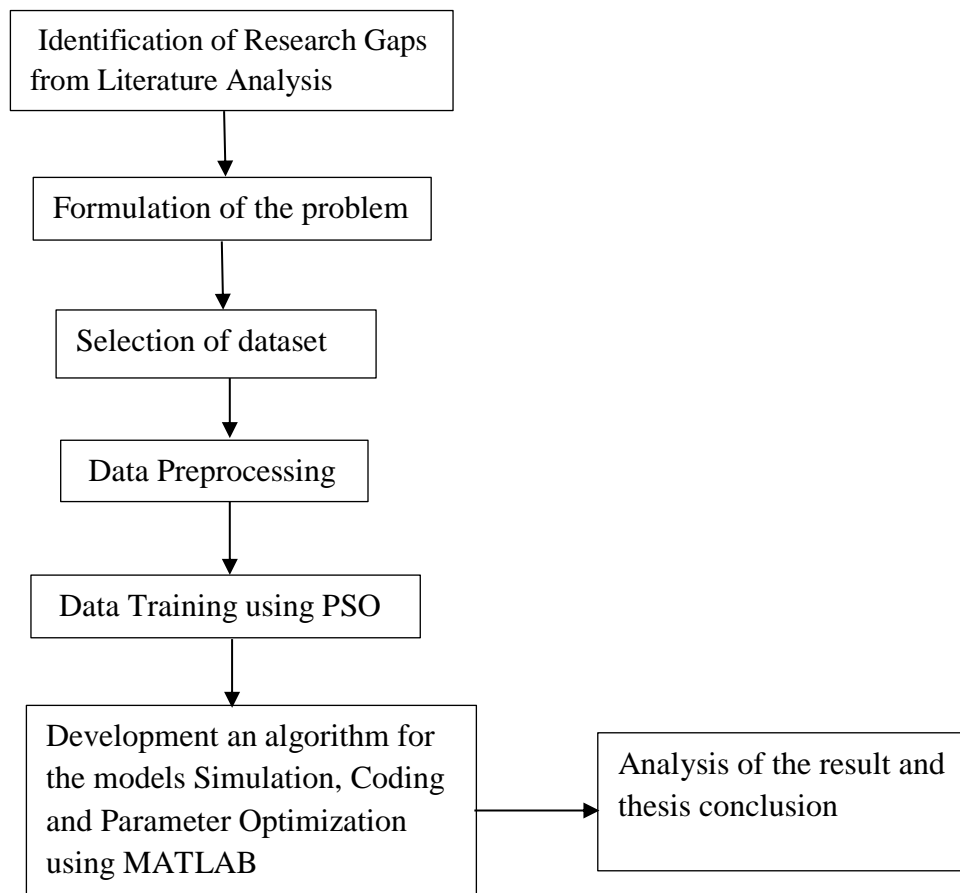


Fig. 3.1: Flow Chart for the Adopted Methodology

3.2 The Proposed Method(s): Artificial Neural Networks (ANN) and Particle Swarm Optimization (PSO)

3.2.1 Data set

The data set used for load, solar, wind forecasting is obtained from GEFCOM 2014. This data contains the historical weather variables and the respective power generation record for the wind and solar power generation plant. The data is classified as monthly, weekly, daily, hourly, 15minutes intervals.

A. Load forecasting

The data required for load forecasting was: historical load demand, the daily average temperature, day of the week (weekday, Saturday, Sunday)

B. Solar power forecasting

The dataset for solar forecasting includes: solar incident radiation, ambient air temperature, global solar irradiance.

C. Wind power forecasting

Wind speed, wind direction, air density, were used as input for wind power forecasting.

3.2.2 Data Pre-processing

3.2.2.1 Data Standardization

The input dataset *from GEFCOM2014* **was** standardized to minimize the probability of getting stuck in local minima and local optima. This was done by ensuring the that the mean of is zero

3.2.2.2 Data Normalization

The input dataset was standardized to minimize the probability of getting stuck in local minima and local optima. It also helps in increasing the speed of training data.

The weather variables are normalized between a value of (-1 to +1) using min- max normalization.

$$Y_j = \frac{X_j - \text{Min}(x)}{\text{Max}(x)} \quad (3.1)$$

The historical power data was normalized using the nominal output capacity. For PV, the nominal output capacity is 737KW

$$P_{normalized} = \frac{P_j}{737} \quad (3.2)$$

3.3 Artificial Neural Network (ANN)

ANNs are models that were developed based on the structure of the brain, inspired with the idea that the brain learns by experience. They are characterized by a parallel architecture comprising of neurons and a large degree of feedback [22].

The human brain comprises numerous neurons that are interconnected to each other and have the capability of sensing external and is composed of billions of neurons (nerve cells) that are interconnected by axons.[23]. External stimuli from the environment are accepted by dendrites and it is these inputs that create electric impulses.

The ANNs is comprised of numerous nodes and neurons that interconnect and interrelate with each other. Each nodes output is called its activation or node value. Artificial Neural Network can learn weights and change their values. ANN structures are classified into:

- i) Feedforward Neural Network (FFNN).
- ii) Feedback Neural Network (FNN).

FFNN: The messages send by the units do not get information from the recipient units. They are ideal for forecasting problems.

FNN: The network structure has feedback loops.

3.3.1 ANN Parameter Optimization

ANN being a complex model its parameters are optimized to obtain a more accurate prediction.

The parameters are categorized as follows:

Data

- Data selection
- Data Pre-preprocessing
- The Number of input Variables and the quality of the data

ANN- Architecture

- Number of neurons in input layer
- Number of hidden layers and number of neurons in hidden layers
- Number of neurons in output layer

Training

- The training Algorithm
- Weights and biases
- Training epoch

Transfer functions

Sigmoid, Purelin, Transig, Hyperbolic, linear

Getting the correct value of all these parameters has always been the main challenge in construction of ANN Model. Most importantly the performance of ANN model is affected by the criterion for optimization of the weights. The main aim is to achieve the optimal weights while training the ANN and to reduce the error between the actual values and the predicted values. In this research PSO was used to train the ANN parameters.

3.4 Particle Swarm Optimization

It is a modification of PSO with evolved computational capabilities known as swarm intelligence. PSO has a disadvantage that in case of inadequate coverage for the whole region by the initial particle population there is usually convergence of particles to a local minima solution. To avoid this limitation, enhanced particle swarm was developed.

Particle swarm optimization is analogies of the birds going randomly to hunt for food, the birds nearest to the found food leaves a hint or signal to attract the flock behind to the found food [19]. If any other birds come closer to the target than the first, then they also give a signal. Until one of the birds in the flock stumbles upon the food the recursion of this reduction pattern continues.

Over a number of repetitions, a group of birds have their values adjusted closer to the member whose value is closest to the food at any given moment. This process is repeated until the best conditions or a food source is discovered. The process of optimization follows the work of these birds' behavior. The solution coordinates indicators and the speed of the particles as the optimal solution is approached is given by the velocity and the particle position [21]. Birds are mapped as particles whereas signals as positions and velocities and finally foods being the solutions.

3.4.1 Presentation of PSO

Each particle defines a velocity vector that dependably affects the location of every single particle. The position and velocity of each particle are updated per iteration as follows:

$$V_{i,iter+1} = \omega V_{i,iter} + C_{1b}r_1(P_{i,iter}^b - X_{i,iter}) + C_{1nb}r_2(X_{i,iter} - P_{i,iter}^{notb}) + C_2r_3(G_{i,iter}^b - X_{i,iter}) \quad (3.3)$$

$$X_{i,iter+1} = (X_{i,iter} + V_{i,iter+1}) \quad (3.4)$$

The coefficients C_{1b} and C_{1nb} are related to the ‘b’ and ‘not-bt’ components.

Advantages of PSO

- i) Adjusts only few parameters
- ii) The computational time is less
- iii) Good stability and global convergence execution
- iv) Does not have particles stuck in local minima

Disadvantages of PSO

- i) Uncertainty of convergence time, however discrete
- ii) Probability distribution changes by iteration

3.4.2 PSO Parameter Optimization

The following ANN_PSO parameters were identified for optimization in order to achieve maximum forecasting precision.

- i) The number of Particles
- ii) The inertia weights
- iii) The number of hidden neurons
- iv) The number of Iterations
- v) Weights for global and local bests

3.5 Modeling for Renewable Energy and Load for a Micro-Grid

3.5.1 Wind Turbine Power Generation Forecasting Model

Simulation code for Matlab was used to model wind power generation model. The algorithm for the simulation code was developed with input and output parameters as shown in Table 3.5.1, the model is based on equation

Table 3.5.1 Wind Turbine Power Generation Forecasting Model

<i>Input Parameter</i>	<i>Output Parameter</i>	<i>Data Type</i>
The average density of air is 1.204 kg/m ³	Wind-Power (kW)	constant
Standard power coefficient range of a wind turbines		Constant
The size of the wind turbine Diameter for the wind farm in metres.		Constant
velocity of wind for zonal and Mediterranean components of wind metres per second		Variable
Number of wind turbines in the farm		Constant
Direction of the wind		Variable

Solar PV forecasting model is established per equation (2.8), with the input and output parameters indicated in Table 3.5.2

3.5.2 Solar PV Power Generation Forecasting Model

Table 3.5.2: Solar PV generation forecasting model parameters

<i>Input Parameter</i>	<i>Output Parameter</i>	<i>Data Type</i>
Solar PV efficiency range	Solar PV- Power (kW)	constant
The average temperature of the air		Variable
Solar incident radiation in kWh/sq.m		Variable
The humidity of the air		Variable
The cloud cover		Variable
The historic PV Solar generation in kW		Variable
Area covered by Solar PV farm in sq. Meter		Constant

3.5.3 Load demand Forecasting Model

Load demand forecasting parameter are as per equation (2.9) the input and output parameters are as shown in Table 3.5.3

Table 3.5.3 Load Demand Forecasting Model

<i>Input Parameter</i>	<i>Output Parameter</i>	<i>Data Type</i>
Historical data for the load kW	Load demand (kW)	Variable
The average daily temperature		Variable
Day of the week		Variable
Power losses within for the power system		Constant

3.5.4 Net Load Forecasting Model

Net load forecasting parameter are as per equation (2.10) the input and output parameters are as shown in Table 3.5.4

Table 3.5.4 Net load Forecasting Model

<i>Input Parameter</i>	<i>Output Parameter</i>	<i>Data Type</i>
Forecasted Load demand in kW	Net load (kW)	Variable
Forecasted wind power generation in kW		Variable
Forecasted solar PV power generation in kW		Variable

3.6 Parameter Mapping for Artificial Neural Network- Particle Swarm Optimization

During the training period of artificial neural network, minimization of errors is done through the particle swarm optimization, which reduces the forecasted error in the network. MAPE (mean absolute % error) is the parameter meant for minimization and is given by equation (3.5)

$$MAPE = \frac{1}{M} \sum_{i=1}^M \frac{|P_{act}^j - P_{forct}^j|}{P_{act}^j} \times 100 \quad (3.5)$$

Where P_{forct}^j = forecasted power, P_{act}^j = actual power and M = number of observations.

Table 3.6 shows mapping of parameter to ANN optimized by PSO in ANN_ PSO algorithm. The parameters were coded and simulated using Matlab platform.

Table 3.6: Mapped Parameters to Artificial Neural Network - Particle Swarm Optimization

Table 3.6. Mapping of the Parameters method to the ANN_PSO function			
No.	Hybrid Method Variable/ operator	variable description	Limits/ Specifications
1.	Gbest	Global best position	A variable
2.	Velocity	Rate of change of positions	Updated in each iteration
3.	Positions	Values assumed by particles	Updated in each iteration
4.	Number of Particles	The area covered in the problem space per iteration of the loop	10
5.	Pbest	Individual Particle best position	A variable
6.	Local Weight (c1)	Acceleration constant that influences global best position	1.5
7.	Local Weight (c2)	Acceleration constant that influences local best position	2.5
8.	Fitness Function	Prediction accuracy	Eqn 3.5
9.	Number of hidden layers	ANN architecture	Range between 10 to 15 (solar, wind and Load Models)
10.	Convergence Criterion	Number of Iterations	500 iterations

Pseudocode

Step 1: Obtain the wind power by converting the wind speed as per equation (2.1) and solar power by converting solar irradiance as per equation (2.7).

Step 2: For the load forecasting, classify the artificial neural network into season, temperature and historical load, while for wind or solar forecasting, classify the direction of the wind, orientation, temperature wind speed and solar radiation intensity deviation.

Step 3: Carry out neural network data normalization, for the inputs to ensure they are between 0.1 to 1

$$Normalized\ Value(N.V) = \frac{Raw\ data\ value}{Maximum\ data\ value} \quad (3.6)$$

Step 4: Carry out particle swarm initialization

Step 5: For solar/ wind and load forecasting, use particle swarm optimization to train the artificial neural network

Step 6: Pbest and Gbest fitness value evaluation for the particles

Step 7: Check if MAPE is minimal, but if Gbest is unchanged, return to step 4.

Step 8: Give the predicted load demand and wind/solar power generated final results if MAPE is maximum iteration or minimum magnitude.

Step 9: Provide the surplus power to grid if predicted load demand is less than predicted wind power and solar power on hourly basis.

Step 10: If the load demand prediction exceeds the capacity of renewable energy generation predicted, buy the difference from the grid

Step 11: End the process.

Figure 3.2 below shows a typical flow chart for load, wind power or solar power forecasting model using PSO-ANN algorithm. The calculation was initialized using the following steps: data normalization, determining number of layers that are hidden. The weights and biases were randomly determined and disseminated to the hidden layer from the input layer. Sigmoid function was activated, each signal was then transferred from the output layer to the hidden layer. The weights and biases were optimized using PSO Algorithm. Firstly, the following was determined: the number of particles, the initial position, the initial velocity of the particles, the search space lower limit and the upper limit and the number of iterations. With iteration the value of the position was changed [18]. Each iteration was evaluated to determine if it was the best position using MAPE equation (3.5). The iterations continue until the global best position with the minimum error to the solution are achieved.

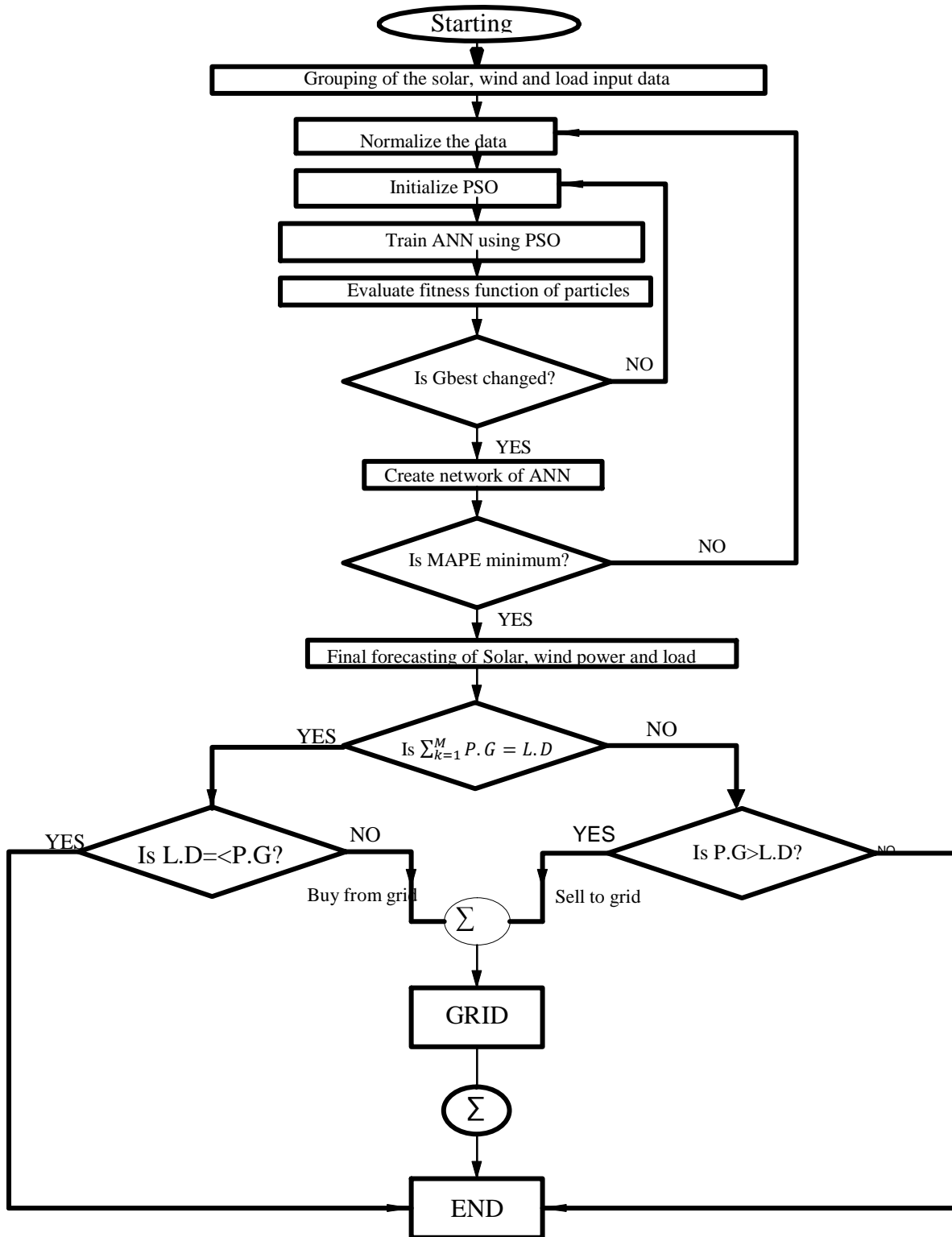


Figure 3.2: Flow-chart for Load, Wind and Solar Forecasting Using PSO-ANN

3.7 Simulation Tool

The simulation tool for the forecasting models was MATLAB 2017a. Relevant data set was fed to determine the system uncertainties, solar and wind power forecasting and load demand expectations of the system.

3.8 Chapter Conclusion

Various methodologies have been used in different researches to forecast load and power generation from renewable energy sources. The advantages and disadvantages of the forecasting methodologies were discussed in this chapter.

In this thesis due to intermittency of the input variables and nonlinearity of the forecasting equation ANN- PSO was used for forecasting. Also, ANN-PSO has not been used before in modelling combined load, wind power generation and solar power generation forecasting models. The code for modeling ANN-PSO and simulation of the forecasting models is shown in section 3.6 and Appendix A. The coding was done using Matlab 2018a software. Forecasted Netload for the micro-grid was the ultimate result obtained by using the load, wind and solar power generation forecast as the input to the netload forecasting model and hence the integration.

CHAPTER FOUR

RESULTS ANALYSIS

4.0 Introduction

The datasets used for load, solar, wind forecasting was obtained from Global Energy Forecast, GEFCOM2014. The dataset was classified into hourly historical data and hourly records of weather variables for the respective forecasting models. The input dataset was standardized to minimize the probability of getting stuck in local minima and local optima. This also helps in increasing the speed of training data. The weather variables are normalized between a value of (-1 to +1) using min- max normalization as shown in equation 3.1.

The ANN-PSO models were used to forecast the next 24hrs. Figure 4.1 to 4.4 show the graphs representing the simulated results, which depicts that the model are effective in predicting the Load, wind power and solar power since the curves of the predicted values was almost similar to the one of the actual values.

4.1 Wind Power Forecasting Dataset

Table 4.1 represents the dataset used for wind power forecasting. The data sets are obtained from a wind power generation station Zone Identification number 10. The data table captures the relevant variables for 24hours, on 1st January, 2012 from 1:00am to midnight 00.00am 2nd February, 2012.

The input variables are as indicated: the Wp represents the historic wind power in kW, U100, V100 and U10 and V10 are the zonal and meridional components of wind speed at the height of 100metres and 10metres respectively. The direction of the wind being a variable in wind power forecasting, is indicated by a negative or a positive sign on the values of the speed of wind. The dataset for wind power is normalized before use. the nominal capacity that is determined from the wind farm is used to normalized the data [23].

Table 4.1 Dataset for Wind Power Forecasting

ZONE ID	TIME STAMP	Wp	U10	V10	U100	V100
10	20120101 1:00	0.594360846	1.655789558	-4.64959	2.024257	-5.99223
10	20120101 2:00	0.569678987	2.178608535	-4.18494	2.623141	-5.31809
10	20120101 3:00	0.330538724	2.228632704	-3.24244	2.645217	-4.05223
10	20120101 4:00	0.211308354	2.07723212	-2.34508	2.432947	-2.91383
10	20120101 5:00	0.172139682	1.814715902	-1.57763	2.097844	-1.9761
10	20120101 6:00	0.151354466	1.438870592	-1.02652	1.620661	-1.30684
10	20120101 7:00	0.160093085	1.230805461	-0.56783	1.376126	-0.74387
10	20120101 8:00	0.086045847	1.207785489	-0.23351	1.39424	-0.32409
10	20120101 9:00	0.059543217	1.220180859	0.315897	1.1231	0.223688
10	20120101 10:00	0.014434204	-0.181823967	0.821006	-0.49864	0.642927
10	20120101 11:00	0	-2.126126208	0.985401	-2.46964	0.647809
10	20120101 12:00	0.009202974	-2.638763275	0.812488	-5.47991	1.12508
10	20120101 13:00	0.099122541	-3.903976345	-0.67899	-7.47242	-3.01579
10	20120101 14:00	0.369193814	-3.281109029	-3.70709	-5.37519	-7.9485
10	20120101 15:00	0.665697186	-3.067731597	-4.39746	-5.02084	-8.82441
10	20120101 16:00	0.660628238	-3.116427691	-4.79525	-5.10858	-9.25395
10	20120101 17:00	0.658992242	-2.760946202	-4.66237	-4.61102	-9.06304
10	20120101 18:00	0.659692559	-2.300546765	-4.44772	-3.82477	-8.88244
10	20120101 19:00	0.662296614	-1.83837656	-4.22157	-2.98192	-8.69261
10	20120101 20:00	0.659621529	-1.163714307	-3.90726	-1.71339	-8.32869
10	20120101 21:00	0.661434186	-0.70862717	-4.0789	-0.73582	-7.76519
10	20120101 22:00	0.657297691	0.5189571	-4.57208	0.713278	-7.08833
10	20120101 23:00	0.659713624	2.707625196	-5.12021	3.493731	-6.97606
10	20120102 0:00	0.660556339	3.499158076	-5.55675	4.525079	-7.44086

4.2 Solar Power Forecasting

Table 4.2 below represents the dataset used for solar power forecasting. The data sets are obtained from a solar PV power generation station Zone Identification number 1. The data table captures the relevant variables for 24 hours, on 1st January, 2012 from 1:00am to midnight 00.00am 2nd February, 2012. The datasets for solar forecasting as obtained from GEFCom2014. The numbers are explained as follows: - VAR78 is the total column liquid water (tclw) kg m^{-2} representing the vertical integral of cloud liquid water content. VAR 79 is the total column ice water (tciw) kg m^{-2} representing the vertical integral of cloud ice water content. 134 is the surface pressure (SP) Pa. VAR157 is relative humidity at 1000 mbar (r) % which is defined with respect to saturation of the mixed phase, i.e., with respect to saturation over ice below $-23\text{ }^{\circ}\text{C}$ and with respect to saturation over water above $0\text{ }^{\circ}\text{C}$. VAR164 is the total cloud cover (TCC) 0–1 derived from model levels using the model's overlap assumption. VAR165 is 10-metre U wind component (10u) m s^{-1} , VAR166 is 10-metre V wind component (10v) m s^{-1} . VAR167 is 2-metre temperature (2T) K, VAR169 is the surface solar rad down (SSRD) in J m^{-2} Accumulated field 175 is the surface thermal rad down (STRD) in J m^{-2} Accumulated field. VAR 178 is Top net solar rad (TSR) J m^{-2} Net solar radiation at the top of the atmosphere accumulated field. VAR228 is Total precipitation (TP) m Convective precipitation+ strati form precipitation (CP+ LSP). The dataset is normalized before use.

Table 4.2 Dataset for Solar Power Forecasting

ZONE ID	TIME STAMP	VAR78	VAR79	VAR134	VAR157	VAR164	VAR165	VAR166	VAR167	VAR169	VAR175	VAR178	VAR228	POWER
1	20120101 01:00	0.001966858	0.0036087	94843.625	60.221909	0.2446011	1.039334	-2.50304	294.4485	2577830	1202532	2861797	0	0.754103
1	20120101 02:00	0.00552449	0.03357481	94757.938	54.678604	0.4571376	2.482865	-2.99333	295.6514	5356093	2446757	5949378	0	0.555
1	20120101 03:00	0.03011322	0.13200879	94732.813	61.294891	0.7714294	3.339867	-1.98254	294.4546	7921788	3681336	8939176	0.001341	0.438397
1	20120101 04:00	0.057167053	0.11064529	94704.063	67.775284	0.9658662	3.106102	-1.44605	293.2615	9860520	4921504	11331679	0.002501	0.145449
1	20120101 05:00	0.051026557	0.18955994	94675	70.172989	0.9446687	2.601146	-1.90449	292.7329	11143097	6254380	13105558	0.003331	0.111987
1	20120101 06:00	0.036995962	0.0990448	94676.938	72.374039	0.6413534	1.333368	-1.72843	292.0771	11815767	7558415	14198503	0.00396	0.057244
1	20120101 07:00	0.080911219	0.12132263	94708.063	81.798737	0.7531424	1.457923	-1.03462	291.0693	12274591	8798617	14925342	0.00497	0.088718
1	20120101 08:00	0.03615883	0.1390686	94748.813	87.854065	0.7883384	2.374826	-1.08904	289.0735	12351290	10041167	15112951	0.006477	0.030064
1	20120101 09:00	0.036372229	0.07260895	94785.813	88.793488	0.5022746	1.985531	-0.96301	288.0313	12351290	11257316	15112951	0.006725	0.000128
1	20120101 10:00	0.014352933	0.03579712	94817.75	90.450668	0.5019183	1.999518	-0.93032	287.4058	12351290	12460132	15112951	0.006745	0
1	20120101 11:00	0.00538747	0.00450134	94847.375	90.676178	0.1567743	1.809739	-0.09818	286.3208	12351290	13599879	15112567	0.00675	0
1	20120101 12:00	0.000869751	0	94852.063	92.928909	0.0143433	1.354908	-0.92226	285.0354	12351290	14724565	15112567	0.00675	0
1	20120101 13:00	0	0	94810.625	94.989517	0.004364	1.256864	-1.15641	284.7332	12351290	15820126	15112567	0.00675	0
1	20120101 14:00	0	0	94758.125	94.810333	0	0.921034	-0.80404	284.4626	12351290	16911888	15112567	0.00675	0
1	20120101 15:00	0.001480103	0	94730.375	95.559967	0.0397644	0.62243	0.318149	284.1331	12351290	17989312	15112567	0.00675	0
1	20120101 16:00	0.005981445	0	94721.563	99.391953	0.3865967	-0.4045	1.343286	282.8701	12351290	19080544	15112567	0.00675	0
1	20120101 17:00	0.020294189	0	94707.75	99.679733	0.9373169	-0.49365	1.279655	282.8855	12351290	20227568	15112567	0.00675	0
1	20120101 18:00	0.043617249	0	94699.688	100.20709	0.9701233	-0.29845	1.204877	283.1572	12351290	21420224	15112567	0.006755	0
1	20120101 19:00	0.047782898	0	94733.313	99.531464	0.8930054	-0.12777	1.207767	283.3142	12351290	22618864	15112567	0.006763	0
1	20120101 20:00	0.043663025	0	94749.813	99.42308	0.891571	-0.23109	1.276311	283.1843	12351290	23790336	15112567	0.006772	0
1	20120101 21:00	0.04499054	0	94769	98.573013	0.6236877	-0.05542	1.248788	283.6531	12417521	24904848	15240341	0.006779	0.006346
1	20120101 22:00	0.038860321	0	94787.938	92.123108	0.8327942	-0.85174	0.972498	286.2585	12947510	26133136	15980090	0.006783	0.071538
1	20120101 23:00	0.035018921	0	94775.25	82.745255	0.9532928	-1.10296	0.310311	288.4182	13965544	27398656	17317616	0.006791	0.229167
1	20120102 00:00	0.074440002	0	94736.125	71.751297	0.9324646	-0.19305	-0.44757	290.2673	15464841	28768880	19196208	0.006801	0.346474

4.3 Load Power Forecasting

The dataset used for load demand forecasting is as shown in Table 4.3. The data obtained from the GEFCom2014-L represent the hourly historic load for a region with Zone ID number1 and the historic weather data variable for the ten weather stations within the same geographical region for a period of one week.

Table 4.3 Dataset for Load Demand Forecasting

ZONE ID	TIMESTAMP	LOAD	w1	w2	w3	w4	w5	w6	w7	w8	w9	W10
1	1112012 1:00	113.1	33	50	33	37	50	52	52	50	39	50
1	1112012 2:00	111.5	33	46	32	35	48	51	52	48	37	50
1	1112012 3:00	110.6	32	45	30	38	48	51	51	48	36	49
1	1112012 4:00	112.7	31	45	31	37	46	52	52	46	37	48
1	1112012 5:00	117.6	31	45	29	38	45	52	50	45	39	47
1	1112012 6:00	131.5	31	45	30	37	45	51	50	45	39	47
1	1112012 7:00	151.9	30	43	28	36	43	51	49	43	37	45
1	1112012 8:00	157.5	31	43	28	33	41	51	48	41	36	44
1	1112012 9:00	147.8	34	45	31	39	45	51	50	45	37	45
1	1112012 10:00	140.8	43	46	38	49	48	54	52	48	45	49
1	1112012 11:00	133.1	50	50	46	55	54	57	56	54	46	55
1	1112012 12:00	125	56	52	53	59	57	58	59	57	50	57
1	1112012 13:00	116.5	59	55	57	62	59	58	60	59	52	60
1	1112012 14:00	112.8	62	55	60	63	61	58	59	61	52	61
1	1112012 15:00	110.7	64	57	62	64	63	60	58	63	54	61
1	1112012 16:00	109.4	64	55	62	65	63	60	59	63	55	59
1	1112012 17:00	114.2	64	55	63	64	61	59	60	61	55	60
1	1112012 18:00	122.7	62	52	59	59	59	57	57	59	50	58
1	1112012 19:00	141.4	52	50	55	59	54	54	55	54	48	55
1	1112012 20:00	152.1	46	45	51	51	50	53	53	50	46	50
1	1112012 21:00	153.3	43	45	46	50	45	52	51	45	45	50
1	1112012 22:00	148.3	39	43	43	53	45	51	50	45	43	49
1	1112012 23:00	138	38	39	40	51	43	51	49	43	43	46
1	1122012 0:00	129.2	36	37	38	45	41	47	47	42	41	46

4.4 Net Load Forecasting

The output for hourly wind- solar- load forecasting models are presented in Table 4.4 be. This dataset represents the results obtained from the separate models for solar, wind power and load. The dataset was then used as input for net load forecasting model using Matlab 2018a. The data is already normalized and covers 24 hours forecasted data.

Table 4.4 Dataset for Net Load Forecasting

TIMESTAMP	Forecasted Wind Power	Forecasted Solar Power	Forecasted Load Demand
1112012 1:00	0.606382826	0.764368165	0.225524749
1112012 2:00	0.511254315	0.577596533	0.066846413
1112012 3:00	0.348344983	0.400917683	0.392035014
1112012 4:00	0.234243485	0.181862544	0.70340128
1112012 5:00	0.185966691	0.103439542	0.867956124
1112012 6:00	0.164580228	0.016924736	1.190165204
1112012 7:00	0.123178202	0.106626641	1.237831327
1112012 8:00	0.078826629	0.055215279	1.397284217
1112012 9:00	0.040683798	0.008645539	1.36467848
1112012 10:00	0.038536238	-0.026956533	1.38687903
1112012 11:00	-0.030851766	-0.029625858	1.437922859
1112012 12:00	0.041895724	-0.008009525	1.231358803
1112012 13:00	0.074443258	0.037181747	1.072413166
1112012 14:00	0.42619717	-0.012723822	0.707178771
1112012 15:00	0.60024652	-0.002475439	0.524585437
1112012 16:00	0.6735236	0.002122192	0.395596739
1112012 17:00	0.682471654	0.001354677	0.418940033
1112012 18:00	0.673479548	0.005751981	0.546136643
1112012 19:00	0.656115921	0.001929875	0.700166188
1112012 20:00	0.628379827	0.000956115	0.923988913
1112012 21:00	0.66786381	0.039287616	0.832441746
1112012 22:00	0.674573347	0.102266783	0.683523703
1112012 23:00	0.622902707	0.163958484	0.610725301
1122012 0:00	0.649423886	0.351554038	0.287494586

Figures 4.1 to 4.4 represent the graphs from the respective models; Wind power, solar power, Load demand and Net load models.

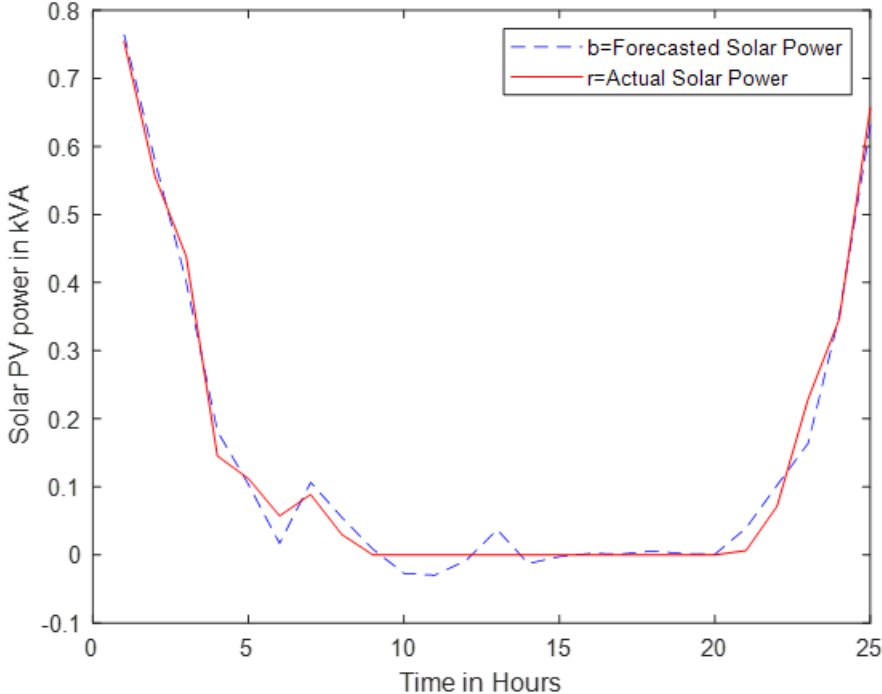


Figure 4.1: Forecasted Solar power

Figure 4.1 is a graph presenting the results obtained from Matlab 2018a tool after running the code. The forecasting was done for the next 24hour hours. The result show that from mid-day which is counted at hour 0 the power production will be decreasing toward zero production at 6 the hour in the evening the production is zero until after 12 hours, that is 6am in the morning the solar power generated increase to maximum in the mid-day. From the graph the forecasted power had minimal error compared to the actual generated power. The level of accuracy is determined by calculating the MAPE as per equation 4.2.

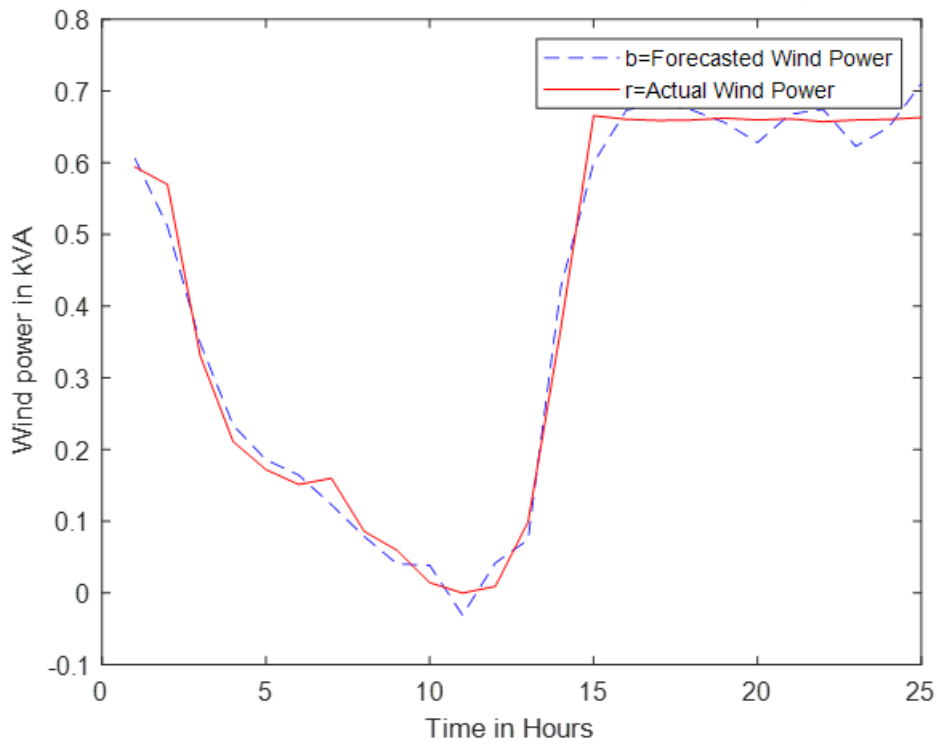


Figure 4.2: Forecasted Wind power

Figure 4.2 above present the result from wind power forecasting model. The forecasted power is distributed within the next 24 hours with low forecasted power production in the midday and peak forecasted power production in midnight. As can be seen in the graph the forecasted power indicated minimal error compared to the actual power produced. MAPE was used to determine the error.

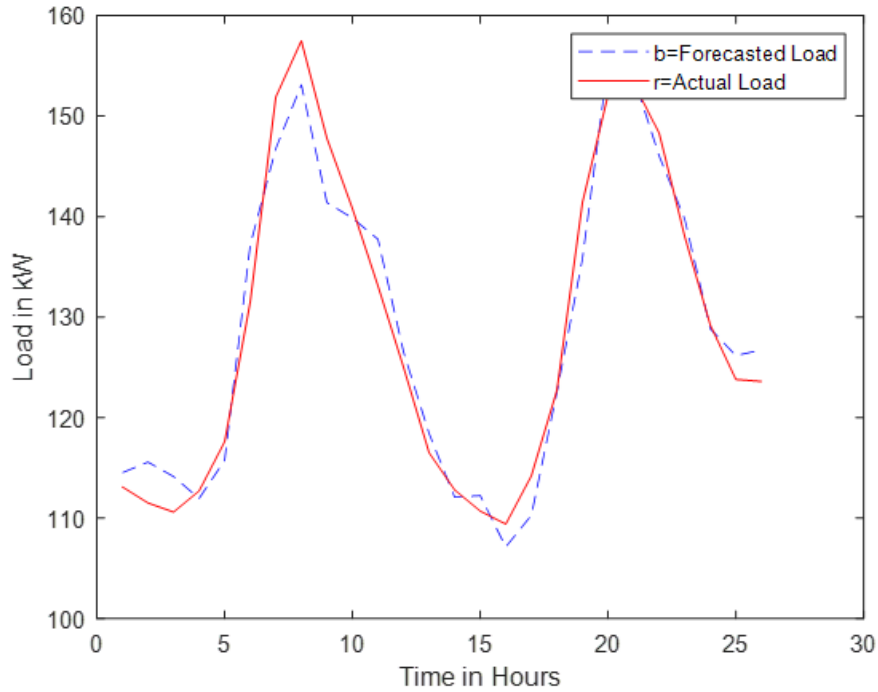


Figure 4.3: Forecasted Load demand

The result for Load demand forecasting model is as shown in Figure 4.3 with peaks and lows upon distribution within the next 24hours. The errors for electricity load demand is attributed to human behaviors as a factor affecting the usage of electricity. In this regard some people control their electricity utilization by manually controlling the electrical appliances in order to save on the electricity bills. In this thesis only weather variables and the specific day of the week were considered.

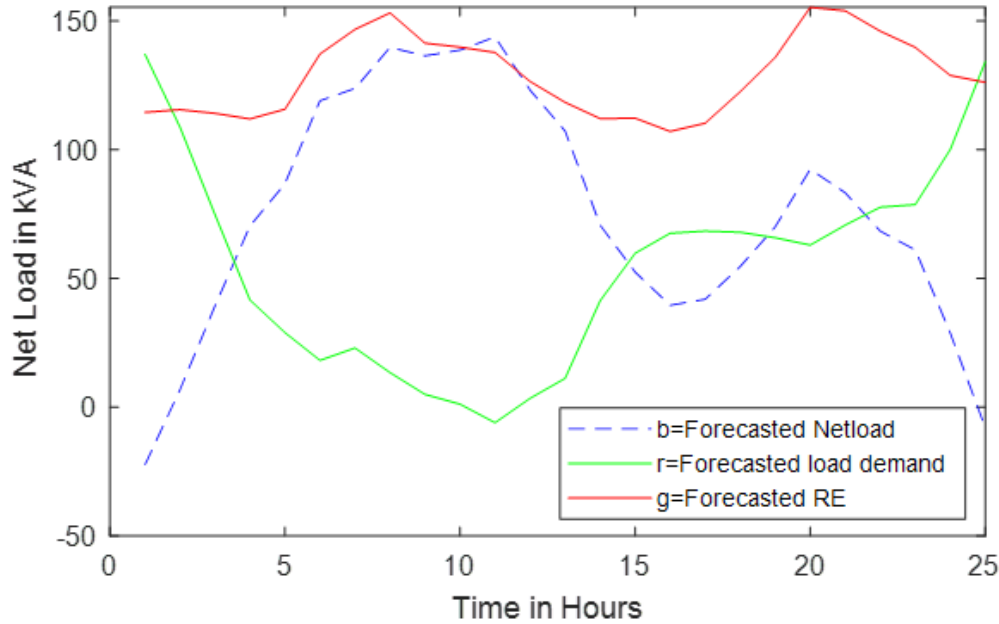


Figure 4.4: Forecasted Net load

Figure 4.4 represents the forecasted net load compared to the forecasted load demand and the total forecasted renewable energy. Negative net load means that the forecasted renewable energy is more than the forecasted load demand. Positive net load means that the forecasted load demand is more than the forecasted renewable energy generation. With positive netload, the power system requires additional power from either the grid or other sources of power supply in order to meet the load demand. The amount netload whether negative or positive can be ready from the graph any specific time withing the next 24 hours. The excess power is either stored or sold to the grid.

The reliability of the model was determined from the Mean Absolute Percentage Error (MAPE), as in equation 4.2 [1]:

$$MAPE = \frac{1}{N} \sum_{j=1}^N \frac{|P_a^j - P_f^j|}{P_a^j} \times 100 \quad (4.2)$$

Where; N denotes number of cases forecasted, P_a^j the actual power and P_f^j the amount of forecasted power. Several iterations are run until the minimum MAPE is achieved. Table 4.5 show the mean absolute percentage error for each of the forecasting model.

Table 4.5: Mean Absolute Percentage Error for the Forecasting Models

Forecasting Model	MAPE
Load demand forecasting	1.370%
Solar power forecasting	0.126%
Wind power forecasting	0.268%
Netload forecasting	0.782%

The results from the forecasting models indicate that the error from the actual values is very small. Table 4.6 show the value of MAPE from the literature of review of similar works done using different methodologies.

Table 4.6: MAPE Values from Literature Review of Similar works

Reference No.	Forecasting Technique Used	Value for M.A.P. E
[1]	feed-forward back propagation neural network (FFBPNN)	MAPE value of electricity demand, wind, and solar power forecasting respectively equal to 0.765%, 6.008%, and 6.414%;
[3]	NN-Modified LUBE	MAPE 14.31%
[4]	ANN	MAPE= 2.37%
[5]	Persistence model for net load forecast Integrated solar power (SVR and ARIMA) and net load forecast.	MAPE= 10.93% (Persistence) MAPE (AR) = 4.6% MAPE (SVR)= 5.47%
[6]	SVM- Grid GA searching	MAPE=2.06%

By comparing the performance of forecasting techniques Table 4.4 and Table 4.6 its evident that the models provided in this thesis using ANN-PSO are reliable. The Mean Absolute Percentage Error is lower comparing the values achieved in the previous works. Although the performance of ANN-PSO forecasting technique was excellent other factors captured in research gaps in previous works and problem formulation also contributed to lower values of MAPE.

4.5 Chapter Conclusion

In this chapter the results for the simulation are obtained. The curves show the forecasted dataset for the renewable power generation and load demand in a microgrid for the next 24 hours. The forecasted net load curve determines whether the forecasted power generation from renewable energy sources is sufficient for the forecasted load demand. The dataset used for forecasting was obtained from GEF2014 and is assumed to be from the same microgrid and same geographical area. The accuracy of the forecasting models was determined by the Mean Average Percentage Error. Compared to other methods in previous researches discussed in chapter 2, ANN-PSO performed better with lower percentages of mean absolute percentage error.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion and implications of the findings

Electric power grids and isolated power systems with high infiltration of renewable energy sources are faced with a challenge of predicting the expected amount of power generation from the renewable generators. This is due to the intermittent nature of weather variables that affect the power generation. It's imperative to have a reliable technique of forecasting power generated from solar and wind power generators and the load demand to aid the power supply managers and operators achieve a balance for supply-demand for power.

In this thesis a forecasting model for load demand, solar power and wind power were created for short term forecasting using ANN- PSO. The main objective was achieved by predicting the load, wind power generation, solar power generation for the next 24 hours. The results from the three models was integrated to determine the predicted net load on hourly basis using ANN- PSO modelling technique. The model is applicable in any micro grid power system that has high penetration of renewable energy. The results and performance of the forecasting models discussed in thesis research reveal that the models are effective and reliable, this because the value of the average MAPE that is used to determine the precision of the wind power, solar power, load demand and Net load forecasting models are 0.268%, 0.126%, 1.370% and 0.782% respectively.

5.2. Recommendations

In order to get more useful and practical results for foresting the netload a microgrid with high penetration of renewable energy its recommended that:

1. In this research work the dataset used for forecasting is assumed to be from the same geographical location therefore covering a micro grid. With the accurate precision discovered in this research, ANN-PSO can also be used for short term forecasting of load and power from renewable sources for a macro grid power system.
2. In this research work only the external factors affecting power generation have been captured and especially the stochastic variables affecting power generation. Other factors that can be determined from the power generators such efficiency of the solar PV

modules, the efficiency of the rotor turbine have not been considered, for accurate results these should be updated on the regularly.

5.3. Areas of Further Study

Further research can be done to explore the possibility of real time forecasting system that updates data online for the renewable energy production and load demand.

With increase of renewable energy generators in power systems whether micro or macro- grid the current studies and researches in forecasting for electricity demand, wind power and Solar pv power generation remain theoretical and are not used in experimented. Most of the researches in forecasting techniques focus on improving precision, algorithms, algorithm optimization there is still a lot to be done in developing products and technical solutions that can actual be applied in power systems.

Also, with the evolving technologies in artificial intelligence, research may be done on the cloud storage technology integrated with big data for power generation and load prediction to form a multi energy forecasting system that is comprehensive.

5.4 Contribution to Knowledge

This work has contributed to knowledge by providing a methodology that give more accurate forecasting solar power generation and wind power generation and Load demand while factoring the effect of weather variable for specific geographical location. Also, the determination of the netload for microgrid with high penetration in renewable energy using the ANN-PSO methodology which from the analysis of results proved to be reliable.

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APPENDICES

Appendix A: Matlab Based Simulation Code for Solar Power Forecasting

```
clc
tic
close all
clear all
rng default
%Import this excel file into the workplace with the sheets labeled as shown
filename = 'SolarData.xlsx';
%sheetname1 = 'Input variables';
%sheetname2 = 'Target Power generated';
%sheetname3 = 'Actual Solar power';
sheetname1 = 'Sheet1';
sheetname2 = 'Sheet2';
sheetname3 = 'Sheet3';

gbest = 0.0;

input = xlsread(filename,sheetname1,'A1:Z100001');

Y = xlsread(filename,sheetname2,'A1:Z10000');

ActualSolarPower=xlsread(filename,sheetname3,'A1:Z10000');

inputs=input';
targets=Y';

% Creating a Fitting Network
Hidden Layer Size = 15;
net = fitnet(hiddenLayerSize);

% Choosing Input and Output Pre/Post-Processing Functions

net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.outputs{2}.processFcns = {'removeconstantrows','mapminmax'};

% Setting up Division of Data for Training, Validation, Testing

net.divideFcn = 'dividerand'; % Divide data randomly
net.divideMode = 'sample'; % Divide up every sample
net.divideParam.trainRatio = 70/100; %70percent of the data will be used for training
net.divideParam.valRatio = 15/100; % 15percent will be used for validation
net.divideParam.testRatio = 15/100;% 15percent will be used for testing
```

```
% Training the Network
```

```
[net,tr] = train(net,inputs,targets);
```

```
% Testing the Network
```

```
outputs = net(inputs);
```

```
errors = gsubtract(targets,outputs);
```

```
performance = perform(net,targets,outputs);
```

```
Recalculating Training, Validation and Test Performance
```

```
train Targets = targets .* tr.trainMask{1};
```

```
val Targets = targets .* tr.valMask{1};
```

```
test Targets = targets .* tr.testMask{1};
```

```
train Performance = perform(net, trainTargets,outputs);
```

```
val Performance = perform(net,valTargets,outputs);
```

```
test Performance = perform(net,testTargets,outputs);
```

```
net=netff(minmax(inputs),(20,1,{'logsig','purelin','trainlm'}))
```

```
m=length(inputs(:,1));
```

```
o=length(targets(:,1));
```

```
n=10; net=feedforwardnet(n);
```

```
net=configure(net,inputs,targets);
```

```
kk=m*n+n+n+o;
```

```
for j=1:kk
```

```
    LB(1,j)=-1.5;
```

```
    UB(1,j)=1.5;
```

```
end
```

```
pop=10;
```

```
for i=1:pop
```

```
    for j=1:kk
```

```
        xx(i,j)=LB(1,j)+rand*(UB(1,j)-LB(1,j));
```

```
    end
```

```
end
```

```
maxrun=1;
```

```
for run=1:maxrun
```

```
    fun=@(x) myfunc(x,n,m,o,net,inputs,targets);
```

```
    x0=xx;
```

```
% pso initialization-----start
```

```
x=x0; % initial population
```

```
v=0.1*x0; % initial velocity
```

```
for i=1:pop
```

```
    f0(i,1)=fun(x0(i,:));m;
```

```
end
```

```
[fmin0,index0]=min(f0);
```



```

pbest=x0;          % initial pbest
gbest=x0(index0,:); % initial gbest
% pso initialization-----end
% pso algorithm-----start
c1=1.5;
c2=2.5;
ite=1;
maxite=500;
tolerance=1;
while ite<=maxite && tolerance>10^-8
    w=0.1+rand*0.4; % pso velocity updates
    for i=1:pop
        for j=1:kk
            v(i,j)=w*v(i,j)+c1*rand*(pbest(i,j)-x(i,j))...
                +c2*rand*(gbest(1,j)-x(i,j));
        end
    end % pso position update
    for i=1:pop
        for j=1:kk
            x(i,j)=x(i,j)+v(i,j);
        end
    end
    % handling boundary violations
    for i=1:pop
        for j=1:kk
            if x(i,j)<LB(j)
                x(i,j)=LB(j);
            elseif x(i,j)>UB(j)
                x(i,j)=UB(j);
            end
        end
    end
end

% evaluating fitness
for i=1:pop
    f(i,1)=fun(x(i,:));
end

% updating pbest and fitness
for i=1:pop
    if f(i,1)<f0(i,1)
        pbest(i,:)=x(i,:);
        f0(i,1)=f(i,1);
    end
end
end

```

```

[fmin,index]=min(f0); % finding out the best particle
ffmin(ite,run)=fmin; % storing best fitness
ffite(run)=ite; % storing iteration count

% updating gbest and best fitness

if fmin<fmin0
    gbest=pbest(index,:);
    fmin0=fmin;
end

% calculating tolerance
if ite>100;
    tolerance=abs(ffmin(ite-100,run)-fmin0);
end
% displaying iterative results
if ite==1
    disp(sprintf('Iteration   Best particle   Objective fun'));
end
disp(sprintf('%8g %8g      %8.4f',ite,index,fmin0));
ite=ite+1;
end
% pso algorithm-----end
xo=gbest;
fval=fun(xo);
xbest(run,:)=xo;
ybest(run,1)=fun(xo);
disp(sprintf('*****'));
disp(sprintf('  RUN  fval   ObFuVa'));
disp(sprintf('%6g %6g %8.4f %8.4f',run,fval,ybest(run,1)));
end
toc
% Final neural network model
disp('Final nn model is net_f')
net_f = feedforwardnet(n);
net_f=configure(net_f,inputs,targets);
[a b]=min(ybest); xo=xbest(b,:);
k=0;
for i=1:n
    for j=1:m
        k=k+1;
        xi(i,j)=xo(k);
    end
end
end
for i=1:n
    k=k+1;

```

```

    xl(i)=xo(k);
    xb1(i,1)=xo(k+n);
end
for i=1:o
    k=k+1;
    xb2(i,1)=xo(k);
end
net_f.iw{1,1}=xi;
net_f.lw{2,1}=xl;
net_f.b{1,1}=xb1;
net_f.b{2,1}=xb2;
%Calculation of MSE
err=sum((net_f(inputs)-targets).^2)/length(net_f(inputs))
%Regression plot
plotregression(targets,net_f(inputs))

disp('Trained ANN net_f is ready for the use');
%Trained ANN net_f is ready for the use
disp('Trained ANN net_f is ready for the use');
%Trained ANN net_f is ready for the use
%Test the Network
outputs = net_f(inputs);
errors = gsubtract(targets,outputs);
performance = perform(net_f,targets,outputs);
view(net);

%OUTPUT RESULTS
Forecasted_Solar_power = sim(net_f, input');

%mape1=abs(mean(abs(Y-Forecasted_load)./(Y)*100));
Ps = Forecasted_Solar_power;

z=Forecasted_Solar_power;

xlswrite('FSolar.xlsx',z(:));

%PLOTTING THE FORECASTED SOLAR PV POWER VERSUS ACTUAL SOLAR PV
POWER USING PSO
figure(2)
plot (Forecasted_Solar_power, 'b--');
hold on
plot(Y, 'r');
hold off
xlabel('Time in Hours')
ylabel(' Solar PV power in kW')

```

```

title('FORECASTED VERSUS ACTUAL SOLAR PV POWER')
legend('b=Forecasted Solar Power','r=Actual Solar Power')

%myfunc
function [f] = myfunc(x,n,m,o,net,inputs,targets)
Tref= 25 degrees % the reference temperature
 $\gamma$ =-0.47% % constant; the temperature coefficient set
 $\alpha$ = 0.11 % is a constant which is the product of the packing factor and efficiency module
IT= n:m % is the solar incident radiation
S= 80 % The insolation level valued in mW/cm2
NOCT= 1:50 % ambient air temperature in degrees
Tcell= Tair + (0.00125*NOCT-0.25) *S % The operating temperature
Ps= IT* $\alpha$ *(1- $\gamma$ *(Tcell-Tref)) % solar power output
k=0;
for i=1:n
    for j=1:m
        k=k+1;
        xi(i,j)=x(k);
    end
end
for i=1:n
    k=k+1;
    xl(i)=x(k);
    xb1(i,1)=x(k+n);
end
for i=1:o
    k=k+1;
    xb2(i,1)=x(k);
end
net.iw{1,1}=xi;
net.lw{2,1}=xl;
net.b{1,1}=xb1;
net.b{2,1}=xb2;
f=sum((net(inputs)-targets).^2)/length(inputs);

```

Appendix B: Matlab Based Simulation Code for Wind Power Forecasting

```
clc
tic
close all
clear all
rng default
% Import this excel file into the workplace with the sheets labeled as shown
filename = 'WindspeedData.xlsx';
%sheetname1 = 'Input variables';
%sheetname2 = 'Target Power generated';
%sheetname3 = 'Actual Wind power';
sheetname1 = 'Sheet1';
sheetname2 = 'Sheet2';
sheetname3 = 'Sheet3';

gbest = 0.0;

input = xlsread(filename,sheetname1,'A1:Z100001');

Y = xlsread(filename,sheetname2,'A1:Z10000');

ActualWindPower=xlsread(filename,sheetname3,'A1:Z10000');

inputs=input';
targets=Y';

% Creating a Fitting Network
hiddenLayerSize = 14;
net = fitnet(hiddenLayerSize);

% Choosing Input and Output Pre/Post-Processing Functions

net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.outputs{2}.processFcns = {'removeconstantrows','mapminmax'};

% Setting up Division of Data for Training, Validation, Testing

net.divideFcn = 'dividerand'; % Divide data randomly
net.divideMode = 'sample'; % Divide up every sample
net.divideParam.trainRatio = 70/100;% 70percent of the data will be used for training
net.divideParam.valRatio = 15/100; % 15percent will be used for validation
```

```
net.divideParam.testRatio = 15/100;% 15percent will be used for testing
```

```
% Training the Network
```

```
[net,tr] = train(net,inputs,targets);
```

```
% Testing the Network
```

```
outputs = net(inputs);
```

```
errors = gsubtract(targets,outputs);
```

```
performance = perform(net,targets,outputs);
```

```
Recalculating Training, Validation and Test Performance
```

```
train Targets = targets .* tr.trainMask{ 1 };
```

```
val Targets = targets .* tr.valMask{ 1 };
```

```
test Targets = targets .* tr.testMask{ 1 };
```

```
train Performance = perform(net,trainTargets,outputs);
```

```
val Performance = perform(net,valTargets,outputs);
```

```
test Performance = perform(net,testTargets,outputs);
```

```
%net=netff(minmax(inputs),(20,1,{'logsig','purelin','trainlm'}))
```

```
m=length(inputs(:,1));
```

```
o=length(targets(:,1));
```

```
n=10; net=feedforwardnet(n);
```

```
net=configure(net,inputs,targets);
```

```
kk=m*n+n+n+o;
```

```
for j=1:kk
```

```
    LB(1,j)=-1.5;
```

```
    UB(1,j)=1.5;
```

```
end
```

```
pop=10;
```

```
for i=1:pop
```

```
    for j=1:kk
```

```
        xx(i,j)=LB(1,j)+rand*(UB(1,j)-LB(1,j));
```

```
    end
```

```
end
```

```
maxrun=1;
```

```
for run=1:maxrun
```

```
    fun=@(x) myfunc(x,n,m,o,net,inputs,targets);
```

```
    x0=xx;
```

```
% pso initialization-----start
```

```
    x=x0; % initial population
```

```
    v=0.1*x0; % initial velocity
```

```
    for i=1:pop
```

```
        f0(i,1)=fun(x0(i,:));m;
```

```
    end
```

```

[fmin0,index0]=min(f0);
pbest=x0;          % initial pbest
gbest=x0(index0,:); % initial gbest
% pso initialization-----end
% pso algorithm-----start
c1=1.5;
c2=2.5;
ite=1;
maxite=500;
tolerance=1;
while ite<=maxite && tolerance>10^-8
    w=0.1+rand*0.4; % pso velocity updates
    for i=1:pop
        for j=1:kk
            v(i,j)=w*v(i,j)+c1*rand*(pbest(i,j)-x(i,j))...
                +c2*rand*(gbest(1,j)-x(i,j));
        end
        end % pso position update
    for i=1:pop
        for j=1:kk
            x(i,j)=x(i,j)+v(i,j);
        end
    end
    % handling boundary violations
    for i=1:pop
        for j=1:kk
            if x(i,j)<LB(j)
                x(i,j)=LB(j);
            elseif x(i,j)>UB(j)
                x(i,j)=UB(j);
            end
        end
    end
    % evaluating fitness
    for i=1:pop
        f(i,1)=fun(x(i,:));
    end
    % updating pbest and fitness
    for i=1:pop
        if f(i,1)<f0(i,1)
            pbest(i,:)=x(i,:);
            f0(i,1)=f(i,1);
        end
    end
end

```

```

[fmin,index]=min(f0); % finding out the best particle
ffmin(ite,run)=fmin; % storing best fitness
ffite(run)=ite; % storing iteration count

% updating gbest and best fitness

if fmin<fmin0
    gbest=pbest(index,:);
    fmin0=fmin;
end

% calculating tolerance
if ite>100;
    tolerance=abs(ffmin(ite-100,run)-fmin0);
end
% displaying iterative results
if ite==1
    disp(sprintf('Iteration Best particle Objective fun'));
end
disp(sprintf('%8g %8g %8.4f',ite,index,fmin0));
ite=ite+1;
end
% pso algorithm-----end
xo=gbest;
fval=fun(xo);
xbest(run,:)=xo;
ybest(run,1)=fun(xo);
disp(sprintf('*****'));
disp(sprintf(' RUN fval ObFuVa'));
disp(sprintf('%6g %6g %8.4f %8.4f',run,fval,ybest(run,1)));
end
toc
% Final neural network model
disp('Final nn model is net_f')
net_f = feedforwardnet(n);
net_f=configure(net_f,inputs,targets);
[a b]=min(ybest); xo=xbest(b,:);
k=0;
for i=1:n
    for j=1:m
        k=k+1;
        xi(i,j)=xo(k);
    end
end
end
for i=1:n

```



```

    k=k+1;
    xl(i)=xo(k);
    xb1(i,1)=xo(k+n);
end
for i=1:o
    k=k+1;
    xb2(i,1)=xo(k);
end
net_f.iw{1,1}=xi;
net_f.lw{2,1}=xl;
net_f.b{1,1}=xb1;
net_f.b{2,1}=xb2;
%Calculation of MSE
err=sum((net_f(inputs)-targets).^2)/length(net_f(inputs))
%Regression plot
plotregression(targets,net_f(inputs))

disp('Trained ANN net_f is ready for the use');
%Trained ANN net_f is ready for the use
disp('Trained ANN net_f is ready for the use');
%Trained ANN net_f is ready for the use
%Test the Network
outputs = net_f(inputs);
errors = gsubtract(targets,outputs);
performance = perform(net_f,targets,outputs);
view(net);

%OUTPUT RESULTS
Forecasted_Wind_power = sim(net_f, input');
z=Forecasted_Wind_power;
xlswrite('Fwind.xlsx',z(:));

%mape1=abs(mean(abs(Y-Forecasted_load)./(Y)*100));
Ps = Forecasted_Wind_power;
%PLOTING THE FORECASTED WIND POWER VERSUS ACTUAL WIND POWER
USING PSO
figure(2)
plot (Forecasted_Wind_power, 'b--');
hold on
plot(Y, 'r');
hold off
xlabel('Time in Hours')
ylabel(' Wind power in kW')
title('FORECASTED VERSUS ACTUAL WIND POWER')
legend('b=Forecasted Wind Power','r=Actual Wind Power')
%myfunc

```

```

function [f] = myfunc(x,n,m,o,net,inputs,targets)
k=0;
for i=1:n
    for j=1:m
        k=k+1;
        xi(i,j)=x(k);
    end
end
for i=1:n
    k=k+1;
    xl(i)=x(k);
    xb1(i,1)=x(k+n);
end
for i=1:o
    k=k+1;
    xb2(i,1)=x(k);
end
net.iw{1,1}=xi;
net.lw{2,1}=xl;
net.b{1,1}=xb1;
net.b{2,1}=xb2;
f=sum((net(inputs)-targets).^2)/length(inputs);

```

%Predicting the wind speeds at a height, ho=10meters above ground

```

VO = sim (net,input2)';
h= 20; %The height of our wind turbines
ho=10; %The height of the measured windspeeds
Vci = 3; %Our cut-in windspeeds, windspeeds below the cut in windspeed
% will lead to zero generation of power
Vco =25; %cut-out windspeeds, windspeeds above or equal to cut out will
%lead to zero generation. To prevent damage to our turbines from
%excess windspeeds.
alpha=0.6;%The ground surface coefficient
Cp=0.4; % Wind energy utilizing ratio
Area=0.5; % Area swept out by the rotating blades of radius 4meters
rho = 1.225; %density of air in Kg/m^3
V = VO*(h/ho).^alpha;
for(i=1:168)
if(VO(i)<Vci)
    PW = 0;
elseif(VO(i)>=Vci&& VO(i)<Vco)
    PW = 0.5*Area*rho*power(V,3)*Cp; %Gives us the theoretical power output of the turbines
elseif(VO(i)>Vco)
    PW=0;
end
end

```

Appendix C: Matlab Based Simulation Code for Load Forecasting

```
clc
tic
close all
clear all
rng default
%Import this excel file into the workplace with the sheets labeled as shown
filename = 'HourlyLoadData.xlsx';
%sheetname1 = 'Historical Hourly Load';
%sheetname2 = 'Target Data';
%sheetname3 = 'Actual Load';
sheetname1 = 'Sheet1';
sheetname2 = 'Sheet2';
sheetname3 = 'Sheet3';

gbest = 0.0;

input = xlsread(filename,sheetname1,'A1:Z100001');

Y = xlsread(filename,sheetname2,'A1:Z10000');

ActualLoad=xlsread(filename,sheetname3,'A1:Z10000');

inputs=input';
targets=Y';

% Create a Fitting Network
Hidden LayerSize = 10;
net = fitnet(hiddenLayerSize);

% Choose Input and Output Pre/Post-Processing Functions

net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.outputs{2}.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing

net.divideFcn = 'dividerand'; % Divide data randomly
net.divideMode = 'sample'; % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

net.trainFcn = 'trainlm'; % Levenberg-Marquardt
```

```

% mse taken as the Performance Function for the network

net.performFcn = 'mse'; % Mean squared error

% Train the Network
[net,tr] = train(net,inputs,targets);

% Test the Network
outputs = net(inputs);
errors = gsubtract(targets,outputs);
performance = perform(net,targets,outputs);

% Recalculate Training, Validation and Test Performance
trainTargets = targets .* tr.trainMask{ 1 };
valTargets = targets .* tr.valMask{ 1 };
testTargets = targets .* tr.testMask{ 1 };
trainPerformance = perform(net,trainTargets,outputs);
valPerformance = perform(net,valTargets,outputs);
testPerformance = perform(net,testTargets,outputs);

% net=netff(minmax(inputs),(20,1,{'logsig','purelin','trainlm'}))

m=length(inputs(:,1));
o=length(targets(:,1));
n=10; net=feedforwardnet(n);
net=configure(net,inputs,targets);
kk=m*n+n+n+o;
for j=1:kk
    LB(1,j)=-1.5;
    UB(1,j)=1.5;
end
pop=10;
for i=1:pop
    for j=1:kk
        xx(i,j)=LB(1,j)+rand*(UB(1,j)-LB(1,j));
    end
end
maxrun=1;
for run=1:maxrun
    fun=@(x) myfunc(x,n,m,o,net,inputs,targets);
    x0=xx;

% pso initialization-----start
x=x0; % initial population

```

```

v=0.1*x0; % initial velocity
for i=1:pop
    f0(i,1)=fun(x0(i,:));m;
end
[fmin0,index0]=min(f0);
pbest=x0; % initial pbest
gbest=x0(index0,:); % initial gbest
% pso initialization-----end
% pso algorithm-----start
c1=1.5;
c2=2.5;
ite=1;
maxite=500;
tolerance=1;
while ite<=maxite && tolerance>10^-8
    w=0.1+rand*0.4; % pso velocity updates
    for i=1:pop
        for j=1:kk
            v(i,j)=w*v(i,j)+c1*rand*(pbest(i,j)-x(i,j))...
                +c2*rand*(gbest(1,j)-x(i,j));
        end
    end % pso position update
    for i=1:pop
        for j=1:kk
            x(i,j)=x(i,j)+v(i,j);
        end
    end
    % handling boundary violations
    for i=1:pop
        for j=1:kk
            if x(i,j)<LB(j)
                x(i,j)=LB(j);
            elseif x(i,j)>UB(j)
                x(i,j)=UB(j);
            end
        end
    end
end

% evaluating fitness
for i=1:pop
    f(i,1)=fun(x(i,:));
end

% updating pbest and fitness
for i=1:pop
    if f(i,1)<f0(i,1)

```

```

        pbest(i,:)=x(i,:);
        f0(i,1)=f(i,1);
    end
end

[fmin,index]=min(f0); % finding out the best particle
ffmin(ite,run)=fmin; % storing best fitness
ffite(run)=ite; % storing iteration count

% updating gbest and best fitness

if fmin<fmin0
    gbest=pbest(index,:);
    fmin0=fmin;
end

% calculating tolerance
if ite>100;
    tolerance=abs(ffmin(ite-100,run)-fmin0);
end
% displaying iterative results
if ite==1
    disp(sprintf('Iteration   Best particle   Objective fun'));
end
disp(sprintf('%8g %8g      %8.4f',ite,index,fmin0));
ite=ite+1;
end
% pso algorithm-----end
xo=gbest;
fval=fun(xo);
xbest(run,:)=xo;
ybest(run,1)=fun(xo);
disp(sprintf('*****'));
disp(sprintf('  RUN  fval   ObFuVa'));
disp(sprintf('%6g %6g %8.4f %8.4f',run,fval,ybest(run,1)));
end
toc
% Final neural network model
disp('Final nn model is net_f')
net_f = feedforwardnet(n);
net_f=configure(net_f,inputs,targets);
[a b]=min(ybest); xo=xbest(b,:);
k=0;
for i=1:n
    for j=1:m
        k=k+1;

```

```

        xi(i,j)=xo(k);
    end
end
for i=1:n
    k=k+1;
    xl(i)=xo(k);
    xb1(i,1)=xo(k+n);
end
for i=1:o
    k=k+1;
    xb2(i,1)=xo(k);
end
net_f.iw{1,1}=xi;
net_f.lw{2,1}=xl;
net_f.b{1,1}=xb1;
net_f.b{2,1}=xb2;
%Calculation of MSE
err=sum((net_f(inputs)-targets).^2)/length(net_f(inputs))
%Regression plot
figure(1)
plotregression(targets,net_f(inputs))
%plotperformance(net_f(inputs,ActualLoad),Legend('Forecasted Load','ActualLoad'))

disp('Trained ANN net_f is ready for the use');

%Trained ANN net_f is ready for the use
%Test the Network
outputs = net_f(inputs);
errors = gsubtract(targets,outputs);
performance = perform(net_f,targets,outputs);
view(net);

%OUTPUT RESULTS
Forecasted_load = sim(net_f, input');

%mape1=abs(mean(abs(Y-Forecasted_load)./(Y)*100));
Pd = Forecasted_load;
%PLOTING THE FORECASTED LOAD VERSUS ACTUAL LOAD USING PSO
figure(2)
plot (Forecasted_load, 'b--');
hold on
plot(Y, 'r');
hold off
xlabel('Time in Hours')

```

```
ylabel('Load in kW')
title('FORECASTED LOAD VERSUS ACTUAL LOAD')
legend('b=Forecasted Load','r=Actual Load')
```

```
z=Forecasted_load;
xlswrite('data.xlsx',z(:));
```

```
%myfunc
function [f] = myfunc(x,n,m,o,net,inputs,targets)
k=0;
for i=1:n
    for j=1:m
        k=k+1;
        xi(i,j)=x(k);
    end
end
for i=1:n
    k=k+1;
    xl(i)=x(k);
    xb1(i,1)=x(k+n);
end
for i=1:o
    k=k+1;
    xb2(i,1)=x(k);
end
net.iw{1,1}=xi;
net.lw{2,1}=xl;
net.b{1,1}=xb1;
net.b{2,1}=xb2;
f=sum((net(inputs)-targets).^2)/length(inputs);
```


Appendix D: Matlab Based Simulation Code for Net Load Forecasting

```
clc
tic
close all
clear all
rng default
filename = 'Fwind.xlsx';

Y = xlsread(filename,'sheet2','A1:A25');

filename2='FSolar.xlsx';
X = xlsread(filename2,'sheet2','A1:A25');
filename3='data.xlsx';
Z = xlsread(filename3,'sheet1','A1:A25');
R=X+Y;
Net_Load=Z-R;
A=Net_Load;
xlswrite('NetLoad.xlsx',A(:));
figure(2)
plot(Net_Load, 'b--');
hold on
plot(R, 'g');
hold on
plot(Z, 'r');
hold off

xlabel('Time in Hours')
ylabel(' Net Load in kW')
title ('FORECASTED NET LOAD')
legend ('b=Forecasted Netload','r=Forecasted load demand','g=Forecasted RE')

Ui=A = Net_Load;
for i=1:24, j=1:2;
if(Ui(i)<0)
fprintf('Borrow from grid %f \n', Ui(i))
elseif(Ui(i)>0)
fprintf('Transfer to Grid %f \n', Ui(i))
else
fprintf('Grid is stable %f \n')
end
end
```

Short-term Forecasting for Integrated Load and Renewable Energy in Micro-grid Power Supply

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Abstract—: For planning and operation activities, accurate forecasting of demand is very important in sustaining the load demand in the electrical power system. Recently there has been increased use of renewable energy and unlike other sources of electricity like diesel generators, estimation of power production from renewable sources is uncertain. Therefore, reliable techniques for forecasting renewable energy and load demand are of paramount importance. Several forecasting techniques have been researched on in the past and are classified into; physical, statistical and AI techniques. The proposed research involves forecasting integrated load and renewable energy (solar and wind) using Artificial Neural Network(ANN) and Enhanced Particle Swarm Optimization (EPSO) techniques. The output of this research is the predicted netload. The analysis of the results depicts ANN_EPSO as a reliable method for forecasting renewable energy and Load demand.

Index Terms— Artificial Neural Network, Enhanced Particle Swarm Optimization, Load Forecasting, Renewable Energy Forecasting.

I. INTRODUCTION

It is impossible to ignore the fact that renewable energy, recently, has substantially been introduced into the power system. Renewable energy has proved to be cost-effective and eco-friendly compared to other sources of energy. Despite the advantages of renewable energy, there have been a challenge in predicting power generation from solar and wind due to their intermittent nature. This is a subject of interest in research since the correct forecasting for renewable energy is imperative for planning and operation purposes [5].

Forecasting is the prediction of the future happening based on present and past trends of various inputs. There are three types of forecasting based on the period of prediction; short term forecasting (STF) which has estimation period of minutes, hours to a day, mid-term forecasting (MLF) has estimation period of several days, week to a month and long term forecasting (LTF) has estimation period of months to several years[2]. In this paper, short term forecasting for renewable energy and load will be discussed.

Forecasting for load and renewable energy is important for planning and operation purposes in the power system,

especially for generation allocation and unit dispatch for generators, marketing, and security system analysis [1].

The load demand is usually non-linear and renewable energy is usually intermittent and stochastic which makes the traditional method of forecasting less accurate and ineffective. Recently the Artificial intelligence and hybridized methods (optimization of AI and optimization techniques) have been used [3].

There has not been much attention given to the optimal net load forecasting for microgrid power systems that are highly infiltrated with renewable energy or that have a renewable energy source as the main supply of power.

The aim of this work is to provide an improved forecasting methodology for a hybrid system that integrates load demand, wind power, and solar power forecast. The main objective is to model integrated renewable energy (Wind and Solar power) and Load demand forecasting for the microgrid. Here, wind power, solar power, and load demand forecasting are done separately before integration using ANN-PSO. The results from the three models are used as input for the Netload forecasting model.

This paper is structured into four sections: Section 1 introduces the topic of research by giving a background of load and renewable energy forecasting. In section 2, a review of literature on previous similar research work is discussed. Section 3 covers the problem formulation for three forecasting models (Load, Solar, and Wind) and the formulation for Netload. The methodology is discussed in section 4, results and analysis are provided in section 5 and finally, the conclusion of the research is done in section 6.

II. LITERATURE REVIEW

Several pieces of research have been done on either load, solar, or wind forecasting separately using different methods. Each system and forecasting technique seeks to get closer to the actual values and to reduce the error between the forecasted values and the actual values. An overview of techniques used for forecasting load, wind, and solar have been discussed in [1], [9]. Separate models for forecasting

load, power generation from solar and wind using Artificial Neural Network Feedforward backpropagation have been discussed in [2]. In [5] the researchers developed a model that forecasts the net load using outputs from solar power forecasting and Load demand forecasting. Support Vector Machine and Autoregressive methods are used respectively. A combined forecasting model that incorporates load, wind power, and solar PV power using Support vector regression Method (SVR) and GA optimization has been presented in [6]. The historical data for load demand data, wind power, and solar power is added by considering wind and solar power as negative loads.

III. PROBLEM FORMULATION

We assume that the only renewable energy generators incorporated into the grid are solar and wind. Weather parameters such as the speed of wind and temperature are used to forecast wind power generation, besides; solar irradiance and humidity have been used to forecast solar power generation.

A. Wind power forecasting

The power output from wind is given by [15]:

$$P_w = \frac{1}{2} \rho A V^3 C_p \quad (1)$$

Where P_w is the ideal power harnessed by the rotor (W), A is swept area by the rotor (m^2), V is the velocity of wind (m/s) and C_p is the power coefficient.

Accounting for the variance in the increasing speed with height, the wind velocity V at turbine height h is given by [12]:

$$V = v_o \left(\frac{h}{h_o} \right)^\alpha \quad (2)$$

Where v_o is the reference wind speed at height h_o , α implies to the friction coefficient based on the ground surface (rough or smooth terrain). Therefore, the effect of land terrain is taken into consideration in the wind power forecast.

To determine the output of wind characteristics, we use the fitting equation illustrated by a sigmoid curve as:

$$P_w(v) = \begin{cases} 0 & 0 \leq V \leq V_{ci} \\ A + \frac{B-A}{1+\exp\left[\frac{C-V}{D}\right]} & V_{ci} < V < V_{co} \\ 0 & V_{co} < V \end{cases} \quad (3)$$

Where $P_w(v)$ is the wind power output for a speed V , v_{ci} is the cut-in speed, v_{co} the cut-out speed (cut-in and cut-out speeds are useful in addressing uncertainties in that we know the productive speeds of wind which lead to power generation). A , B denote asymptotes acting horizontally, C is the point of inflection on the curve and D represents the scale parameter.

A 24hr future wind forecasting is employed through the ANN approach. Statistical features will be used as inputs to the ANN-EPSo model by considering the cluster approach for

the network output [16], [17]. The input vector I is given as a function of W_{avg} , T_{avg} , W_{dir} , yd as:

$$I = [W_{avg}, T_{avg}, W_{dir}, yd] \quad (4)$$

Where W_{avg} the average velocity of wind for the past 24hrs, T_{avg} denotes the mean temperature for the past 24 h, W_{dir} represents the direction of wind for the last 24hrs and yd denotes the specific day of the year [16].

The parameters T_{avg} , W_{dir} , and yd are used to reduce uncertainty and improve accuracy. ANN model output gives the expected production of power for 24hrs ahead.

B. Solar Power Forecasting

The power output for a PV module is given by [9], [10];

$$P_s = I_T \alpha \{1 - \gamma(T_{cell} - T_{ref})\} \quad (5)$$

Where I_T is the solar incident radiation, α is a constant which is the product of the packing factor and efficiency module estimated to be about 0.11, T_{ref} is the reference temperature set at 25°C and γ is the temperature coefficient set at -0.47%. The operating temperature T_{cell} is given by [10]:

$$T_{cell} = T_{air} + (0.0125NOCT - 0.25)S \quad (6)$$

Where $NOCT$ is taken to be 50°C, T_{air} is the real-time data on the ambient air temperature and S is the insolation level valued at 80 mW/cm².

$$I = [I_T, T_{air}] \quad (7)$$

I_T and T_{air} will be the input variables I for the artificial neural network.

C. Forecasting the load demand

The load demand will also be predicted using ANN. EPSo algorithm will replace the inbuilt backpropagation algorithm for the training method in the ANN structure. This would help reduce the forecasting error of the ANN [11].

For accurate forecasting, the days of the week will be divided up as Monday type, Weekday type, Saturday type, and Sunday type. The input to the ANN will be as follows in equation 8;

$$L = [P_h, T_h, X_s] \quad (8)$$

Where P_h the historical is hourly load demand, T_h is the daily average temperature and X_s is the type of day. Type of day is divided up as Sunday, Saturday, and Weekday types.

Load data will be taken on an hourly basis, temperature on an hourly basis, and season input as a number from one to four.

The output will be the forecasted load for 24hrs ahead.

D. Net forecasted Load

To achieve the forecasted netload, the results from forecasted wind power, solar power generation and forecasted load demand are used as inputs. The forecasted power from the wind turbines and PV solar generators are treated as negative loads. The difference between the forecasted load demand and the forecasted power produced from renewable energy generators is considered the forecasted net load demand. The forecasted net load $NL(t)$ is important for the management of the total hourly energy balance.

$$NL(t) = Pd(t) - (P_w(t) + P_s(t)) \quad (9)$$

Where $Pd(t)$ is the forecasted load and $P_w(t)$ is the total forecasted power production by wind turbines and $P_s(t)$ is the forecasted solar power. If $NL(t) < 0$, there is an excess production compared to demand. Surplus energy is thus sold to the grid or managed by the energy management system. If $NL(t) > 0$, the load demand exceeds production and the difference is bought from the grid (this ensures there is no loss of power supply).

Total power required to be generated will be given by:

$$\sum_{i=1}^N P_w + P_s + \sum_i P_{grid} \geq P_D + P_{loss} \quad (10)$$

Where P_D is the forecasted total load power demand, P_{grid} is the total power supply from established traditional methods for example (hydropower) and P_{loss} is the transmission power losses.

Figure 1 represents the forecasting model for solar power, wind power, and load. The outputs are then used as inputs for the net load forecasting.

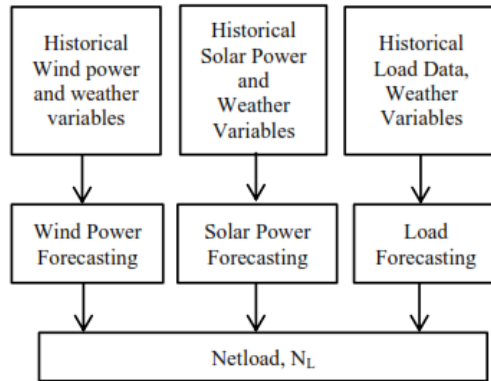


Figure 1: Proposed forecasting Model

IV. METHODOLOGY: ARTIFICIAL NEURAL NETWORKS (ANN) AND ENHANCED PARTICLE SWARM OPTIMIZATION (EPSO)

A. Artificial Neural Network (ANN)

ANNs are models that were developed based on the structure of the brain, inspired by the idea that the brain learns by experience. They are characterized by a parallel architecture comprising of neurons and a large degree of feedback [22].

The ANNs is comprised of numerous nodes and neuron that interconnect and interrelate with each other. Each node's output is called its activation or node value. Artificial Neural Network can learn weights and change their values.

B. Enhanced Particle Swarm Optimization

Particle swarm optimization is analogies of the birds going randomly to hunt for food; the birds nearest to the found food leave a hint or signal to attract the flock behind to the found food. [19]. If any other birds come closer to the target than the first, then they also give a signal until one of the birds in the flock stumbles upon the found the recursion of this reduction pattern continues.

Over several repetitions, a group of birds has their values adjusted closer to the member whose value is closest to the food at any given moment. This process is repeated until the best conditions or a food source is discovered. The process of optimization follows the work of these birds' behavior. The solution coordinates indicators and the speed of the particles as the optimal solution is approached is given by the velocity and the particle position. [21]. Birds are mapped as particles whereas signals as positions and velocities and finally foods being the solutions.

EPSO is used to optimize the ANN parameters.

Presentation of EPSO

The position and velocity of each particle are updated per iteration as follows:

$$V_{i,iter+1} = \omega V_{i,iter} + C_{1b} r_1 (P_{i,iter}^b - X_{i,iter}) + C_{1nb} r_2 (X_{i,iter} - P_{i,iter}^{notb}) + C_2 r_3 \quad (11)$$

$$X_{i,iter+1} = (X_{i,iter} + V_{i,iter+1}) \quad (12)$$

The coefficients C_{1b} and C_{1nb} are related to the 'b' and 'not-b' components.

C. Data preparation

The datasets used for load, solar, wind forecasting is obtained from Global Energy Forecast, GEFCOM2014. The dataset is covers a period of one month and is classified into hourly historical data and hourly records of weather variables for the respective forecasting models. It is assumed that data is obtain from the same region and that both solar PV and wind turbine generators are serving the same micro-grid

The input dataset is standardized to minimize the probability of getting stuck in local minima and local optima. It also helps in increasing the speed of training data.

The weather variables are normalized between a value of (-1 to +1) using min-max normalization.

$$Y_j = \frac{X_j - \text{Min}(x)}{\text{Max}(x)} \quad (13)$$

D. ANN-EPSO Forecasting Model

The ANN-EPSO model discussed in this paper is used to forecast wind power, solar power generation, load demand and the net load for the next 24hrs.

For modeling ANN_EPSO, Matlab 2018a is used. The Structure for ANN is developed as shown in figure 2. The network is created by defining and configuring the number of inputs, hidden layers, the number of neurons in each layer,

and the number of output. The activation function, biases and weights are defined and initialized. The Network is then trained using EPSO. EPSO optimizes the network by giving the optimum values for biases and weights of the ANN network. The output from each model; Load, wind power, and solar power forecasting model are used as input for the net load forecasting model.

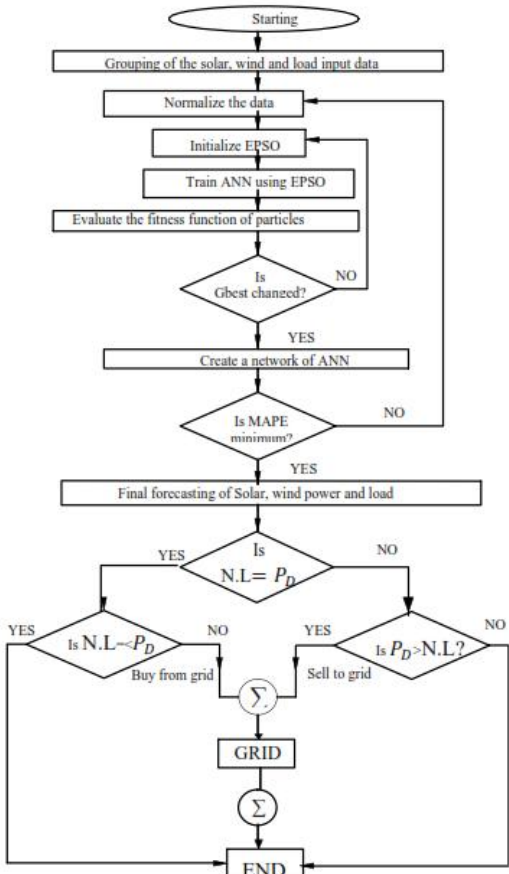


Figure 2: Flow-chart for Load, Wind and Solar forecasting using ANN- EPSO

V. RESULTS AND ANALYSIS

Figure 3-5 shows the graphs representing the simulated results, which depicts that the forecasting models are effective in predicting Load demand, wind power, and solar power generation since the curves of the predicted values are almost similar to one of the actual values.

The reliability of the model is determined from the Mean Absolute Percentage Error (MAPE), as in equation 14 [1]:

$$MAPE = \frac{1}{N} \sum_{j=1}^N \frac{|P_a^j - P_f^j|}{P_a^j} \times 100 \quad (14)$$

Where; N denotes the number of cases forecasted, P_a^j actual power, and P_f^j the amount of forecasted power.

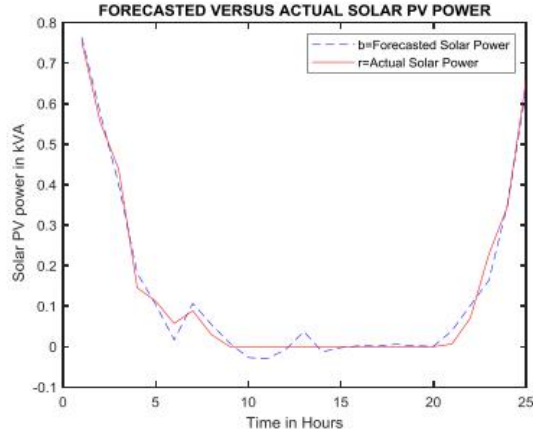


Figure 3: Forecasted Solar power

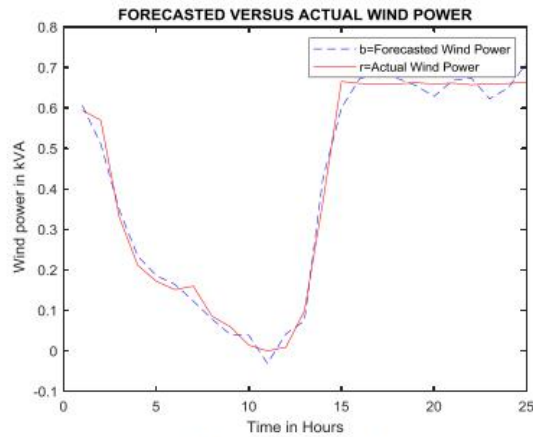


Figure 4: Forecasted Wind power

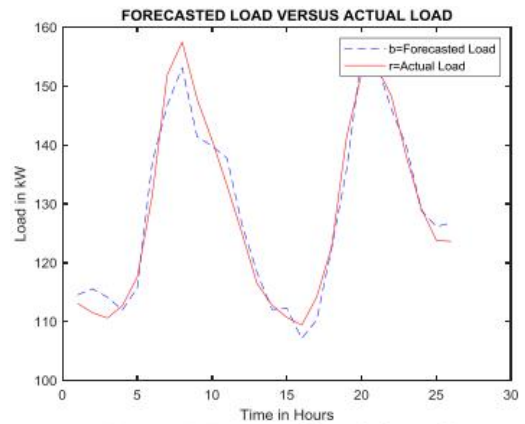


Figure 5: Forecasted Load demand

Table I: Mean Absolute percentage Error for the forecasting model

Forecasting Model	MAPE
Load demand forecasting	1.370%
Solar power forecasting	0.126%
Wind power forecasting	0.268%

The results indicate that the error from the actual values is small for the three forecasting models.

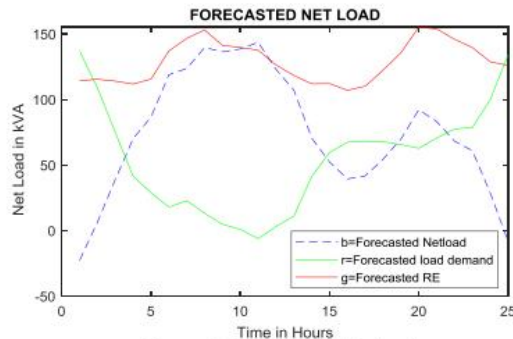


Figure 6: Forecasted Netload

Figure 6 represents the forecasted net load compared to the forecasted load demand and the total forecasted renewable energy. Negative net load means that the forecasted renewable energy is less than the forecasted load demand and therefore requires additional power from either the grid or other sources of power supply to meet the load demand. A positive net load means that the forecasted renewable energy generation is more than the forecasted load demand; the excess power is either stored or sold to the grid

VI. CONCLUSION AND RECOMMENDATION

Electric power grids and isolated power systems with high infiltration of renewable energy sources are highly faced with the challenge of predicting the expected amount of power generation from renewable generators. This is due to the intermittent nature of weather variables that affect power generation. In this research load demand, solar power and wind power generation are forecasted on separate models on hourly basis. The results from the three models integrated to predict the hourly net load for the power system. This model is applicable in any microgrid power system that has a high penetration of renewable energy. Based on the error indicators, the hybrid model using ANN-EPSo gives an improved performance compare to ANN model used in [2] and Support Vector machine model used in [6]. Further research can be done to explore the possibility of a real-time forecasting system that updates data online for renewable energy production and load demand.

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Appendix F: Plagiarism Report - Similarity Index

This thesis was scanned fully on Turnitin for similarity index check (All sections: Cover page, preliminary pages, all chapters, references page and appendices have been scanned. The overall similarity index is 14% all from internet sources.

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Dr Peter Musau, Supervisor. Signature:



Date: 01/11/2021

Appendix G: Table of Corrections Made on the MSC Thesis After Examination

S/N	RECOMMENDATIONS	CORRECTIONS DONE	MODIFIED SECTION OF THESIS	REF. PAGE
1.	Section 1.6, the research contribution be streamlined to showcase the novelty of the work.	Done as recommended	Section 1.6	Page 3
2.	Use portrait and re-do table 2.1 and include a column showing the title of the referenced paper, to help synthesize the contribution of the paper or use column one for the same.	Titles of the referred works has been added as recommended	Literature Review	Page 8
3.	Correct and reference the value C_p used in equation (2.1)	Done as recommended	Problem Formulation	Page 13
4.	Define PD in equation (2.19)	Done as recommended	Overall Formulation	Page 18
5.	Section 2.4 be moved to chapter 3, since they are methods and formulation without references	The problem formulations were meant to expand the research gaps and problem statement that had not been addressed by previous researchers. It's hence decided to keep these sections 2.3 and 2.4 immediately following the research gap for continuity of flow of ideas	Chapter 2: Literature	Page 13
6.	The research gap to be properly formulated since it is the one that streamlines the research niche.	The problem formulations were meant to expand the research gaps and problem statement that had not been addressed by previous researchers. As shown by sections 2.3 and 2.4 immediately following the research gap for continuity of flow of ideas	Chapter 2: Literature	Page 13
7.	Justify how the values of the selected parameters were chosen in mapping.	The vales are constants given in the equations as per the references.		Page 13,15

S/N	RECOMMENDATIONS	CORRECTIONS DONE	MODIFIED SECTION OF THESIS	REF. PAGE
8.	Chapter 3 to start with a flow chart of the entire methodology. This puts the chapter in perspective	A flow chart has been provided in section 3.1 as suggested (Figure 3.1)	Section 3.1	Page 22
9.	The whole of section 3.1 and 3.2 belongs to Literature Review and need to be moved there.	Moved to Literature Review as recommended	Section 2.5 and 2.6	Page 19
10.	After developing data in tables 3.4.1 to 3.4.4, where have they been applied?	Table 3.41 to 3.4.4 where applied in the ANN-PSO Algorithm	Appendix A, B, C, D	Page 49
11.	The methodology to be in tandem with the specific objectives.	Done as recommended		Page 27
12.	The key for Table 4.1 to be realigned for ease of eligibility	Done as recommended	Section 4.1	Page 35
13.	Clarify if the data used was obtained as already standardized, or was the standardization done in the current work.	The data was pre-processed; however, standardization and normalization of dataset was done in the current work.	Section 3.2.2	Page 19
14.	Check the use of the term “Reliability” introduction and address it sufficiently in the Results and Analysis (Chapter 4).	Done as recommended	Section 4.4	Page 44
15.	Explain/Discuss Figure 4.4 further. The statement “Negative net load means that the forecasted renewable energy is more than the forecasted load demand” should be quantified.	Explained as recommended	Section 4.4	Page 39
16.	Validate the Results “ANN-PSO performed better with lower percentages of mean absolute percentage error” This performance be explained.	Done as recommended	Section 4.4	Page 44
17.	Include a section on Contribution to Knowledge, say (5.4).	Done as recommended	Section 5.5	Page 46
18.	The conclusive remarks to show the key findings and how it relates with the specific objectives of the thesis.	Done as recommended	Section 5.1	Page 44