Electric Load and Solar Irradiance Forecasting in Microgrid using High Order MIMO Fuzzy Logic Approach

Gurpreet kaur[1] and Manpreet Singh[2]

[1,2] Department of Electrical Engineering, Baba Banda Singh Bahadur Engineering College, Fatehgarh Sahib, Punjab, India
Email[1]: reetkaur3005@gmail.com, Email[2]: manpreet.khalsa@bbsbec.ac.in

Abstract— *In the modern world, the concept of microgrid is rising at a very rapid rate. With the high participation of the renewable energy resources, the system is considered to be highly advantageous. But, with such integration comes the problem related to their uncertain nature. The major source of energy in the microgrid is considered to be the solar PV which depends upon the value of solar irradiance i.e. uncertain in nature. This uncertainty is dependent upon the various weather based parameters like temperature, wind speed, rain etc. Along with the uncertain source, the load in the system is also variable in nature; depending upon the similar weather based parameters. Thus in this paper, using the high order multi input multi output (MIMO) fuzzy logic approach the forecasting of both the solar irradiance and electric load has been done. The proposed approach is validated by comparing with the real time values of the parameters.*

Keywords— ***Forecasting, Solar Irradiance, Load, Microgrid, MIMO, Fuzzy Logic.***

I. INTRODUCTION

For the utmost few years, the use of renewable energy sources (REs), especially, solar energy has been in vogue across the globe. So, in less than a decade, the most famous: solar energy has achieved a growth of 40-50 % as the unquestionable origin of electricity generation [1]. With the fast and linearly increasing growth of these resources, their incorporation with the main utility grid has been encouraged by many developing nations across the globe, including the European, African states and specially in Asian states like India. Plainly, this integration of REs mainly solar, wind and biomass with the grid possesses various overall benefits to the power system, but also includes several challenges like its inter integration, high initial capital cost, operation and maintenance cost, frequency or voltage mismatch, limited system expansion, and so on [2].

Apart from these challenges, the primary being utility grid integration and frequency mismatch resulting in power supply unbalancing and finally fluctuations, the other problem connected to the REs is their unpredictable power generation, whereas in case of the microgrid system the unpredictable nature of the load is also a concerned issue. Initially, the solution identified for treating such problems was the battery energy storage system (BESS). Merely, the issues pertained due to its functioning, high cost, large space requirement and requirement for charging and discharging and thus restricted its applications. Therefore, leading towards a true and suitable solution of forecasting (solar forecasting) [3].

Sweeping over the drawbacks of BESS, solar power forecasting can be specified as the expectation of the future value of solar power generation depending upon the various uncertain meteorological parameters and the latter, i.e. the load can be defined as the prediction of the future value of the electric load based on the previous available data [4]. In accession to this, the solar power generation depends upon the value of solar irradiance (SI) or precisely the global horizontal irradiance (GHI) which further relies upon the various weather based parameters like temperature, wind speed, movement of the cloud, amount of rain, location, humidity, shadowing effect, etc. Similar to solar, the electric load too depends upon the alike parameters. Thus, the foremost step in the solar power forecasting system is the forecasting of available GHI along with the data analysis of the various parameters for load forecasting [5]. Hence, with the accessibility of accurate solar irradiance and the load. many problems like uncertainty in solar power generation, system's reliability and stability concerns can be resolved. With the principle advantage of accurate solar and electric load forecasting affecting the operation and economics of power system, it too includes the diminution in cost of BESS, thus, a preferred solution [6] [7].

Thus, increasing the role of the solar based REs; dependent upon the various meteorological parameters, the need of accurate forecasting of the solar irradiance

and further solar power along with the prediction of the total electric load of the location (known as microgrid) for its incorporation with the grid is very important [8].

Presenting the concept of accurate forecasting into the microgrid environment, the power system has various short and long term advantages. Amending the system characteristics, these advantages can be identified on the footing of their time interval as well as the length. Being time and distance dependent, these advantages are classified as:

- Short term benefits: The problem of potential difference and frequency regulation can be easily rectified within a short time interval, i.e. ranging from 0-15 kms and a few min. and a few min. Moreover, the issue of grid stability present at the local level can also be solved by the very short term forecasting of both the solar based power and the electrical load.

- Medium term benefits: Considering the medium term, i.e. for a few hundreds of kms and a few hours, working in microgrid environment, forecasting of the total available load and the power generation source provides the benefit of burning down the transmitting and distribution (T&D) cost, i.e. by reducing the T&D losses of the arrangement. It also minimizes the overall cost of storage system by optimally scheduling the size of the reserves.

- Long term benefits: Depending upon the long term forecasting, i.e. on monthly to yearly basis and mostly at the state level, the issues related to congestion management, generation planning, system expansion, etc. can be eliminated. As well, offering diverse types of incentives to the power system; accurate forecasting leads to successful power trading of the imaginations.

The various other benefits include:

- Improved unit commitment
- Optimal planning
- Optimal power generation

- Power trading
- Smart Grid integration
- Reliability issues

Thus, there are several benefits of the forecasting in microgrid and the power system environment. Solar irradiance forecasting is the foremost step in the solar power forecasting under with the impact of various weather based parameters. In summation, these particular parameters affect other very essential ingredient of the microgrid system, i.e. electrical load. Thus, the various independent parameters, i.e. the meteorological parameters affecting the solar irradiance forecasting are shown in Figure 1.

The figure shows parameters like season of the year, time of the day, temperature, wind speed, rain and humidity etc. that directly affects the GHI and the electrical load, along with cloud movement, dust and the aerosol particles that affect the level of GHI available. Whereas, the effect of these parameters also depends upon the location of forecasting. Moreover, the identification of various measurable parameters is of utmost importance when dealing with the effect of parameters, i.e. the meteorological parameters which can be easily measured in the real time. The identified parameters like relative temperature, wind speed, relative humidity, rain, time of day/ season of year and atmospheric pressure can be measured using devices like anemometer and barometer, i.e. relative humidity, relative temperature and wind speed can be measured using anemometer whereas, barometer device can be used for measuring atmospheric pressure [9] [10].

In the past, various forecasting techniques such as time series based statistical method; physical methods, ensemble methods, etc. have been proposed [11]. These widely used methods utilize the historic data of various parameters for the purpose of forecasting. In addition to these statistical and physical forecasting approaches, artificial intelligence and fuzzy logic based approaches
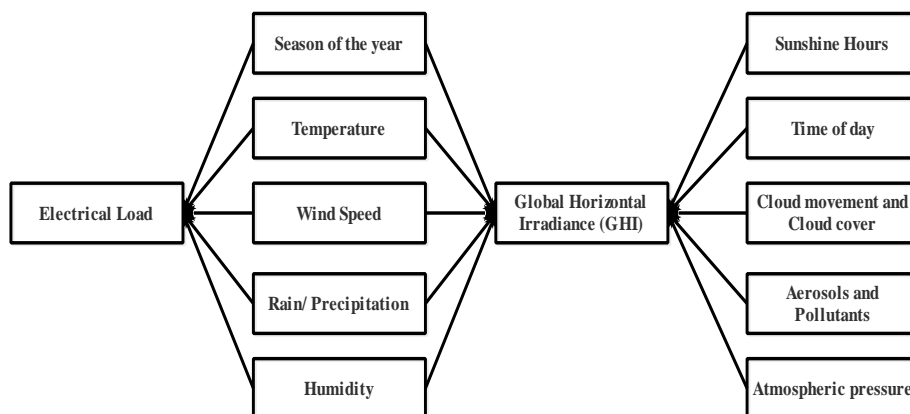

Fig.1: Various parameters affecting electrical load and GHI

form an integral part of accurate estimation of solar energy [12] [13]. Fuzzy logic based system being user friendly, robust and simple to design is preferred over the Artificial Neural Network (ANN) [14] [15]. As per the literature, the work done in the area of forecasting these parameters are well discussed in [16] [17], [18] [19] [20] [21] [22] [23] and [24].

For effective and efficient forecasting, in addition to various methodologies, the other important parameter is the time horizon of forecasting. Basically, it can be defined as the time interval for which the forecasting is intended for. These horizons can be classified as long term, medium term, short term and very short. Among all, the very short term, i.e. few minutes to a few hours ahead and short term, i.e. few hours to a few days ahead are highly effective. The reason lies in the fact that, very short and short term time horizon provides high accuracy level and least calculated error. Referring to the accuracy of the forecasting method, the error evaluation of a certain method is done using various conventional methods like Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Bias Error (MBE) and Mean Square Error (MSE) [25].

Thus, the main objectives of the work is to accurately forecast the available solar irradiance and the real time electrical load dependent upon various parameters and further in future to analyze its role in the planning of a solar based microgrid. To achieve the objective, i.e. accurate forecasting, the high order MIMO fuzzy logic based approach has been used. The proposed method uses the real time data of measurable parameters. These parameters can be measured using various devices like pyranometer, anemometer, rain gauge and barometer. The accurate evaluation of the proposed system is done using various error indices like MAPE, MBE and RMSE.

II. PROPOSED METHODOLOGY

Being simple, robust and user friendly, the fuzzy logic based approach can be termed as the simplified form of classical logics involved in forecasting. The working of fuzzy logics is based on the non-linear mapping of input variables, i.e. uncertain parameters to the output. The benefit of using fuzzy logics concerning the purpose of forecasting lies in the absence of the exact model of the situation or in other words the presence of uncertainty or ambiguity in the system. Fuzzy logic allows solving difficult decision making problems with many inputs and output variables. The Figure 2 shows the basic architecture of the fuzzy logic system with all its major components.

The blocks, membership function editor, rule editor and fuzzy system editor are the path to provide the input

and its related conditions to the system, whereas, the rule viewer and surface viewer give the output of the system.
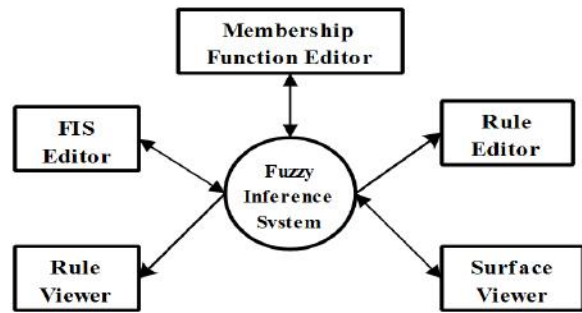

Fig.2: Components of Fuzzy logic models (FIS)

The generalized flowchart for developing fuzzy logic prediction models is given in Figure 3, showing basic steps used for the fuzzy logic approach.

The input given to the designed FIS system, i.e. the uncertain parameters can be defined as the crisp values limited to a specific range. Following the input process, the fuzzification of these inputs, i.e. these crisp values are evaluated in parallel using the fuzzy reasoning system, i.e. designed rules, which includes IF-THEN logics. The results of the activated rules are combined together and defuzzification is done.
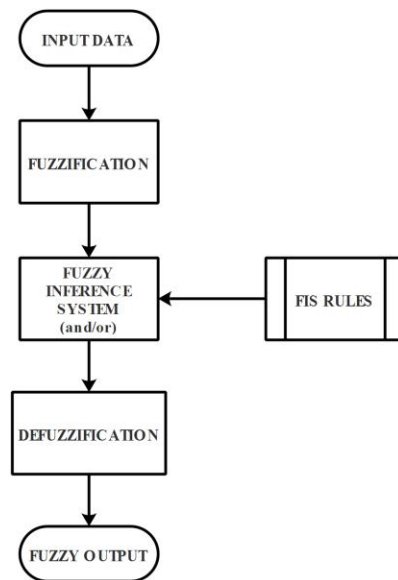

Fig.3: Working flow chart for fuzzy logic models

The output of the system after defuzzification process depending upon the various uncertain parameters (input variables) and the designed set of rules is again a crisp value. Considering the property of fuzzy logic system, all these uncertain inputs and dependent output are to be fuzzified in respective membership function in the range of [0, 1].
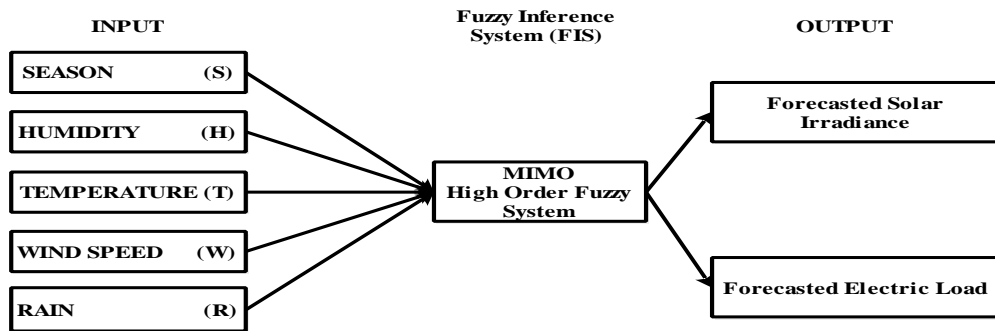
Fig.4: Layout of proposed model

2.1 Layout of proposed methodology

Utilizing the advantage of the fuzzy tool in Matlab Software which includes verifying its ability to correlate the various parameters with each other and give accurate output depending upon the rule base. Thus, on the basis of the literature survey, the measurable parameters on which the forecasting of solar irradiance and the electric load are directly dependent are identified as season of the year, relative temperature, relative humidity, wind speed and rain. The output of the designed system is the forecasted solar irradiance (W/m2) and the electrical load (kWh). The block layout for the fuzzy logic based approach is shown in Figure 4. The figure shows all the above mentioned five uncertain input parameters and the required output parameter as solar irradiance and the electric load. Here, season of year is represented by S, humidity by H, relative temperature by T, wind speed by W and rain by R.

The system has been termed as the MIMO high order fuzzy system due to its multi number of inputs and the multi number of output and high order as high order system is the one depending upon the number of inputs and their respected membership functions, thus resulting in large number of rules (up to 450) to be designed. Also, increasing the number of rules leads to increase of accuracy level of the system such that a number of rules are dependent on the number of membership functions. Thus, depending upon the minimum and maximum values of each parameter observed, the membership functions for all are distributed. Below the Figure 5 to Figure 10 shows membership functions all the input and output parameters, designed on the behalf of their maximum and minimum observed values.

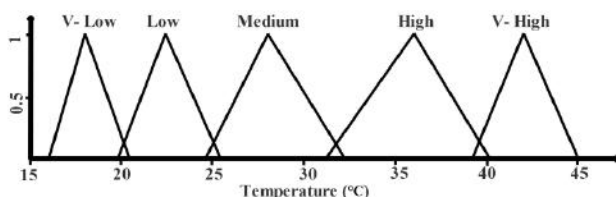For the proposed system, the various membership functions are given as:

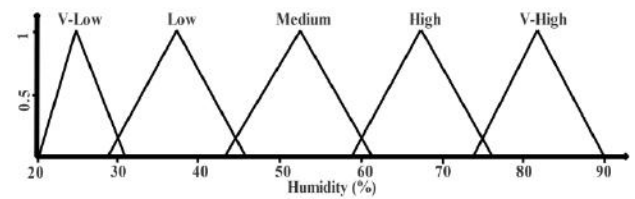*Figure 5 Membership function for temperature input*

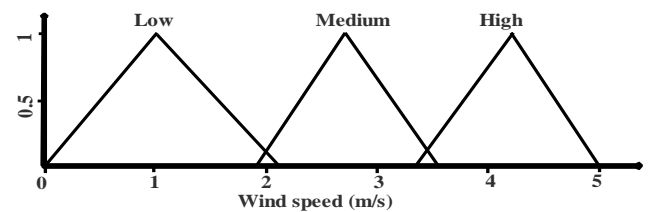*Fig.6: Membership function for humidity input*

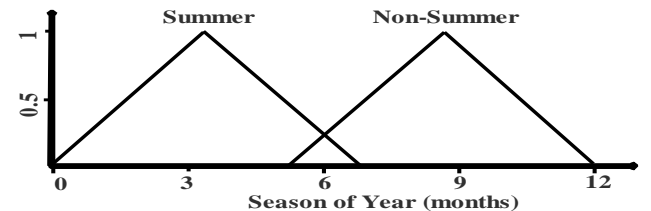*Fig.7: Membership function for wind speed input*

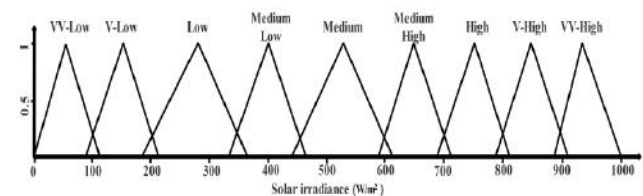*Fig.8: Membership function for season of year input*

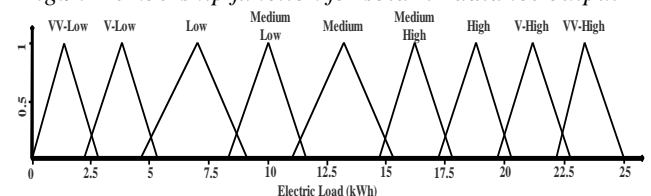*Fig.9: Membership function for solar irradiance output*

Fig.10: Membership function for electric load output

In reference to the above model and the membership functions, below the sample set of rules are given as:

Table.1: Sample set of rules for fuzzy logic system

Season	Temp.	Hum.	Wind speed	Rain	Solar Irr.	Electric Load
Summer	Very High	Med.	Med.	High	H	MH
Summer	Very High	Med.	High	High	MH	MH
N-Summer	Very Low	Low	High	High	VL	M
N-Summer	Low	Very Low	Med.	Low	M	MH
N-Summer	Med.	High	High	High	ML	L
N-Summer	High	High	Med.	Low	M	L
N-Summer	Very High	Med.	High	Low	MH	L

For the purpose of data collection of various parameters, the different devices have been studied and used which includes, the pyranometer device for solar irradiance, anemometer device for temperature, humidity and wind speed, rain gauge for the precipitation and the energy meters for electric load data. Below the sample data has been shown in table 2.

For the purpose of system validation in comparison to the real-time values of the parameters, few error indices are given as: mean bias error (MBE), mean absolute error (MAE), root mean square error (RMSE), mean square error (MSE) and mean absolute percentage error (MAPE) [equation 1- 5]

$$MBE = \frac{1}{N}\sum_{i=1}^{N}[Y'_i - Y_i] \qquad (1)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Y'_i - Y_i| \qquad (2)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y'_i - Y_i)^2} \qquad (3)$$

Table.2: Sample set of real time data logged using various measuring devices

Date	Time	Temp.	Unit	Hum.	Unit	Wind Speed	Unit	Rain	Unit	Solar Irradiance	Unit	Load	Unit
01-01-18	12.30	20.6	°C	20.9	%	1.56	m/S	0.7	mm	235	W/sqmtr	10.54	kWh
15-01-18	3.30	23.5	°C	22.37	%	1.4	m/S	0.7	mm	290	W/sqmtr	13.22	kWh
02-02-18	12.30	20.9	°C	25	%	1.29	m/S	0.71	mm	330	W/sqmtr	14.76	kWh
15-02-18	3.30	22.8	°C	24.29	%	1.04	m/S	0.738	mm	406	W/sqmtr	13.43	kWh
02-03-18	4.30	23.6	°C	24	%	0.7	m/S	0.76	mm	465	W/sqmtr	11.49	kWh
02-03-18	4.30	23.6	°C	24	%	0.7	m/S	0.76	mm	465	W/sqmtr	11.49	kWh
02-04-18	2.30	32.5	°C	10.06	%	1.24	m/S	0.35	mm	739	W/sqmtr	15.89	kWh
02-05-18	11.30	24.6	°C	20.4	%	1.85	m/S	0.90	mm	759	W/sqmtr	7.21	kWh
03-06-18	2.30	28.6	°C	30.2	%	2.33	m/S	0.91	mm	840	W/sqmtr	16.84	kWh
06-07-18	12.30	29.8	°C	24.3	%	2.03	m/S	0.89	mm	795	W/sqmtr	15.65	kWh
13-09-18	12.30	24.9	°C	55.6	%	3.10	m/S	2.08	mm	450	W/sqmtr	14.98	kWh
16-10-18	2.30	23.5	°C	35	%	2.63	m/S	1.96	mm	420	W/sqmtr	11.8	kWh
14-11-18	10.30	15.6	°C	26.8	%	2.98	m/S	1.85	mm	197	W/sqmtr	16.65	kWh
18-12-18	4.30	9.65	°C	30.6	%	1.59	m/S	1.65	mm	265	W/sqmtr	18.65	kWh

MSE

$$= \frac{1}{N}\sum_{i=1}^{N}(Y'_i - Y_i)^2 \qquad (4)$$

MAPE =

$$\frac{100}{N}\sum_{i=1}^{N}\left|\frac{Y_i - Y'_i}{Y_i}\right| \qquad (5).$$

III. RESULTS AND DISCUSSIONS

Corresponding to the five input parameters; time of day, relative temperature, relative humidity, wind speed and rain, the MIMO high order fuzzy logic based systems have been developed. Considering the membership functions of each parameter the number of rules calculated are 450, out of which sample rules are given in Table 1 as mentioned in section 2. The results of the developed system shown in Figure 11 with input values: 4th month of the winter season, relative temperature 32.5 °C, relative humidity 10 %, wind 1.24 m/s and rain of 0.35mm on per unit scale.
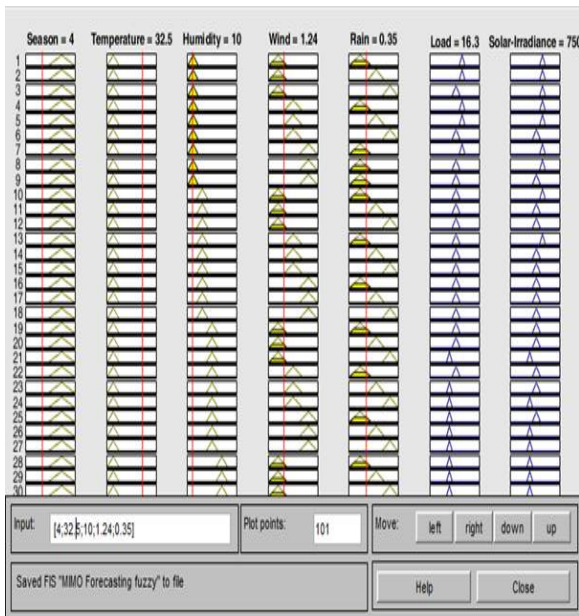

Fig.11: Rule viewer of Fuzzy Logic approach

The rule viewer window to the designed fuzzy logic system shows the crisp value of all input variables and its corresponding output i.e. forecasted solar irradiance which is 750 W/m2 whereas the forecasted load is 16.3 kWh. Thus, the result obtained from the developed fuzzy model which is forecasted solar irradiance for a particular value of season of year, relative temperature, wind speed, relative humidity and level of rain, given by 750 W/m2 and must be compared with the actual value of the solar irradiance which is 739W/m2 and electric load value of 15.89 kWh for the purpose of model validation.

The graph plots display the comparison of the proposed approach with respect to the actual values measured. Also, for the purpose of system validation,

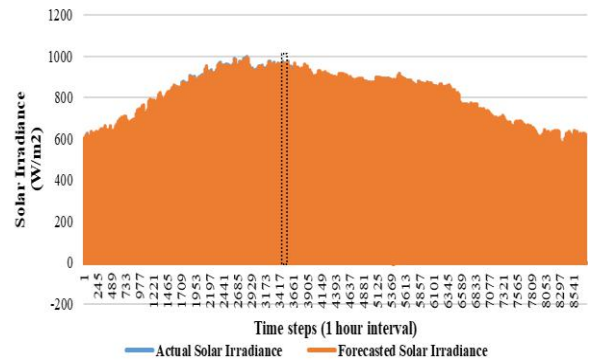various error indices like MBE, RMSE and MAPE have been used.

Fig.12: Graph Plot for Actual irradiance and Fuzzy forecasted irradiance

The graph plot in Figure 12, shows the comparison of fuzzy forecasted solar irradiance with the actual solar irradiance value. As discussed above, fuzzy logic based forecasting methodology being more flexible and accurate shows very less variation in comparison to the actual value of solar irradiance, such that at only few instances the high value of error exists.
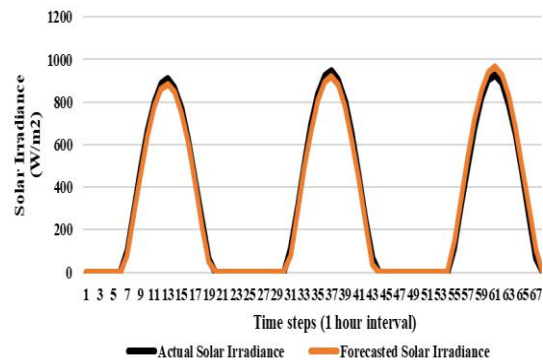

Fig.13: Graph Plot for Actual irradiance and forecasted irradiance (Close in view)

Referring to the above plot, the Figure 13 shows the close in view of the compared values such that to witness the fluctuations in the forecasted value of the solar irradiance. Thus, based on the recorded values of the solar irradiance in the year 2017, the forecasted value of the solar irradiance is compared with the values of the next year i.e. 2018. The plot significantly shows little deviation in the forecasted values from the actual values, whereas follows the similar trend of high irradiance in the mid of the day and low in the other time of day.

Alike, the previous comparison of actual solar irradiance with the forecasted irradiance, in Figure 14 the comparison of actual electric load with the forecasted electric load in kWh has been shown. The plot shows the variation in the electric load with the passing time of the year whereas the average load being around 10.34 kWh with the peak at 20.65 kWh and minimum at 2.17 kWh.

The dotted block represents the close in view represented in the figure shown below.
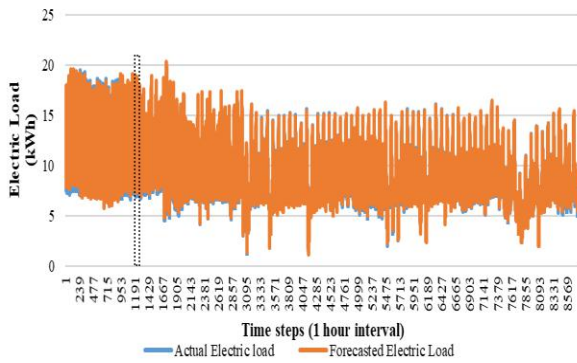

Fig.14: Graph Plot for Actual Electric load and Fuzzy Forecasted load

As per the figure, the variation in the electric load. i.e. between the actual electric load and the MIMO fuzzy forecasted electric load is evident in nature such that the error between the two has been evaluated using the MAE, RMSE and the MAPE respectively.
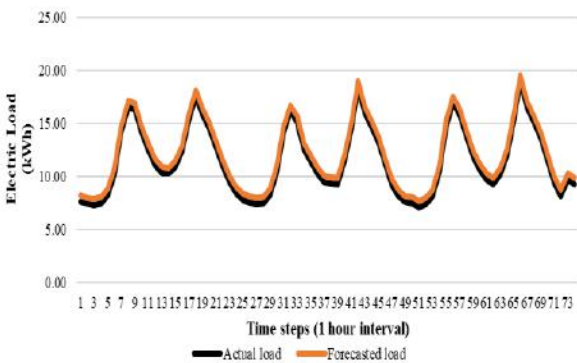

Fig.15: Graph Plot for Actual Electric load and Fuzzy Forecasted load (close in view)

Using Equation 1, Equation 3 and Equation 5 mentioned in section 2, the error analysis in the proposed fuzzy logic system with the actual values of the load and the available solar irradiance has been done and shown in Table 3.

The table shows the error available in the forecasted values against the actual values of both the parameters, i.e. solar irradiance and the electric load. Whereas, the system can be considered fit for the future work as the error percentage (MAPE) and the RMSE value are in the satisfactory range.

Table 3 Error evaluation of proposed methodologies

	Error Evaluation		
	MBE	RMSE	MAPE (%)
Proposed Methodology (Solar irradiance)	1.948858	0.051538	9.285
Proposed Methodology (Electric load)	0.086467	0.239733	2.446480

IV. CONCLUSION

In this paper, considering relative temperature, relative humidity, wind speed, rain and the season of year as independent uncertain input variables, a high order MIMO fuzzy logic based approach for short term solar irradiance and electrical load forecasting has been done. For the purpose of real time data measurement of parameters at the set location, i.e. 30° 21′ 21.63″ N and 76° 22′ 19.71″ E, various devices like Pyranometer and anemometer devices have been used. The results of the proposed high order fuzzy logic based approach dependent upon the designed rule base of 450 rules show crisp value for forecasted solar irradiance and electrical load with an error of 0.051 and 0.239 RMSE respectfully and 9.285% and 2.446% MAPE respectfully in comparison to the real time observed values. In addition, for the purpose of solar power generation and the variations present in it the power equation for the solar panel depending on the forecasted values of solar irradiance and the standard test conditions of solar panel has been well discussed.

REFERENCES

[1] IEA, "Trends in photovoltaic applications – Survey report of selected IEA countries between 1992 and 2011," International Energy Agency, Technical Report, pp. 1-44, 2012.

[2] Banerji. A, et al. (2013). Microgrid: A review. IEEE Global Humanitarian Technology Conference: South Asia Satellite (GHTC-SAS), Trivandrum. 27-35.

[3] Nobre. A. M, et. al. (2016). PV power conversion and short-term forecasting in a tropical, densely-built environment in Singapore. Renewable Energy. (94), 496-509.

[4] Kirmani. S, Jamil. M, Rizwan. M. (2015). Empirical Correlation of Estimating Global Solar Radiation using Meteorological Parameters. International Journal of Sustainable Energy. 34(5), 327-339.

[5] Lorenz. E. et. al. (2011). Regional PV power prediction for improved grid integration. Progress in Photovoltaics: Research and Applications. 19(7), 757–771.

[6] Wu. Y. K, Chen. C. R, Rahman. H. A. (2014). A Novel Hybrid Model for Short Term Forecasting in PV Power Generation. International Journal of Photo energy. 2014, 1-9.

[7] Cheng. H, Cao. W. S, Ge. P. J. (2012). Forecasting Research of Long-Term Solar Irradiance and Output Power for Photovoltaic Generation System.

International Conference on Computational and Information Sciences. 1224-1227.

[8] Rizwan. M, Jamil. M, Kirmani. S, Kothari. D. P. (2014). Fuzzy Logic based Modelling and Estimation of Global Solar Energy using Meteorological Parameters. Energy. 70, 685-691.

[9] Hayden. E. (2013). Introduction to Microgrids. Securicon Report. 1–13.

[10] Coimbr. C. F. M. (2015). Current Status and Needs in Solar Forecasting. Center for energy Research: UC San Diego. 5, 1–16.

[11] Sobri. S, Kamali. S. K, Rahim. N. A. (2017). Solar photovoltaic generation forecasting methods: A review. Energy Conversion and Management. 156, 459-497.

[12] Jeong. Y, Lee. S, Han. K, Ryu. D, Jung. Y. (2015). Design of Short-term Forecasting Model of Distributed Generation Power for Solar Power Generation. Indian Journal of Science and Technology. 8(1), 261–270.

[13] Reikard. G. (2009). Predicting Solar Radiation at High Resolutions: A Comparison of Time Series forecasts. Solar Energy. 83(3), 342-349.

[14] Hong. T, Wang. P. (2014). Fuzzy Interaction Regression for Short Term Load Forecasting. Fuzzy Optimization and Decision Making. 13(1), 91-103.

[15] Sivaneasan. B, Yu. C. Y, Goh. K. P. (2017). Solar Forecasting using ANN with Fuzzy Logic Pre-processing. Energy Procedia. 143, 727-732.

[16] Mehta. S, Kaushal. J, Basak. P. (2018). Tariff calculation using hybrid smart energy meter and fuzzy inference system. 2018 IEEMA Engineer Infinite Conference (eTechNxT). 1-6.

[17] Boata. R. S, Gravila. P. (2012). Functional fuzzy approach for forecasting daily global solar irradiation. Atmospheric Research. 112, 79–88.

[18] Chen. S. X, Gooi. H. B, Wang. M. Q. (2013). Solar radiation forecast based on fuzzy logic and neural networks. Renewable Energy. 60, 195–201.

[19] Chugh. A, Chaudhary. P, Rizwan. M. (2015). Fuzzy logic approach for short term solar energy forecasting. Annual IEEE India Conference (INDICON), 1-6.

[20] Ali. D, Yohanna. M, Puwu. M. I, Garkida. B. M. (2016). Long-term load forecast modelling using a fuzzy logic approach. Pacific Science Review A: Natural Science and Engineering. 17(2), 123–127.

[21] Suganthi. L, Iniyan. S, Samual. A. A. (2015). Applications of fuzzy logic in renewable energy systems - A review. Renewable and Sustainable Energy Reviews. 48, 585–607.

[22] Kamble. S. R, Deokar. S. D, Latke. S. M, Hapse. M. M. (2017). Load forecasting using fuzzy logic," Int. Res. J. Eng. Technol. 5(6), 31–34.

[23] Anoop. K.J., Kanchana. K. (2017). Short Term Load Forecasting Using Fuzzy Logic Control. IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI-2017). 2983–2986.

[24] Vinutha. H. D, Gouda. K. C, Chandan. K. N. (2014). Electric Load Forecasting using a Neural Network Approach. Int. J. Comput. Trends Technol. 11(6), 245–249.

[25] Inman. R. H, Pedro. H. T. C, Coimbra. C. F. M. (2013). Solar forecasting methods for renewable energy integration. Progress in Energy and Combustion Science. 39(6), 535–576.