Chapter 43
Fuzzy Logic-Based Solar Generation Tracking

Anish Agrawal and Anadi Shankar Jha

Introduction

With the already humungous and rapidly growing demand for electrical power, there has been an increase in exploitation of the natural fossil fuels for power generation leading to increased pollution. It has become extremely vital for the integration of renewable and non-polluting energy sources with the electric grid for sustainable development keeping in mind the needs of the future. Solar energy is one of the vast inexhaustible energy sources available for use. However, the uncertainty in solar power generation leads to a critical problem in grid integration of such systems. Solar generation varies with the solar irradiance humidity temperature as well as other weather conditions.

Chakraborty et al. [1] discuss techniques for forecasting their applications, advantages, and their requirements. Neves et al. [2] show a study on an isolated microgrid system based on its demand response, and its performance has been studied keeping in mind the uncertainties in solar power. Use of hybrid solar irradiance forecasting methodology for microgrid with electric vehicles as load has been presented in [3]. Corsetti et al. [4] discuss the short-term forecasting of solar generation for the erection of microgrid system which has been analyzed using neural networks.

Vermaak et al. [5] provide a hardware module for the logging of load power to an external storage device with the help of a smart power meter. The data logged is then transferred to an android application which is capable of visually displaying in the form of graphs. Hussain et al. [6], in his paper, reveal the process of bidirectional energy flow using smart meters and emphasize the role of rooftop system of solar panels for grid-connected power generation.

A. Agrawal (✉) · A. S. Jha
Delhi Technological University, New Delhi 110042, India
e-mail: anish.agrawal.2009@gmail.com

A. K. Singh and M. Tripathy (eds.), *Control Applications in Modern Power System*, Lecture Notes in Electrical Engineering 710,
https://doi.org/10.1007/978-981-15-8815-0_43

Kenner et al. [7] present a software for data collection and analyses for a reference smart grid. The Modbus TCP/IP protocol a RESTful web service is studied for the basis of collecting data. Geetha and Jamuna [8] offer a digital meter model that shows real-time power usage to evaluate energy use and expenditure using different graph, tabulated and manipulated data forms.

Gaga et al. [9] address the design and implementation of a photovoltaic system based on an enhanced P&O algorithm and verify its efficacy by simulating PowerSim simulator and by using MPPT algorithms, classical and enhanced perturb and observe algorithms under the developed framework. Bonganay et al. [10] use an automatic meter reading system interface. The platform, via python, uses the integration of ZigBee protocol into Raspberry Pi single-board machine.

Chugh et al. [11] offer a simplified fuzzy logic model developed for short-term solar energy forecasts using solar irradiance data. The model's efficiency is measured on the basis of a mean absolute percentage error (MAPE). Mbarek and Feki [12] provide a novel approach to solar irradiance forecasting using flexible and accurate fuzzy logic and robust multi-linear regression.

Saez et al. [13] propose fuzzy interval prediction models which integrate uncertainty representation of future predictions. The suggested models of forecast cycles would help build a reliable microgrid energy management framework. Hippert [14] advises the use of the artificial neural networks (ANNs) for load prediction. The paper looks objectively at the ways the proposed NNs are built and checked.

Tee et al. [15] study the development of exogenous multivariable input (NARX) and nonlinear autoregressive artificial neural networks (ANNs) to efficiently predict short-term loads. In this article, with the introduction of the discussed method, the mean actual percent errors in the prediction were reached in the range of 1%. Liu et al. [16] discuss the practical techniques, namely fuzzy logic, neural networks, and autoregressive model for very short-term load forecasting his paper.

This paper describes a Mamdani, fuzzy logic-based prediction system trained on a vast dataset of values to obtain accurate and reliable results. The power generation data from the data logger system is used to validate the result. Section 43.1 comprises of the introduction to the research. Section 43.2 describes solar setup and measuring devices. The design of the fuzzy logic system has been discussed in Sect. 43.3. The results obtained have been discussed in Sect. 43.4 with the conclusion in Sect. 43.5.

Data Collection System

A data logger system has been implemented for the generation and gathering of data. The variables being logged are temperature (°C), solar irradiance (W/m2) and humidity (%) as the inputs and power(W) as output for the fuzzy system. The block diagram of the data logger system has been shown in Fig. 43.1.

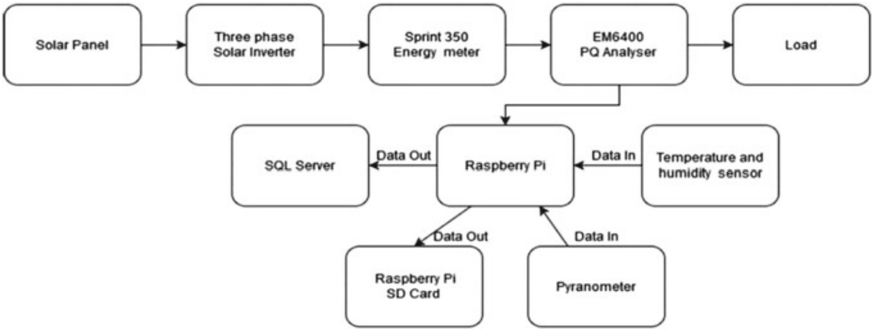


Fig. 43.1 Data logger block diagram

Hardware Devices

Solar Panels: A total of 5-kilowatt power generation capacity has been provided by 20 solar panels each of 250 watts. The system comprises of two strings of equal number of solar panels connected in parallel with the max voltage of 307.2 volts and 16.3 A DC.

Solar Inverter: The generated solar power is converted into three-phase AC power. Considering the present system and keeping in mind potential upgrades to the system, 10-kilowatt three-phase grid connected luminous solar inverter has been used which converts DC power to three-phase AC power at 50 Hertz. As the laboratory has various equipment running at three-phase voltage, this particular inverter has been used.

Energy Meter: An energy meter has been connected after the solar inverter to keep track of solar power generation. A Sprint 350 energy meter has been used for this application. It is suitable for residential, business, and industrial applications. It is connected in a system of three-phase wiring. This meter has four effective current ranges which are of 5–30 A, 10–40 A, 10–60 A, and 20–100 A. This meter has a voltage range of 230 V phase or 415 V line. This meter operates at 50 Hz $\pm$ 5% key frequency.

Raspberry Pi: The data logger system requires a processing unit for data handling capabilities. A Raspberry pi 3 is a small debit card-sized microprocessor-based development board. The Pi also has wireless communication capabilities such as Wi-Fi and Bluetooth support. The Raspberry Pi provides 40 GPIO pins for data input and output, along with 4 USB ports. A user-defined python script can be installed on the Raspberry Pi in this setup which can be modified to meet future expansion needs.

Temperature Sensor: The DHT22 is a digital temperature and humidity sensor which is simple and low cost. It uses a capacitive humidity sensor for humidity measurement and a thermistor to measure the ambient temperature of the air around the panels and sends out a digital signal on the output pin.

Pyranometer: A pyranometer sensor SR03 is used for the measurement of sun irradiance. It has an angle of view of 180°. The pyranometer monitors the hemispheric solar radiation using concentric disks and has a flat response throughout the entire solar spectrum of irradiation.

Data Collection

The devices mentioned in Sect. 43.2.1 constitute the data logger system and solar setup. Using this setup, the required data necessary for the prediction system has been acquired. The data is stored in external SD card, and the data can be transferred to the laptop in the form of an excel sheet. Radiance has been measured by the pyranometer. Temperature and humidity are measured by the DHT22 sensor.

The data for solar generation has been measured at electrical engineering department at Delhi Technological University. The data logger logs data at a sample rate of once per 2 min. A random sample set of logged data for a single day has been used for validity of fuzzy output.

Fuzzy Logic System

The fuzzy system has been designed with four uncertain inputs which are time of day, irradiance, temperature, and humidity. These inputs are fuzzified with the membership functions having a range between 0 and 1. The distribution of membership functions for the four inputs has been done on the basis of the observed maximum and minimum value for each parameter. Figure 43.2 shows the various inputs and outputs for the system.

The linguistic variable for temperature and humidity has five membership functions, whereas for irradiance there are nine membership functions. The division for the membership functions is based on producing a minimal error in the prediction system.

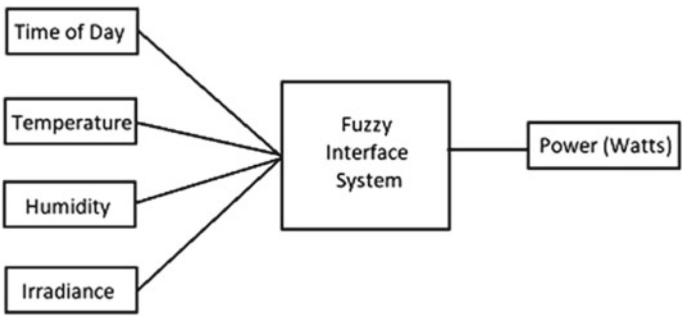


Fig. 43.2 Layout of the proposed fuzzy system

The membership function of temperature has five triangular fuzzy functions which are V low, Low, Optimum, High, and V high. The other membership functions are described in a similar manner. In this proposed system, solar power generation has thus been predicted upon different parameters.

Figure 43.3 shows the input and output variable memberships for the proposed fuzzy interface system. The inputs are temperature, humidity, and irradiance whereas power is the output for the system.

Rule Base: A total of 256 viable rules have been formed using the logged data. Out of all the possible rules, many rules were deemed to be unfeasible and were not included in the rule base. The below given Fig. 43.4 depicts the surface view of input variables, irradiance and temperature, and output variable, power associated with each other.

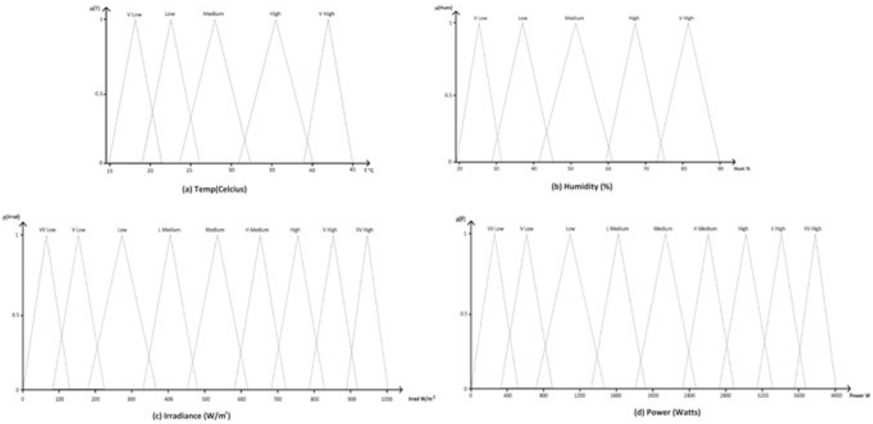
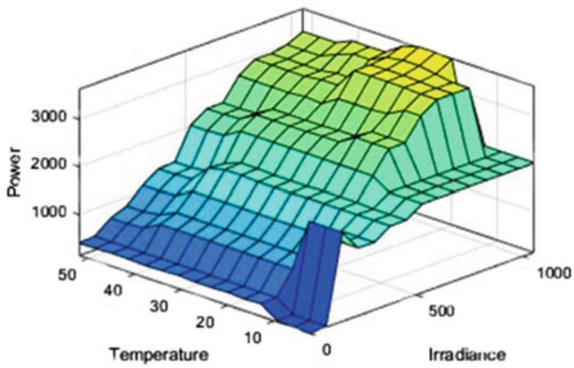


Fig. 43.3 Input-output membership functions

Fig. 43.4 Surface view of FIS rule base



Result

Dataset from National Renewable Energy Laboratory (NREL) was used to obtain the output of the system of the fuzzy system. In this dataset, data is logged at an interval of 1 h, so the output for the same is obtained. The data chosen was for a typical sunny day. Figure 43.5 shows the input irradiance and temperature conditions.

The input temperature conditions varied between a minimum of 23.9 °C and a maximum of 38.3 °C. The irradiance conditions for the power-producing hours varied between 220 and 1052 W/m2. The power output for the 5 kW system varied from 920 watts to 3.34 kW as shown in Fig. 43.6. Figure 43.6 also shows the predicted solar output versus the actual solar generation output.

Figure 43.7 shows the magnitude of the error percentage of the fuzzy system. The error varies between a maximum of 3.25% and a minimum of 0.45%. The maximum percentage error point is during sunset hours, where less solar power is being generated by the system.

The minimum percentage error point is present during the maximum power generation hours with average error for the same being less than 2%. However, the magnitude of error is more or less similar with an error of 40 50 watts in magnitude of the entire day.

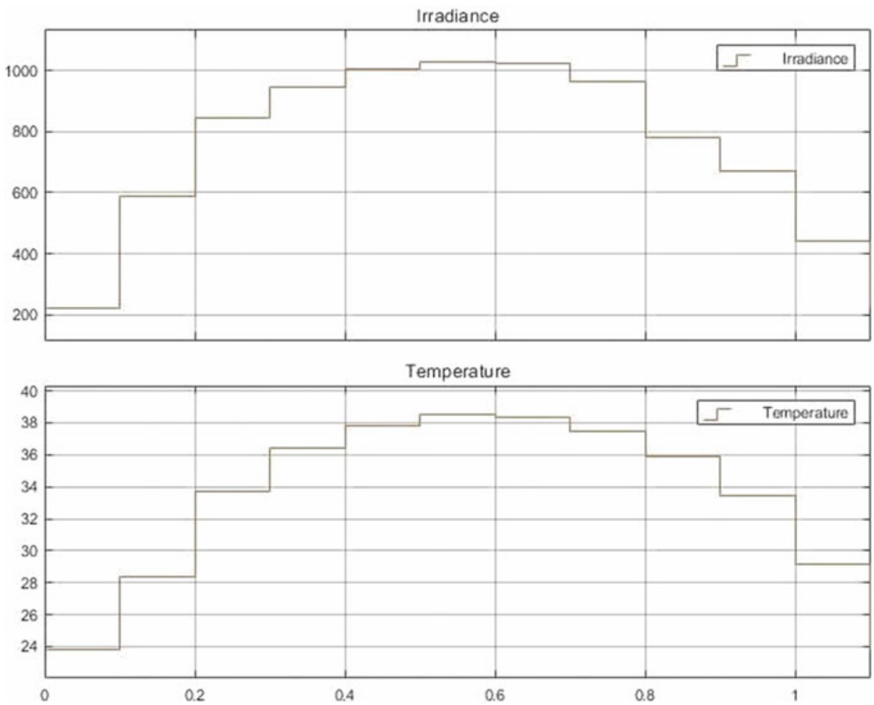


Fig. 43.5 Input temperature and irradiance curve

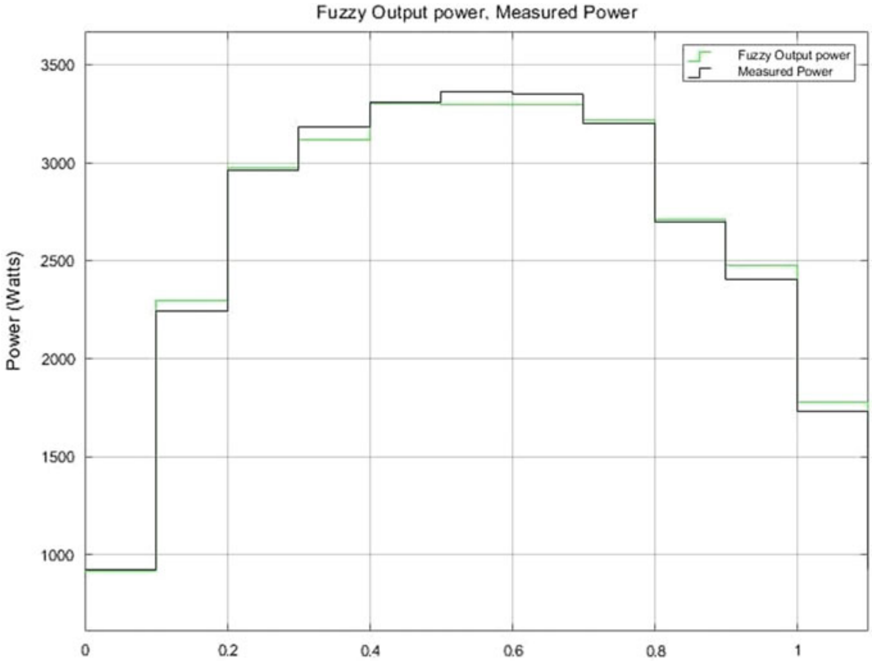


Fig. 43.6 Output power curve

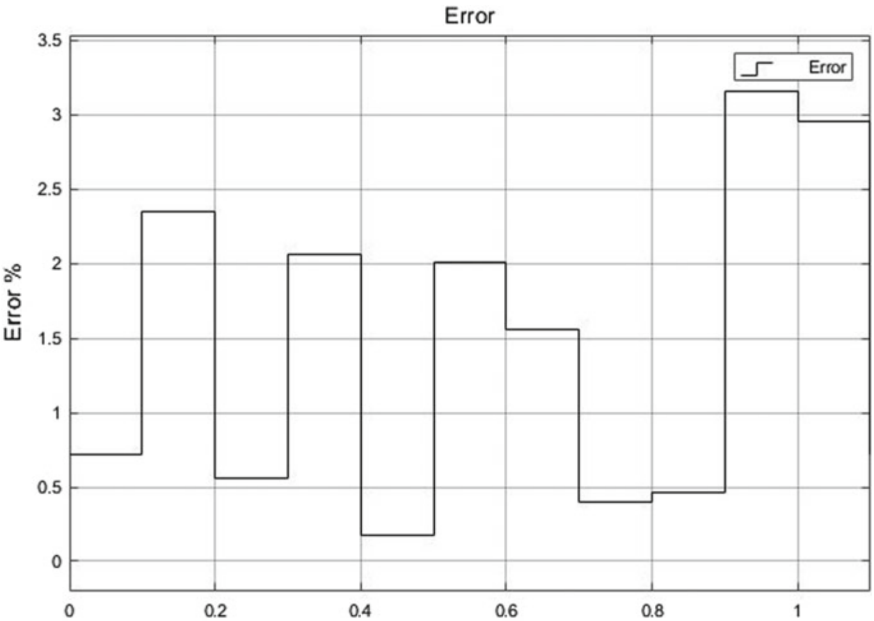


Fig. 43.7 Error curve

Conclusion

A fuzzy-based solar power generation forecasting model has been successfully implemented. A further addition to this model for a solar irradiance prediction system using fuzzy analysis is being performed. Cost versus performance analysis for the solar system is underway using the data logged by the data logger system.

Acknowledgements We thank our project supervisor and mentor Dr. M. Rizwan for his constant support and guidance for making this research possible. We would also like to thank Prof. Uma Nangia, Head of the Electrical Engineering Department, Delhi Technological University for the same.

References

1. Chakraborty S, Weiss MD, Simoes MG (2007) Distributed intelligent energy management system for a singlephase high-frequency AC microgrid. IEEE Trans Ind Electron 54(1):97–109
2. Neves D, Brito MC, Silva CA (2016) Impact of solar and wind forecast uncertainties on demand response of isolated microgrids. Renew Energ 87:1003–1015
3. Duverger E, Penin C, Alexandre P, Thiery F, Gachon D, Talbert T (2017) Irradiance forecasting for microgrid energy management. In: 2017 IEEE PES innovative smart grid technologies conference Europe (ISGT-Europe), Torino, pp 1–6
4. Corsetti E, Guagliardi A, Sandroni C (2016) Recurrent neural networks for very short term energy resource planning in a microgrid. In: Mediterranean conference on power generation, transmission, distribution and energy conversion (MedPower 2016), Belgrade, pp 1–9
5. Vermaak N, Gurusinghe N, Ariyarathna T, Gouws R (2018) Data logger and companion application for time-of-use electricity. In: 2018 IEEE international conference on industrial electronics for sustainable energy systems (IESES), Hamilton, pp 465–470. https://doi.org/10.1109/ieses.2018.8349921
6. Hussain SMS, Tak A, Ustun TS, Ali I (2018) Communication modelling of solar home system and smart meter in smart grids. IEEE Access 6:16985–16996. https://doi.org/10.1109/ACCESS.2018.2800279
7. Kenner S, Thaler R, Kucera M et al (2017) EURASIP J Embedded Syst Springer Int Publishing, 12. https://doi.org/10.1186/s13639-016-0045-7
8. Geetha A, Jamuna K (2013) Smart metering system. In: 2013 International conference on information communication and embedded systems (ICICES), Chennai, pp 10471051. https://doi.org/10.1109/icices.2013.6508368
9. Gaga A, Errahimi F, Es-Sbai N (2014) Design and implementation of MPPT solar system based on the enhanced P and O algorithm using Labview. In: 2014 International renewable and sustainable energy conference (IRSEC), Ouarzazate, pp 203–208. https://doi.org/10.1109/IRSEC.2014.7059786
10. Bonganay ACD, Magno JC, Marcellana AG, Morante JME, Perez NG (2014) Automated electric meter reading and monitoring system using ZigBee-integrated raspberry Pi single board computer via Modbus. In: 2014 IEEE students' conference on electrical, electronics and computer science, Bhopal, pp 1–6. https://doi.org/10.1109/sceecs.2014.6804531
11. Chugh A, Chaudhary P, Rizwan M (2015) Fuzzy logic approach for short term solar energy forecasting. In: Annual IEEE India conference (INDICON), New Delhi, pp 1–6
12. Mbarek MB, Feki R (2016) Using fuzzy logic to renewable energy forecasting: a case study of France. Int J Energ Technol Policy 12(4):357–376

13. Saez D, Avila F, Olivares D, Canizares C, Marin L (2015) Fuzzy prediction interval models for forecasting renewable resources and loads in microgrids. IEEE Trans Smart Grid 6(2):548–555
14. Hippert HS, Pedreira CE, Souza RC (2001) Neural networks for short-term load forecasting: a review and evaluation. IEEE Trans Power Syst 16(1):44–55
15. Tee CY, Cardell JB, Ellis GW (2009) Short-term load forecasting using artificial neural networks. In: North American power symposium, Starkville, MS, USA, pp 1−6
16. Liu K et al (1996) Comparison of very short-term load forecasting techniques. IEEE Trans Power Syst 11(2):877–882