ANN Based Day-Ahead Load Demand Forecasting for Energy Transactions at Urban Community Level with Interoperable Green Microgrid Cluster

S. N. V. Bramareswara Rao*‡, Kottala Padma**

*Department of Electrical and Electronics Engineering, Sir C. R. R. College of Engineering, Eluru, West Godavari Dist., Andhra Pradesh-534007, India

**Department of Electrical Engineering, Andhra University College of Engineering (A), Visakhapatnam, Andhra Pradesh-530003, India

(snvbrao.eee@sircrrengg.ac.in, padma315@gmail.com)

‡ Corresponding Author: S. N. V. Bramareswara Rao; Department of Electrical and Electronics Engineering, Sir C. R. R. College of Engineering, Eluru, West Godavari Dist., Andhra Pradesh-534007, India, Tel: +91 810 610 8690,

snvbrao.eee@sircrrengg.ac.in

Received: 28.01.2021 Accepted:26.02.2021

Abstract- Microgrids are formed with the rapid penetration of renewable energy sources (RES) into the distribution grid (DG) network, which increases the complexity of DG system and at the same time the conventional grid is getting overloaded due to the urbanization. So, to reduce the stress on the utility grid and for safe and reliable operation of microgrid (MG), it is necessary to develop proper Energy Management System (EMS) with adequate real time control. With this motivation in this paper Artificial Neural Network (ANN) is used along with EMS in the proposed microgrid cluster for making energy transactions based on the availability of localized green energy sources. Energy management system uses day-ahead load demand forecasted by ANN for scheduling the energy sources and managing the energy transactions between the proposed system and utility grid during surplus/shortage power conditions. The cluster is formed by interconnecting two interoperable areas and each area associated with two microgrids. The proposed system with ANN in this paper is modeled and implemented in MATLAB software with Simulink and NN tool box. The simulated test results showed the accuracy of ANN for forecasting day-ahead load demand of the proposed system when compared with Linear Regression (LR).

Keywords: Renewable Energy Sources (RES), Distribution Grid (DG), Microgrid (MG), Artificial Neural Network (ANN), Energy Management System (EMS), Linear Regression (LR), Utility grid.

1. Introduction

In this present urbanization era, it is globally accepted reality that the 70% of world population moves towards urbanization by 2050 [1]. At the same time the emission of green house gases increases, from the past few years with the excessive usage of conventional fuels. Hence, researchers are looking for alternative sources of energy in order to meet the consumer energy requirements for sustainable growth in developing/ undeveloped countries. Now a days the definition of distribution grid is completely changed with the use of power electronic based microgrids. MG's are initially used as small power generating sources which are installed in the rural areas to supply the uninterruptable electricity, where there is no access to electrical power. Microgrids are interconnected with localized green energy sources such as 'solar', 'wind' and 'fuel cells', because these are cleaner in operation, more efficient and are located nearer to the site [2]. However the people in rural areas are also living with more sophisticated lives, so rural areas are also emerging as urban communities. This situation leads to create heavy burden on the conventional grid, so to decrease the additional stress on the utility grid researchers are focusing on clustering of adjacent microgrids with interoperability [3].

Microgrid cluster is the only solution to reduce the additional stress on utility grid created by urbanization with less cost, more reliability and scalability [4]. With the effective utilization of resources in order to improve the reliability and to reduce the cost neighboring microgrids are interconnected to share the power with other microgrids during excess/deficit power conditions [5, 6]. Protection strategies for improving the reliability in DC microgrids cluster was discussed by N. Bayati et.al [7].

S. Konar and A. Ghosh [8] discussed about DC microgrids interconnection for improving the reliability. These MG's are interconnected with BDC and multi winding transformer used. J. Mírez [9] proposed two DC microgrids interconnection which are associated with generations, loads and storage devices also the Central controller has been designed for communicating with other microgrids in the same network. M. L. Herrera et.al [10] proposed the possible interconnection configurations with two microgrids were along with control schemes, cost optimization schemes. This manages the power flow in the system considered. F. Díaz et.al [11] discussed different topologies and control approaches of interconnected microgrids along with update power electronic technologies. At the same time the operator at distribution grid network faces many challenges [12]with respect to centralized EMS for computing it in the real time and the task of decision making. Hence it is very important to employ proper distribution control to perform smooth operations and maintains the coordination between the adjacent MG's or in between cluster and conventional grid. Along with this, the accurate prediction of load demand and managing the availability of energy resources are needed for scheduling the transactions of energy between the adjacent microgrids in deregulated energy market. The major task of operating interconnected MG's is day-ahead load forecasting of energy sources and demand in that selected area or location. For having consistency in the operation, proper and accurate forecasting model [13] is required. With, the lack of knowledge in estimating (under) the loads leads to risk in operation and insufficient plant maintenance. Similarly, estimating (over) the loads leads to operating more number of units than required and purchasing the more power causes poor management of energy. So, in this regard following are some of the previous research works were carried out by the researchers.

A. K. Singh et.al [14] presented a review on load forecasting techniques such as short term, medium and long term by providing suitable methodologies based on the type of prediction. Later, authors in [15] used an application of artificial intelligence i.e., ANN for short term load forecasting of a microgrid performed by considering geographical location and electricity market [16]. Ramazan Bayindir et.al [17] presents hourly demand forecast of a high voltage feeder and comprehensive comparison was made by considering MA, WMA, ARMA, ARIMA models. However, A. Lahouar, J. Ben Hadj Slama in [18] discussed about day-ahead forecast of the load demand by considering random forest and expert selection as inputs. Later, authors in [19] performed the short term load forecasting by considering weather based machine learning technique, feed forward neural networks [20], Mean Absolute Percentage Error (MAPE) [21]. Moreover, Corentin Kuster et.al [22] has given a brief review on the short term and very short term forecasting models i.e. machine learning algorithms and time series analysis such as ARIMA and ARMA models. Later, W. Kuo et.al [23] proposed a novel frame work for short term load forecasting for energy management system of a microgrid. This consists of for strategies such as input parameter processing, exponential smoothing, peak load, and temperature factors. Judith Foster et.al [24] performed the day a head load demand forecasting for both linear and nonlinear models by considering new conditions such as auto regressive and exogenous inputs only models with regressors obtained from greedy selection method. J. Izzatillaev and Z. Yusupov [25] introduced two methods namely group method of data handling and ANN to predict the short term load demand for analyzing energy consumption, area of applicability and advantages and disadvantages of power consumption. However authors discussed, a fuzzy logic based intelligent power flow management was implemented with ANN for solar power forecasting [26], a hybrid deep learning framework for short term PV power forecasting in a time series manner in [27] and genetic wind driven optimization algorithm [28] and linear regression (LR) method [29] for day a head load demand fore casting.

The literature details discussed so far are limited to forecast the load demand of a single or two microgrids. In this paper a microgrid cluster is formed by interconnecting two areas and each area is associated with two microgrids. An efficient Energy Management System (EMS) is developed with 'Artificial Neural Network (ANN)' to make energy transactions. With the availability of green energy sources, this model is used to forecast the load demand along with scheduling for maintenance. The rest of the paper is arranged as follows: Section 2 describes the interconnected microgrid system and its constituents. Section 3 presents the proposed ANN structure and Energy Management System. The detailed analysis of simulated results was discussed in detail in Section 4 and conclusion is presented in Section 5.

2. Mathematical formulation of constituents

The architecture of interconnected microgrid system under study is as shown in Fig. 1. The cluster is formed by interconnecting two interoperable areas such as area-1 and area-2 which are further connected to conventional grid via the PCC. Each area consists of two microgrids which are interconnected and integrated with localized green energy sources available in that location. Each area is associated with a local MG controller, load demand forecaster i.e. ANN and Real Time Data (RTD) measurement. Proposed system is designed to work in both isolated and grid-connected modes. The intelligent predictor (ANN) in each area consists four inputs such as temperature, irradiance, wind speed and load demand.

2.1. Modeling of PV system:

Consider one diode model of PV system shown in Fig. 2 due to its adverse advantages. Mathematically it can be realized as given in Eq. (1) to Eq. (5) [30].

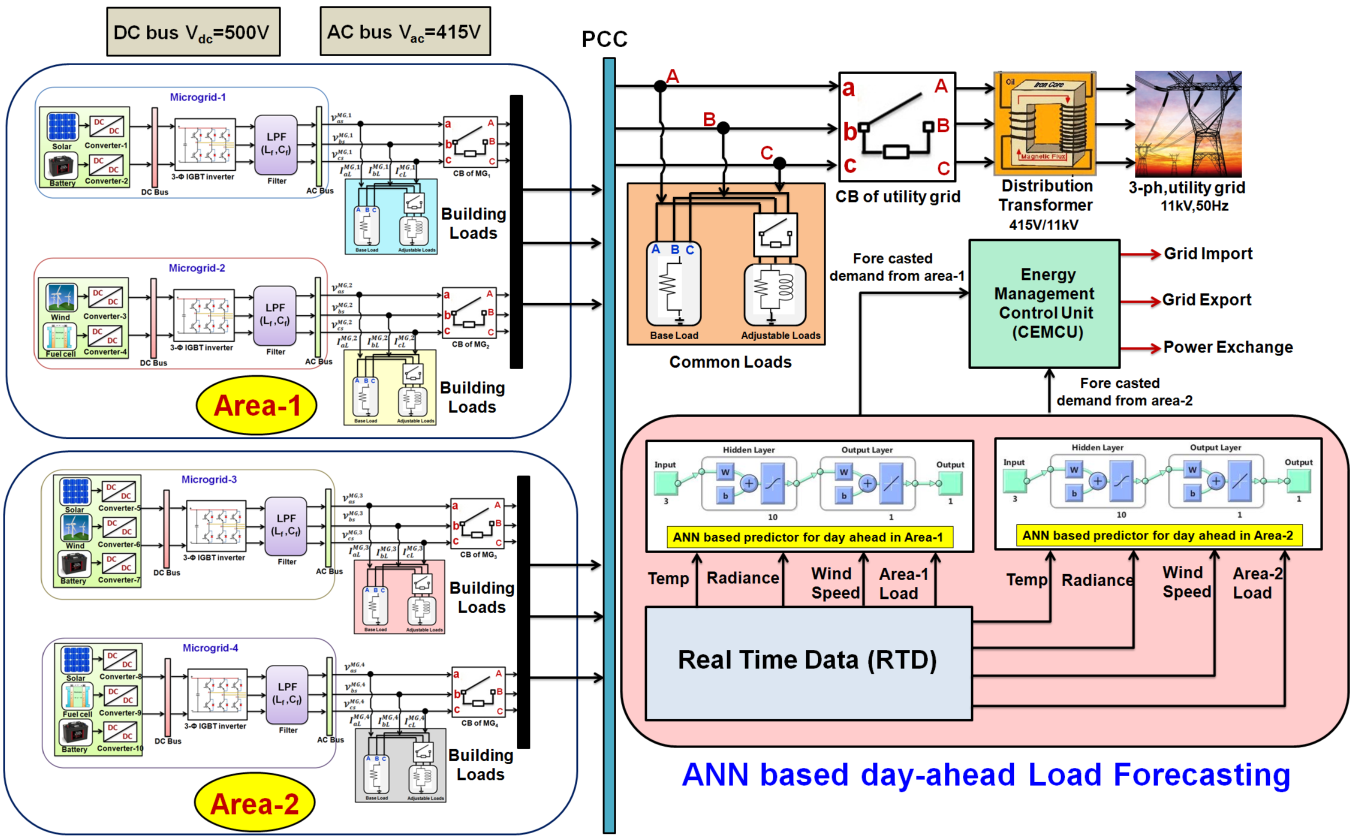

Fig. 1. General architecture of interconnected microgrids

From Fig. 2, we can obtain the mathematical equations for developing PV model in MATLAB/Simulink

$$\hat{I}_{ph} = \left[\hat{I}_{sc} + T_{sc}(T-298)\right] * \left(\frac{I_R}{1000}\right) \tag{1}$$

Here, $\hat{I}_{ph}$-photo current of module, $\hat{I}_{sc}$-short circuit current, T_{sc}-short circuit current temperature at 25^{0}C, 1000W/m^2, T- Module operating temperature in Kelvin and I_R is irradiance of PV cell. The reverse saturation current of PV module is calculated from Eq. (2).

$$\hat{I}_{rs} = \frac{\hat{I}_{sc}}{\exp(qV_{OC}/n_s kAT) - 1} \tag{2}$$

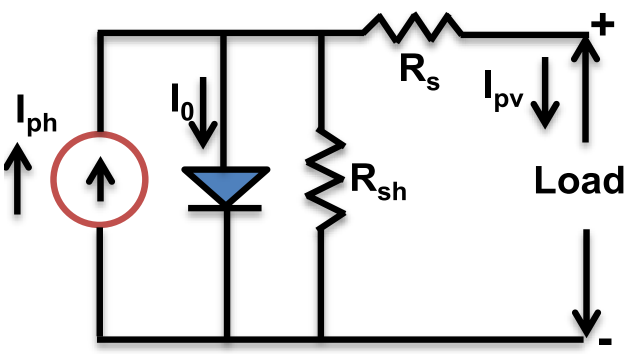

Fig. 2. Single diode model of PV system

Where, q - electric charge (1.6x 10^{-19} C), V_{OC} - open circuit voltage, k is Boltzman's constant (1.3805x10^{-23}J/K), n_s - PV cells connected in series, A - ideality factor are parameters considered for PV cell. The module saturation is varying with the temperature is given in (3).

$$\hat{I}_0 = \hat{I}_{rs}\left(\frac{T}{T_N}\right)^3 * \exp\left(\frac{qE_{g0}}{Ak}\left\{\frac{1}{T_N} - \frac{1}{T}\right\}\right) \tag{3}$$

Here, T_N - normal temperature (298.15 K) and E_{g0} - energy gap of semi conductor=1.1 eV. The output current of PV module is given in Eq. (4)

$$\hat{I} = n_p * \hat{I}_{ph} - n_p * \hat{I}_0 * \exp\left(\frac{q(V/n_s + I.R_s/n_p)}{A.\left(\frac{k.T_N}{q}\right)} - 1\right) - I_{sh} \tag{4}$$

$$\text{Where, } I_{sh} = \frac{1}{R_{sh}}\left(V.\frac{n_p}{n_s} + I.R_s\right) \tag{5}$$

Here, n_p - No. of PV cells in parallel, R_s - Series resistance (Ω), and V - Diode voltage of PV cell.

2.2. Modeling of wind turbine:

The energy (kinetic) of wind speed is converted to mechanical torque by rotor module and the power obtained from the wind turbine is computed by Eq. (6) [31, 32].

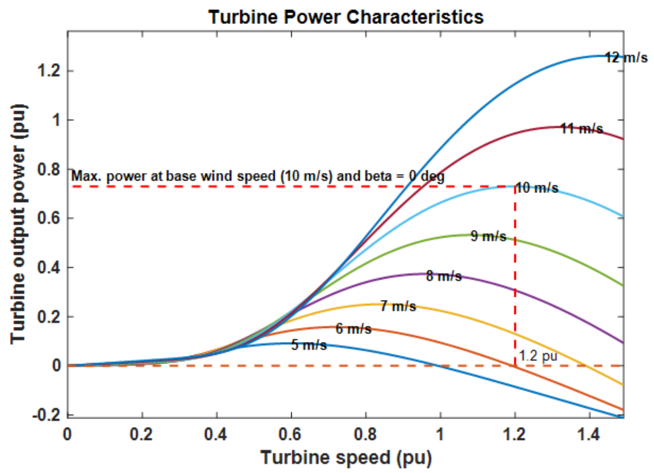

Fig. 3. Wind turbine speed vs. power characteristics

$$P_{wind} = 0.5.\tau_p.\rho.A_s.u^3 \tag{6}$$

Where P_{wind} - wind power, τ_p -coefficient of power, A_s - rotor area (swept) in m^2, ρ -density of air in kg/m^3 and u- wind speed in m/s. The characteristics of wind turbine are as shown in Fig. 3.

2.3. Modeling of fuel cell

The fuel cell output voltage is expressed as given in Eq. (7) [33].

$$V_{fc} = E_{NER} - V^{act} - V^{ohm} - V^{conc} \tag{7}$$

Where, E_{NER} - Nernst voltage, V^{act} - actual loss, V^{ohm} - ohmic loss and V^{conc} - concentration losses of fuel cell (PEM). By substituting standard values we get fuel cell voltage (reverse) as given in Eq. (8),

$$E_{NER} = 1.3 - 0.85 * 10^{-3}(\tau - 298) + 4.31 * 10^{-5} * \tau(\ln(\rho H_2) + 0.5\ln(\rho O_2)) \tag{8}$$

2.4. Modeling of a battery

The generic battery described in this section is modeled as controllable dc source (ideal) is in series with resistance (internal). The non linear model of the battery considered in this paper is as shown in Fig. 4, and the battery no load voltage can be obtained as given in Eq. (9), Eq. (10) [34].

$$E = \left(E_0 - K\frac{Q}{Q - \int idt}.i + A_1.\exp(-B.\int i.dt) \right) \tag{9}$$

$$V_{batt} = E - R.i_{batt} \tag{10}$$

Where, E_0 - constant voltage, K - polarization voltage, Q - capacity in Ah, A_1, B are the parameters related to the battery

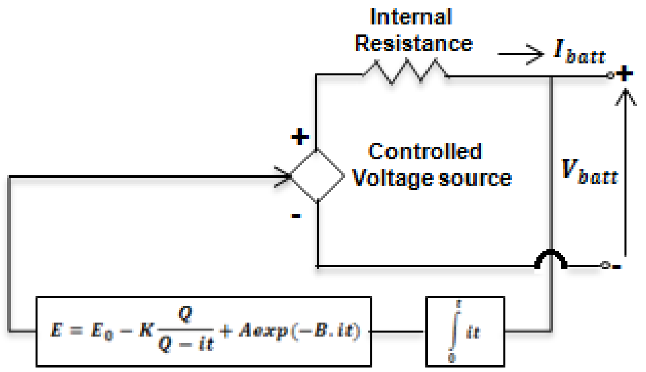

Fig. 4. Non linear model of the battery

2.5. Modeling of DC/DC converter

The renewable sources such as solar, wind are considered to be free sources and are intermittent in nature. These sources produce fluctuating voltage at its output and which is not sufficient to meet the power requirements. So, to obtain constant voltage for grid connected RES it is very essential to design DC/DC converter [35] properly.

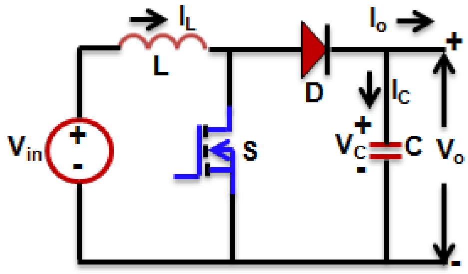

Fig. 5. Equivalent circuit of boost converter

The equivalent circuit of converter is shown in Fig. 5. Consider I_L and V_C are two state variables and modeling boost converter can be obtained by considering average state space model of converter in continuous current conduction mode given in Eq. (11), Eq. (12).

$$\begin{bmatrix} \frac{dI_L}{dt} \\ \frac{dV_C}{dt} \end{bmatrix} = \begin{bmatrix} 0 & \frac{-(1-\delta)}{L} \\ \frac{(1-\delta)}{C} & \frac{-1}{RC} \end{bmatrix} \begin{bmatrix} I_L \\ V_C \end{bmatrix} + \begin{bmatrix} \frac{1}{L} \\ 0 \end{bmatrix} V_{in} \tag{11}$$

$$V_0 = \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} I_L \\ V_C \end{bmatrix} \tag{12}$$

2.6. Modeling of DC/AC converter

The power electronic inverters play an important role in distributed generation systems. The MATLAB/Simulink model for implementing conventional DC/AC converter or inverter is shown in Fig. 6. In this work three phase five level multi level inverter (MLI) is considered [36].

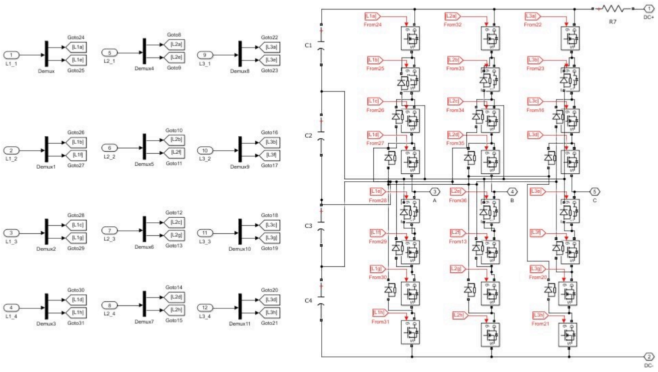

Fig. 6. Conventional MLI implemented in Simulink

3. Proposed Methodology

3.1. Structure of Artificial Neural Network (ANN):

The concept of ANN was used in different applications from past several years, due to their capacity in forecasting the data and effective controlling the system response. It is the best method to find the solution for nonlinear problems in real time.

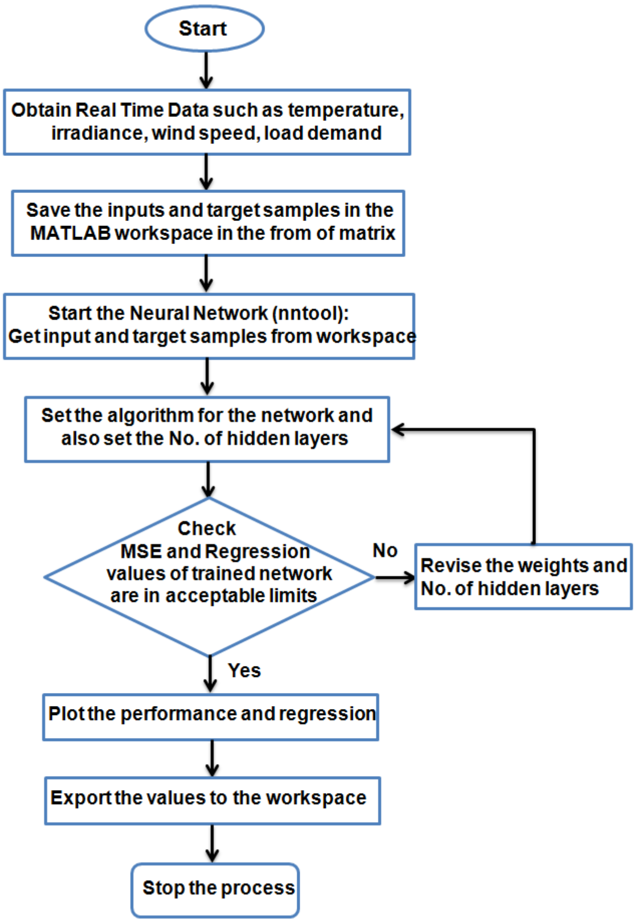

Fig. 7. Flow chart of ANN implemented in MATLAB

Some important aspects of ANN are listed below.

- ANN is faster in operation and more reliable.
- ANN allows modeling the parameters of large systems without complex mathematical framework and experimental data.
- ANN is a non linear model, due to the nonlinearity it is easily implemented, when compared it with other statistical methods.

ANN can be easily adopted for complex problems. The sequence of steps to be followed to train the ANN are given as,

1) *Selection of input samples*: Temperature, Diffused Horizontal Irradiance (DHI), Wind speed and load demand of selected location are considered as input samples to ANN.
2) *Selection of hidden layers:* Number of hidden layers depends up on the complexity of the system. In this paper one hidden layer is considered with 10 neurons. In general number of neurons is the mean integer value of input and output.
3) *Selection of activation function*: Tan sigmoid transfer function is used for hidden layer and pure linear transfer function is used for output layer.

The developed ANN is trained with 'Levenberg-Marqurardt Feed Forward Back Propagation Algorithm'. The flow chart for training ANN in MATLAB environment is as shown in Fig. 7. From the feed forward network, the relation between output, input, hidden outputs can be obtained using Eq. (13),

$$\psi_k = \zeta_n\left(\sum_{j=0}^{h} \omega(n)_{\theta j} \cdot \rho_j\right) \tag{13}$$

$$\text{Where, } \rho_j = \zeta_{n-1}\left(\sum_{i=0}^{N} \omega_{(n-1)ji}\,\mu_i\right) \tag{14}$$

Here, N - input layer dimensions, h - hidden layer dimensions, k - output layer dimensions, $\omega_{(n)\theta j}$ - output layer weights, $\omega_{(n-1)ji}$ - hidden layer weights of, ζ_n - activation function.

3.2. Development of Energy Management System (EMS):

The flow chart of Energy Management System (EMS) used for energy transactions between the two interconnected areas in the cluster and microgrid controller are as shown in Fig. 8, Fig. 9. Consider $\Delta P_{area,1}$ is the total power difference in area-1, which is obtained using Eq. (15) and Eq. (16)

$$\Delta P_{area,1} = P_1 + P_2 \tag{15}$$

$$\text{Where, } P_1 = P_{G,1} - P_{D,1} \text{ and } P_2 = P_{G,2} - P_{D,2} \tag{16}$$

In the Eq. (16), $P_{G,1}$ and $P_{G,2}$ are the total power generations and $P_{D,1}$ $P_{D,2}$ are the total demand powers of MG_1, MG_2.

Similarly, $\Delta P_{area,2}$ is the total power difference in area-2 which is calculated using Eq. (17) and Eq. (18)

$$\Delta P_{area,2} = P_3 + P_4 \tag{17}$$

$$\text{Where, } P_3 = P_{G,3} - P_{D,3} \text{ and } P_4 = P_{G,4} - P_{D,4} \tag{18}$$

In the Eq. (18), $P_{G,3}$ and $P_{G,4}$ are the total power generations and $P_{D,3}$ $P_{D,4}$ are the demand powers of *MG3*, *MG4*. The ANN predicts the load demand in each area based on the real time data obtained from measuring devices. The predicted data of two areas are input signals to EMS.

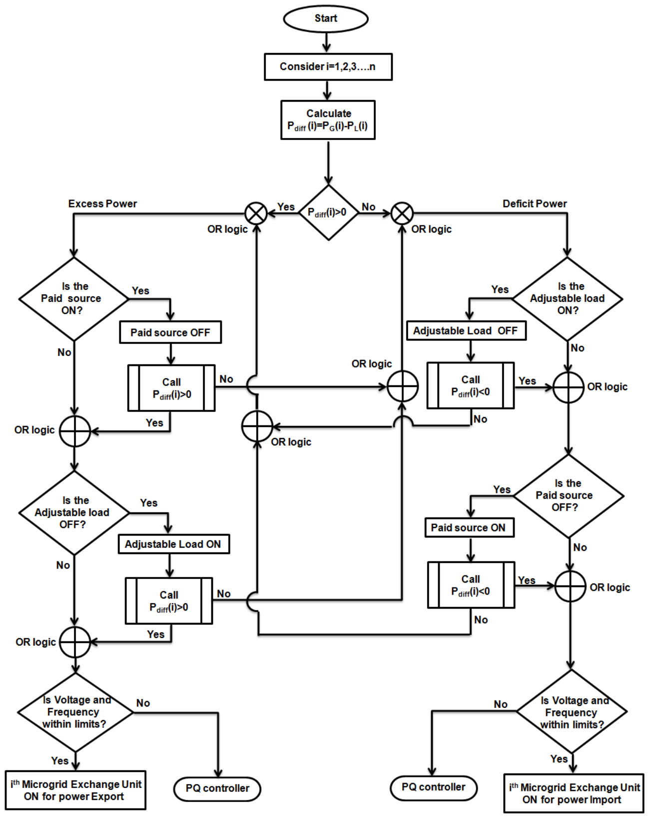

Fig. 8. Flow chart of MG controller implemented in MATLAB/Simulink

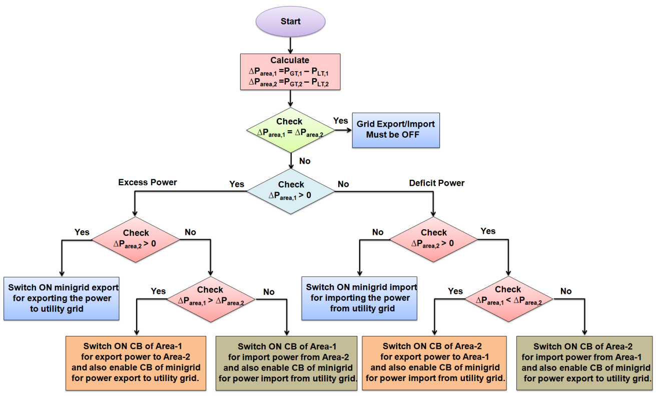

Fig. 9. Flow chart of EMS implemented in Simulink

Correspondingly it operates the circuit breaker (CB) of MG cluster to make transactions with utility grid during surplus/shortage of power conditions. The operation of EMS is explained as follows,

Step 1: Calculate $\Delta P_{area,1}$ and $\Delta P_{area,2}$.

Step 2: Check the condition $\Delta P_{area,1} = \Delta P_{area,2}$ is satisfied or not.

Step 3: if step 2 is holds good then EMS will disable the MG cluster export/import, otherwise go to step 4.

Step 4: 1) if $\Delta P_{area,1} > 0$ is satisfied, it indicates that excess power is available in area-1. Then EMS checks the condition $\Delta P_{area,2} > 0$, if it satisfies then CB of cluster is ON for export the power to utility grid. If the condition $\Delta P_{area,2} > 0$ does not holds good then EMS checks whether $\Delta P_{area,1} > \Delta P_{area,2}$ is satisfied or not, if the condition is true then the CB of area-2 is ON to import the power from area-1 and CB of cluster is ON for export the power to utility grid. Similarly if the condition $\Delta P_{area,1} > \Delta P_{area,2}$ does not satisfies then CB of area-1 is ON for import the power from area-2 and CB of cluster is ON to import the power from utility grid.

2) If the condition $\Delta P_{area,1} > 0$ is not satisfied, then it indicates that deficit power is available in area-1. EMS checks the condition $\Delta P_{area,2} > 0$, if it is true then again EMS again checks the condition $\Delta P_{area,1} < \Delta P_{area,2}$ is satisfied or not, if it is satisfied then the CB of area-2 is ON to export the power to area-1 and CB of microgrid cluster is ON for import the power from utility grid. Similarly, if the condition that $\Delta P_{area,1} < \Delta P_{area,2}$ does not satisfies then CB of area-1 is ON for export the power to area-2 and CB of microgrid cluster is ON to export the power to utility grid.

Step 5: Stop the process.

4. Analysis of Simulated results and Discussion

The MATLAB/Simulink modeling of microgrid cluster with proposed ANN is as shown in Fig. 10. Proposed system is divided into two interoperable areas with four urban community microgrids viz., *MG1, MG2, MG3, MG4*, area-1 is associated with *MG1, MG2* and area-2 is associated with *MG3, MG4* along with their building loads. Each *MG* is equipped with a switch gear mechanism controlled by EMS before it connects with adjacent *MG* or with other *MG's* in other area; further the two areas are connected to utility grid via the PCC and switch gear mechanism.

4.1. Performance validation and Regression analysis of ANN in two areas:

We have simulated the microgrid cluster, by considering the real time values obtained from RTD. We have collected

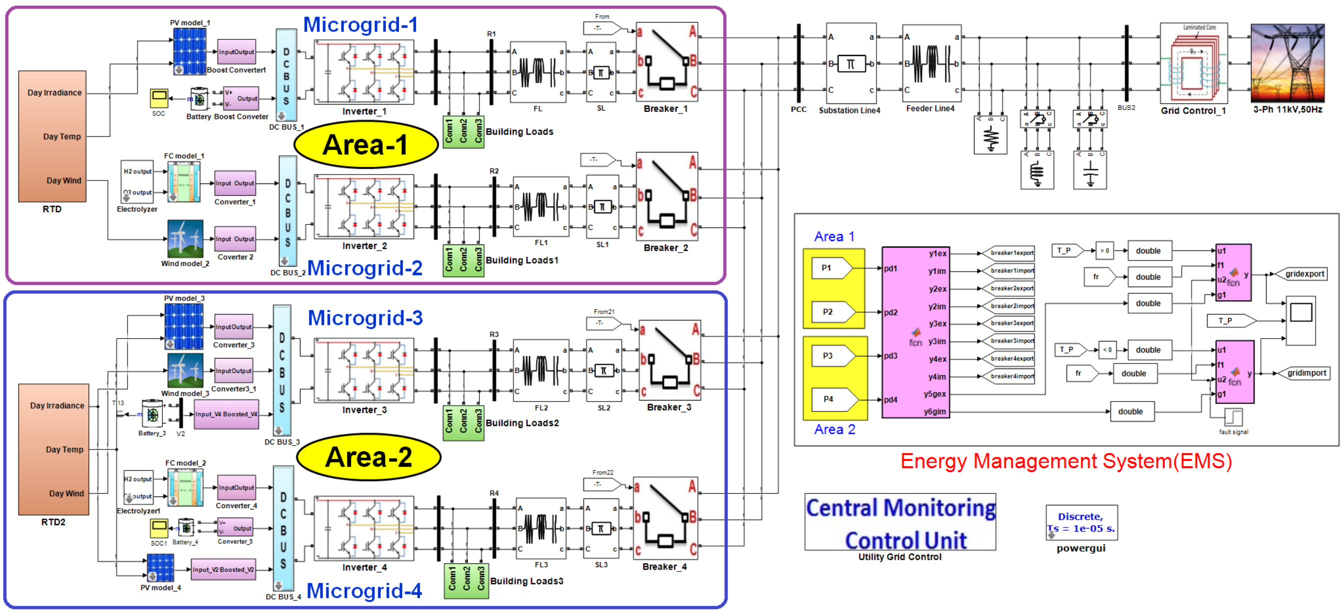

Fig. 10. MATLAB/Simulink implementation of microgrid cluster with ANN and EMS

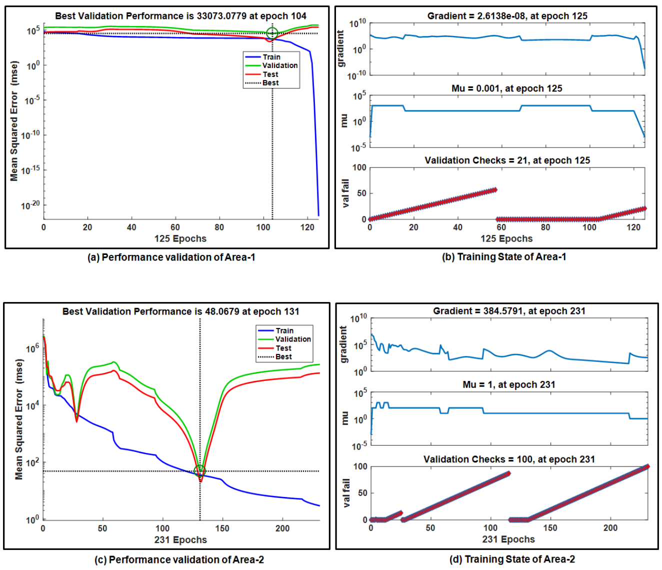

Fig. 11. Performance validation and Training state plots of area-1 and area-2.

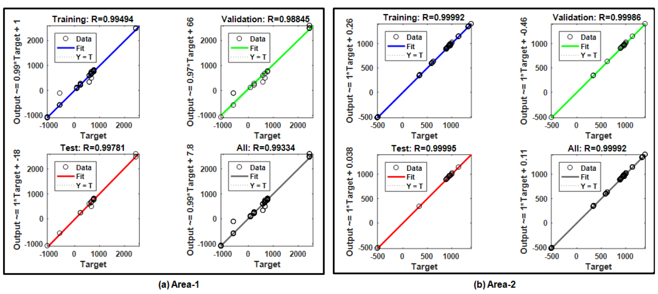

Fig. 12. Regression plots of area-1 and area-2

the information of solar and wind parameters from the location of Vijayawada city in the state of Andhra Pradesh, India [37] with a Location ID: 44665, Latitude-16.55^0 and Longitude -80.55^0. The performance of ANN can be obtained by calculating mean square error (MSE) value given in Eq. (19).

$$MSE = \frac{\sum_{1}^{k} \mu_a - \mu_b}{k} \tag{19}$$

Where, μ_a -Measured value, μ_b - Predicted value, k - No. of the patterns used. From Fig. 11, it is observed that the best performance of the system connected in area-1 is obtained at epoch 104 and for area-2 it is obtained at epoch 131. Figure 12 shows the regression plots of area-1 and area-2 and from the obtained results in simulation it is observed that, how effectively the data is fitted. The value obtained from regression indicates the relation between target samples and output samples with respect to data training, data validation and test data. In the regression plot, if R=1 indicates the line lies at an angle of 45^0 with respect to x-axis, which means that both target and output are equal. The value of 'R' may be one when there may be a close relationship between output sample and target values. In the case of specified location, in both areas the regression values are above 0.98 which means that the curve fitting is reasonably valid.

4.2. Measured and forecasted load demands with LR and ANN:

Consider the microgrid cluster is operated in grid connected mode. Unscheduled static test loads are incorporated in MG_1, MG_2 of area-1 and MG_3, MG_4 of area-2 at different instants of time from t=0sec to 0.55sec along with the actual load demands. Figure 13 shows the load profiles (actual and predicted) of area-1 and area-2 for 24 hrs duration. The real time values of solar and wind parameters and load demand at the foresaid location from 10/01/2019 to

15/01/2019 are considered. The measured values of load demands of microgrid cluster is considered as the benchmark for comparison of forecasted loads using proposed ANN and Linear Regression (LR) in time series model.

LR in statistics is a linear approach to estimate the relation between dependant and independent predictors. The equation of LR is given in Eq. (20) [29].

$$y = \mu + \lambda i \tag{20}$$

Where İntercept $\mu = \dfrac{\sum Y.\sum I^2 - \sum I.\sum IY}{M(\sum I^2) - (\sum I)^2}$ (21)

Slope $\lambda = \dfrac{M(\sum YI) - \sum I.\sum Y}{M(\sum I^2) - (\sum I)^2}$ (22)

Here, i- Independent variable, y-Dependant variable, M- No. of values, I-Score 1, Y- Score 2. From the results shown in Fig.13 (a) it is observed that in area-1 there are some deviations occurred between target values and predicted values using proposed ANN because R= 0.99494 (Training), R=0.98845 (Validation) and R= 0.99781 (Test). But, form Fig. 13 (b) it is clearly observed that in area-2 the measured and predicted values are almost equal because R= 0.99992 (Training), R=0.99986 (Validation) and R= 0.99995 (Test).

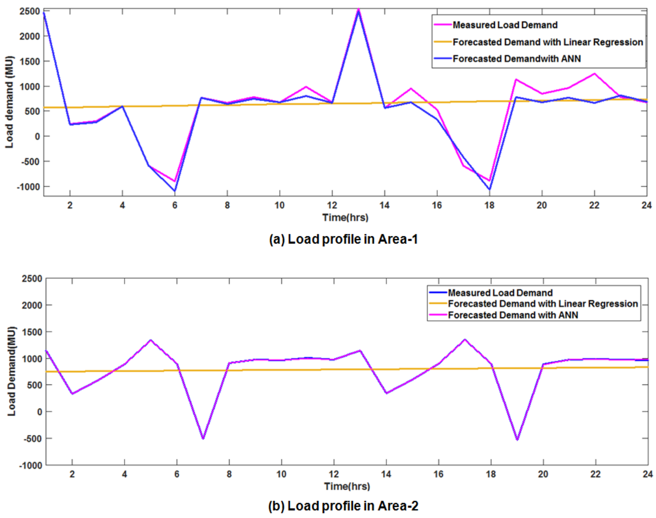

Fig. 13. Comparison of measured and forecasted load demands of area-1, area-2 with LR and ANN

The actual and forecasted load demand profiles of a microgrid cluster for 24hrs duration are as shown in Fig. 15. Also the predected load demands for both LR method and proposed ANN are compared and it is concluded that the proposed method shows superiority in forecasting the load demands in the cluster.

4.3. *Energy Transactions between* microgrid cluster *and utility grid :*

In this case, the concept of interoperability is verified by considering different load profiles at different instants of time. The energy management system (EMS) is modeled to operate the cluster effectively by scheduling the availability of green resources used in the MG's. Due to the interoperability, the interconnected MG's in two areas will share the load during excess/deficit power conditions without creating burden on the utility grid. Fig. 14 shows the cluster power available at PCC for making energy transactions with utility grid.

Form the simulated results shown in Fig. 14 it is observed that from 0 sec to 0.2 sec and from 0.25sec to 0.32sec the power available at PCC of cluster is excess, so in this zone CB of cluster is closed to export the power to utility grid. Similarly, from 0.2sec to 0.25 sec the zone is said to excess/deficit zone accordingly CB of microgrid cluster close/open to import/export the power from/to utility grid. So, from the above results it is concluded that the EMS of microgrid cluster works satisfactorily for the real time data to make energy transactions. The day-ahead load demand forecasted values on 24hrs basis are clearly listed in Table 1.

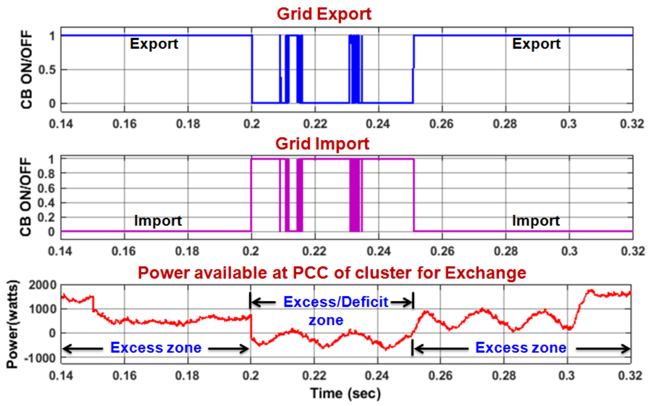

Fig. 14. Power available at microgrid cluster for exchange

5. Conclusion

The ANN used in this paper accurately predicts the day-ahead load demand in the system based on the availability of energy sources in the specified location when compared with LR method. The EMS developed in the microgrid cluster effectively functions to operate the renewable sources based on their availability to meet the load requirements at all the time in a day and also schedules the energy transactions between interconnected and interoperable microgrids in both areas of a cluster and the utility grid. Hence the proposed configuration of the system allows the power exchange with utility grid for meeting the load requirements by utilizing the localized energy sources during deficit/excess power conditions. Due to this, the reliability of the system is increased and system becomes economical. Based on the aforesaid operations planning engineers may plan the maintenance schedule for adding a new unit for meeting the potential increase in the growth of energy.

Acknowledgement

This research work was made possible by the support from Digital India Corporation formerly known as Ministry of Electronics and IT, Govt. of India (MEITY-PHD-2367).

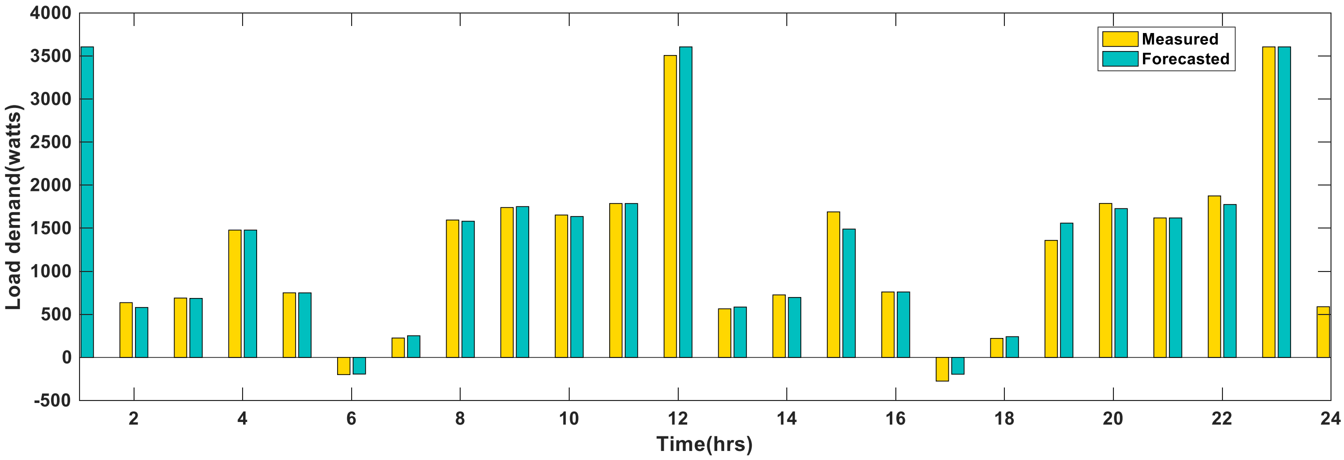

Fig. 15. Comparison of measured and forecasted load demands in a microgrid cluster

Table 1. Day-Ahead load demand forecasting of microgrid cluster during 18/01/2019 to 23/01/2019

Day	Time	Microgrid cluster **load demand in watts**						**Utility Grid**	
		Area-1		**Area-2**		**Total Power**		**Export**	**Import**
		M	**F**	**M**	**F**	**M**	**F**		
Mon	12:00pm	2462	2470.43	1144	1143.91	Excess	Excess	✓	×
Tues	10.00am	-1091	-1100.11	896	895.038	Deficit	Deficit	×	✓
Wed	14.00pm	-590	-116.71	1351	1352.57	Excess	Excess	✓	×
Thu	11.00am	666	678.44	905	905.23	Excess	Excess	✓	×
Fri	09.00am	593	583.17	933	933.44	Excess	Excess	✓	×
Sat	16.00pm	-590	-597.25	1340	1340.11	Excess	Excess	✓	×

***M-Measured**, **F- Forecasted**

References

[1] J. S. Vardakas, I. Zenginis, N. Zorba, C. Echave, M. Morato and C. Verikoukis, "Electrical Energy Savings through Efficient Cooperation of Urban Buildings: The Smart Community Case of Superblocks' in Barcelona," in IEEE Communications Magazine, vol. 56, no. 11, pp. 102-109, Nov.2018,10.1109/MCOM.2017.1700542.

[2] S. N. V. B. Rao, K. Padma, “A Review on Schemes for Interconnecting Microgrids of Urban Buildings,” Book chapter, Springer, DOI: 10.1007/978-981-15-3828-5_45.

[3] F. Ayadi, I. Colak and R. Bayindir, "Interoperability in Smart Grid," 2019 7th International Conference on Smart Grid, Newcastle, Australia, 2019, pp. 165-169, DOI: 10.1109/icSmartGrid48354.2019.8990680.

[4] Eduard Bullich-Massague, Francisco Díaz-González, Monica Aragues-Penalba, “Microgrid clustering architectures” International Journal of applied Energy, Vol.212, pp 340-361, Feb 2018, DOI: 10.1016/j.apenergy.2017.12.048.

[5] Navid Bayati, Hamid Reza Baghaee, Amin Hajizadeh, Mohsen Soltani, Zhengyu Lin, Mathematical morphology-based local fault detection in DC Microgrid clusters, Electric Power Systems Research, Vol.192, 2021, DOI: 10.1016/j.epsr.2020.106981.

[6] G. V. Somanath Reddy, V. P. Mini, N. Mayadevi and R. Hari Kumar, "Optimal Energy Sharing in Smart DC Microgrid Cluster," 2020 IEEE International Conference on Power Electronics, Smart Grid and Renewable Energy (PESGRE2020), 2020, pp. 1-6, doi: 10.1109/PESGRE45664.2020.9070405.

[7] N. Bayati, A. Hajizadeh, M. Soltani, Zhengyu Lin, “A Distribution-Sensitive Poverty Index-Based Protection Scheme for Interconnected DC Microgrids”, International Conference on Developments in Power System Protection (DPSP 2020), 2020 page (6 pp.), DOI: 10.1049/cp.2020.0111.

[8] S. Konar and A. Ghosh, "Interconnection of islanded DC microgrids," 2015 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC), Brisbane, QLD, Australia, 2015, pp. 1-5, DOI: 10.1109/APPEEC.2015.7380986.

[9] J. Mírez, "A modeling and simulation of optimized interconnection between DC microgrids with novel strategies of voltage, power and control," 2017 IEEE Second International Conference on DC Microgrids (ICDCM), Nuremburg, 2017, pp. 536-541, DOI: 10.1109/ICDCM.2017.8001098.

[10] M. L. Herrera, S. A. Subramanian and X. Zhang, "Robust Control and Optimal Operation of Multiple Microgrids with Configurable Interconnections," 2019 IEEE Green Technologies Conference (Green Tech), Lafayette, LA, USA, 2019, pp. 1-4, DOI: 10.1109/GreenTech.2019.8767153.

[11] F. Díaz, M. Rivera and P. Wheeler, "Architectures for Microgrids Interconnection," 2019 IEEE CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON), Valparaiso, Chile, 2019, pp. 1-6, DOI: 10.1109/CHILECON47746.2019.8988091.

[12] M. Yesilbudak and A. Colak, "Integration Challenges and Solutions for Renewable Energy Sources, Electric Vehicles and Demand-Side Initiatives in Smart Grids," 2018 7th International Conference on Renewable Energy Research and Applications (ICRERA), France, 2018, pp. 1407-1412, 10.1109/ICRERA.2018.8567004.

[13] A. Dolara, A. Gandelli, F. Grimaccia, S. Leva and M. Mussetta, "Weather-based machine learning technique for Day-Ahead wind power forecasting," 2017 IEEE 6th International Conference on Renewable Energy Research and Applications (ICRERA), 2017, pp. 206-209, DOI: 10.1109/ICRERA.2017.8191267.

[14] A. K. Singh, Ibraheem, S. Khatoon, M. Muazzam and D. K. Chaturvedi, "Load forecasting techniques and methodologies: A review," 2012 2nd International Conference on Power, Control and Embedded Systems, 2012, pp. 1-10, DOI: 10.1109/ICPCES.2012.6508132.

[15] Hernandez L, Baladrón C, Aguiar JM, Carro B, Sanchez-Esguevillas AJ, Lloret J. Short-Term Load Forecasting for Microgrids Based on Artificial Neural Networks. Energies. 2013; 6(3):1385-1408, DOI: 10.3390/en6031385.

[16] K. B. Sahay and M. M. Tripathi, "Day ahead hourly load forecast of PJM electricity market and iso new england market by using artificial neural network," ISGT 2014, Washington, DC, 2014, pp. 1-5, DOI: 10.1109/ISGT.2014.6816486.

[17] R. Bayindir, M. Yesilbudak, U. Cetinkaya, H. I. Bulbul and F. Arslan, "Statistical Scenarios for Demand Forecast of a High Voltage Feeder: A Comparative Study," IEEE, International Conference on Machine Learning and Applications (ICMLA), Miami, FL, USA, 2015, pp. 1056-1061, doi: 10.1109/ICMLA.2015.34.

[18] A. Lahouar, J. Ben Hadj Slama, Day-ahead load forecast using random forest and expert input selection, Energy Conversion and Management, Volume 103, 2015, pp. 1040-1051, 10.1016/j.enconman.2015.07.041.

[19] A. Dolara, A. Gandelli, F. Grimaccia, S. Leva and M. Mussetta, "Weather-based machine learning technique for Day-Ahead wind power forecasting," 2017 IEEE 6th International Conference on Renewable Energy Research and Applications (ICRERA), San Diego, CA, 2017, pp. 206-209, 10.1109/ICRERA.2017.8191267.

[20] A. Alzahrani, P. Shamsi, M. Ferdowsi and C. Dagli, "Modeling and simulation of a microgrid using feedforward neural networks," 2017 IEEE 6th International Conference on Renewable Energy Research and Applications (ICRERA), San Diego, CA, 2017, pp. 1001-1006, 10.1109/ICRERA.2017.8191208.

[21] J.Jiménez, K. Donado and C. G. Quintero, "A Methodology for Short-Term Load Forecasting," in IEEE Latin America Transactions, vol. 15, no. 3, pp. 400-407, March 2017, 10.1109/TLA.2017.7867168.

[22] Corentin Kuster, Yacine Rezgui, Monjur Mourshed, Electrical load forecasting models: A critical systematic review, Sustainable Cities and Society, Volume 35, 2017, Pages 257-270, 10.1016/j.scs.2017.08.009.

[23] W. Kuo, T. Hsieh, H. Chen, C. Chi and Y. Huang, "A Novel Framework Short-Term Load Forecasting for Micro-grid Energy Management System," 2018 IEEE International Conference on Smart Energy Grid Engineering (SEGE), Oshawa, ON, 2018, pp. 279-283, DOI: 10.1109/SEGE.2018.8499492.

[24] Judith Foster, Xueqin Liu, Seán McLoone, Load forecasting techniques for power systems with high levels of unmetered renewable generation: A comparative study, IFAC-Papers on Line, Volume 51, 2018, pp. 109-114, 10.1016/j.ifacol.2018.06.245.

[25] J. Izzatillaev and Z. Yusupov, "Short-term Load Forecasting in Grid-connected Microgrid," 2019 7th International Istanbul Smart Grids and Cities Congress and Fair (ICSG), Istanbul, Turkey, 2019, pp. 71-75, DOI: 10.1109/SGCF.2019.8782424.

[26] D. R., G. N.P. and M. G. Nair, "ANN Based Solar Power Forecasting in a Smart Microgrid System for Power Flow Management," 2019 Innovations in Power and Advanced Computing Technologies (i-PACT), Vellore, India, 2019, pp. 1-6, DOI: 10.1109/i-PACT44901.2019.8960168.

[27] H. Zhou, Y. Zhang, L. Yang, Q. Liu, K. Yan and Y. Du, "Short-Term Photovoltaic Power Forecasting Based on Long Short Term Memory Neural Network and Attention Mechanism," in IEEE Access, vol. 7, pp. 78063-78074, 2019, 10.1109/ACCESS.2019.2923006.

[28] Hafeez G., Javaid N., Riaz M., Ali A., Umar K., Iqbal Z. "Day Ahead Electric Load Forecasting by an Intelligent Hybrid Model Based on Deep Learning for Smart Grid", Advances in Intelligent Systems and Computing, vol. 993. Springer, doi: 10.1007/978-3-030-22354-0_4.

[29] Ade-Ikuesan, Oyedeji, Osifeko, "Linear Regression Long-Term Energy Demand Forecast Modelling in Ogun State, Nigeria," J. Appl. Sci. Environ. Manage, Vol. 23 (4), pp 753-757 April 2019, DOI: 10.4314/jasem.v23i4.28.

[30] Jieming Ma, Ka Lok Man, T. O. Ting, Nan Zhang, Sheng-Uei Guan, Prudence W. H. Wong, "Approximate Single-Diode Photovoltaic Model for Efficient I-V Characteristics Estimation", The Scientific World

Journal, vol. 2013, Article ID 230471, 7 pages, 2013. https://doi.org/10.1155/2013/230471.

[31] Yasser E, N. H. Saad, Abdalhalim ZekryBassam Zafar, "Assessing Wind Energy Conversion Systems Based on Newly Developed Wind Turbine Emulator", International journal of Smart Grid, vol. 4, no. 4, pp. 139-148, 2020.

[32] S. N. V. B. Rao, K. Padma, Y. V. P. Kumar, "Implementation of minigrid with hybrid renewable energy sources for urban community buildings," Inter. Journal of Recent Technology and Engineering, vol. 8, no. 4, 2019, DOI: 10.35940/ijrte.D4412.118419.

[33] Mohamed I. Mosaad, H.S. Ramadan, "Power quality enhancement of grid connected fuel cell using evolutionary computing techniques", International Journal of Hydrogen Energy, 2018, DOI: 10.1016/j.ijhydene.2018.02.001.

[34] M. Farrokhabadi, S. Konig, Claudio A. Canizares Kankar Bhattacharya, Thomas Leibfried, "Battery Energy Storage System Models for Microgrid Stability Analysis and Dynamic Simulation", IEEE Transactions on Power Systems, vol. 33, no 2, 2018, DOI: 10.1109/TPWRS.2017.2740163.

[35] H. Abdel-Gawad and V. K. Sood, "Small-signal analysis of boost converter, including parasitics, operating in CCM," IEEE Power India International Conference (PIICON), 2014, pp. 1-5, DOI: 10.1109/POWERI.2014.7117622.

[36] Stefanos N. Manias, "Inverters (DC–AC Converters)" Power Electronics and Motor Drive Systems, a book chapter-6, pp 271-500, 2017, 10.1016/B978-0-12-811798-9.00006-8.

[37] Harsh G. Kamath, J. Srinivasan, "Validation of global irradiance derived from INSAT-3D over India," Inter. J. of Solar energy, vol. 202, 2020, pp. 45-54, DOI: 10.1016/j.solener.2020.03.084.