Fuzzy Logic Based MPT Algorithm for Reconfigurable Photovoltaics

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***Abstract*—The number of fire-related incidents is increasing worldwide, which affects the local economy and environment. A terrestrial-based fire detection system that continuously monitors the essential environment parameters such as smoke, temperature, carbon monoxide, and others is one of the most effective ways to identify an occurrence of fire at infancy stages. A hybrid of battery and CMOS embedded photovoltaics (PV) will be an ideal candidate to power such a system. In this paper, fuzzy logic based model to reconfigure the PV module for maximum power transfer (MPT) to the battery is presented. To model and simulate the fuzzy logic system, we use Simulink MATLAB. The results of the system are shown to be effective in matching the load requirement with power generated, thereby maximizing the power transfer to the battery.**

Keywords—Photovoltaics (PV), complementary metal-oxide-semiconductor (CMOS), fuzzy logic, infra-red (IR) sensor, LIDAR, partial shading.

I. Introduction

The forest fires caused by human negligence or natural disaster affect the flora, fauna, health, air quality, government resources, and many other essential parameters crucial for the growth of the local economy. In recent times, there is an increase in the number of forest fire incidents in California, which has affected a vast land area, as shown in Fig. 1 [1], [2]. Over the years, California has a done a remarkable job in reducing greenhouse gas emissions [3]. However, if the frequent forest fire is not reduced gradually, it will reverse all the steps taken by the California government to reduce greenhouse gas emissions. Since it is shown in [4], frequent forest fires contribute to global greenhouse gas emissions.

Over the years, several techniques were proposed and explored for early detection and mitigation of forest fire. A multispectral imaging system at terrestrial, aerial, and satellite-based fire detection techniques was presented in [5]. A geostationary satellite-based fire detection and monitoring system improved the temperature estimate of the fire at 4 x 4 km^2 [6]. Though the satellite-based fire detection and monitoring system can cover a vast area, they are expensive and need additional time to process captured images since the collected images must be sent to the base station. An unmanned ariel vehicle (UAV) or drones based forest fire detection has shown effectiveness in detecting forest fire [7]–[10]. They are very cost-effective and can cover a vast landmass. However, a continuous monitor of forest fire requires proper scheduling of different UAVs.

The last option left for forest fire detection and monitoring is to deploy terrestrial wireless sensors networks. This enables

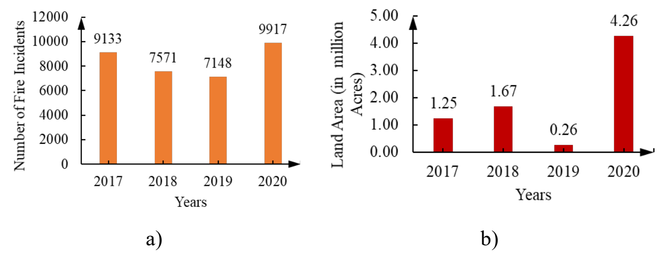


Fig. 1 a) Number of fire incidents across the state of California b) landmass getting affected by the forest fire incidents

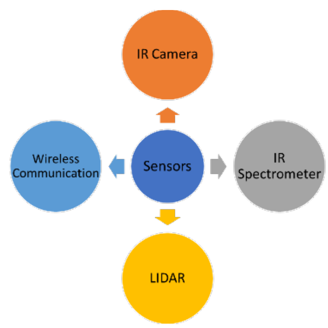


Fig. 2. Basic necessary detection sensors that are required by terrestrial based forest fire detection systems

real-time measuring of essential factors such as temperature, humidity, smoke, and movements of humans and animals to predict and minimize the forest fire impact accurately. In [11], different kinds of sensors were recommended for terrestrial-based fire detection systems to predict fire during infancy. These necessary sensors are shown in Fig. 2. The infra-red (IR) camera will able to detect heat flow and recognize smoke. Similarly, the IR spectral camera enables the terrestrial fire detection system to identify the spectral characteristics of the fire. A LIDAR sensor will empower the system to detect the range and spread of the fire for real-time monitoring of the fire. Lastly, a wireless communication mechanism such as a 4G or 5G network to alert the fire authority and transfer the measured data to the base station.

For the terrestrial fire prediction and detection system to be effective, they need a reliable power source. A battery-based system requires regular replacement with a fresh one which is a tedious process. Photovoltaics (PV) based power source will be one of the options for powering the sensors network around the forest. However, the PV panel cannot work at night, and the lighting will change throughout the year and daytime. Hence, such kind of power source will reduce the performance of the sensor network. Therefore, there is a need for a reliable power source for terrestrial fire prediction and monitoring systems.

Complementary metal-oxide-semiconductor (CMOS) embedded PV panel has demonstrated effectiveness in reducing the impact of the partial shading condition [12]–[14]. A hybrid battery/CMOS embedded PV panel will be an ideal power source for these applications since the CMOS embedded PV panel will power the sensors and charge the battery in the daytime in different lighting conditions. During the nighttime, the battery will power the sensors networks. However, the partial shading detection and mitigation algorithm in a CMOS embedded PV module are tedious [12]–[14]. Since the algorithm first needs to identify the location of the shaded PV cells in the panel. Later, the algorithm determines the ideal configuration (number of PV cells in parallel x number of PV cells in series) based on location and number of shaded PV cells. Sood et al. used machine learning (ML) classifications to determine the number of shaded PV cells in the CMOS embedded PV panel [15].

This paper presents a fuzzy logic-based technique to reconfigure the CMOS embedded PV module for maximum power transfer (MPT) to the load. By observing the generated power of the PV module, the fuzzy logic model will predict the optimal configuration, which results in early charging of the battery.

II. PV Cells And Design Of Complete System

A. Type of PV Cells

This paper uses a GaAs/Ge-based single-junction PV cell manufactured by AMO Sunlight (135.3 mW/cm^2). The parameters of the PV cells from the datasheet are presented in TABLE I. Some of the parameters such as R_S (resistance in series), R_P (resistance in parallel), and saturation current density of diode (J_{01} and J_{02}) are extracted by using curve-fitting on SPICE-based equivalent double diode based PV modeling technique [16]. In the SPICE simulation, the diode's ideality factor is equal to 2.

The PV module consists of ten PV cells. The current vs. voltage (I-V) and power vs. voltage (P-V) characteristics of the GaAs/Ge for different configurations (number of PV cells in parallel x number of PV cells in series) are shown in Fig. 3 and Fig. 4, respectively. The characteristics are obtained using the SPICE-based double diode based equivalent PV module modeling presented in [16]. For simplicity, the ON resistance of the CMOS transistors is ignored for being too small.

TABLE I. GaAs/Ge Based PV Cells Parameters.

Parameters	Description
Dimension	7 cm x 7 cm
J_{SC}	30.5 mA/cm^2
V_{OC}	1.025 V
Efficiency	19.0%
R_S	28 mΩ
R_P	100 KΩ
J_{01}	0.16 aA/cm^2
J_{02}	1.2 pA/cm^2

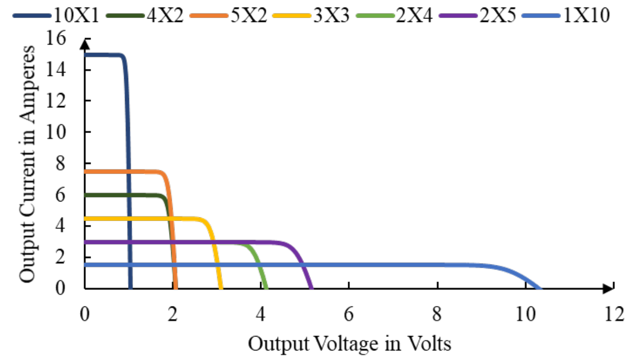


Fig. 3. Current vs. Voltage (I-V) characteristics of GaAs/Ge based PV cells at 28°C. The solar irradiation is 1000 W/m^2.

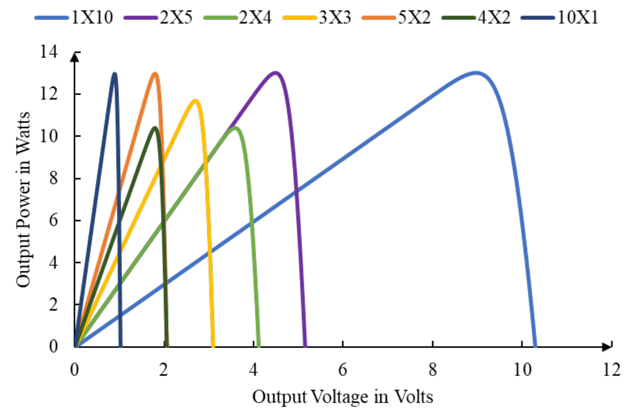


Fig. 4. Power vs. Voltage (P-V) characteristics of GaAs/Ge based PV cells at 28°C. The solar irradiation is 1000 W/m^2.

B. Complete Systems Descriptions

The complete block diagram of the CMOS embedded PV powered fire detection sensors is shown in Fig. 5. The circuit level description of CMOS switches used on the PV module is presented in [17]. The PV module's total current generated, I_{PV}, and output voltage, V_{PV}, is fed to the Raspberry Pi-based embedded system. The fuzzy logic model then uses the measured power of the PV module to determine the optimal configuration of the CMOS embedded PV module. Accordingly, the Raspberry Pi generates data packets which are then sent to the PV panel along with the Clk (clock) and Reset signals, as shown in Fig. 5.

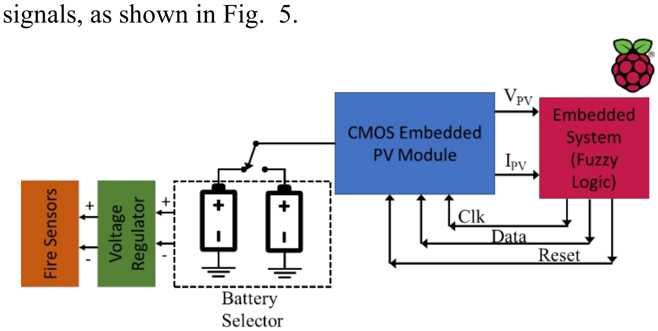


Fig. 5. Block diagram of PV based fire prediction and monitoring system

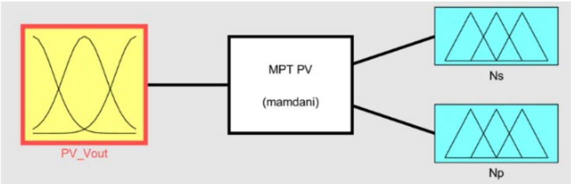


Fig. 6. Structure of the fuzzy logic system with one input and two outputs. PV_Vout is the output voltage of the PV module.

The power generated by the PV panel is sent to the battery selector circuit. The battery selector will connect the discharged battery with the PV module. The fully charged battery will power the fire sensors through the voltage regulator.

III. Fuzzy Logic Based MPT Modelling

This section will model the fuzzy logic model in SIMULINK MATLAB for reconfiguring the PV module based on the power generated. Initially, the P-V characteristics of different configurations (number of PV cells in parallel x number of PV cells in series) are generated using the SPICE-based double diode equivalent PV module [16]. Later from the generated dataset, for the output voltage ranging from 0V to $N_S \times V_{OC} = 10.25V$, the maximum power and configuration $(N_P \times N_S)$ is recorded. Hence, the Simulink Matlab based fuzzy logic model shown in Fig. 6 uses the output voltage of the PV module as the input function. The membership function for the two outputs is shown in Fig. 8. The abbreviation used in the input membership functions is described in Table II. The output N_S indicates the optimal number of PV cells connected in series to maximize the power generation by the PV module. Similarly, the output N_P shows the number of PV cells in parallel.

Table II. Description of the abbreviations used in the input membership function

Abbreviation	Description
MC	Maximum current
MCSV	Maximum current some voltage
BP	Balanced power
MVSC	Maximum voltage some current
MV	Maximum voltage

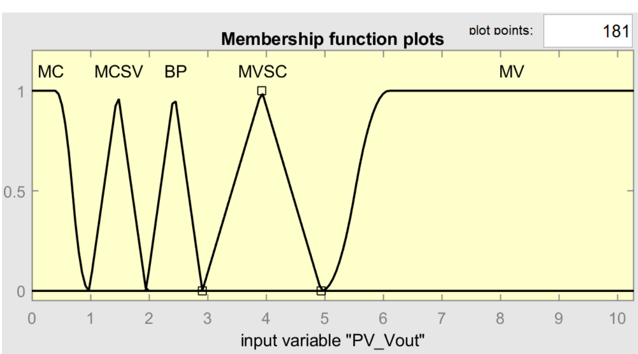
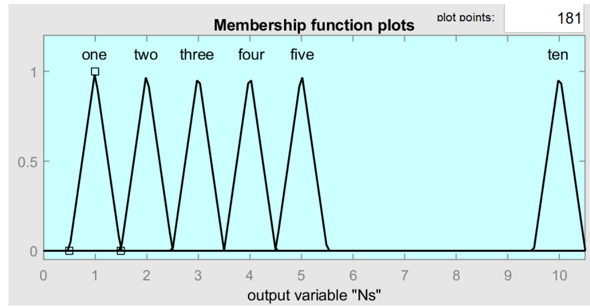
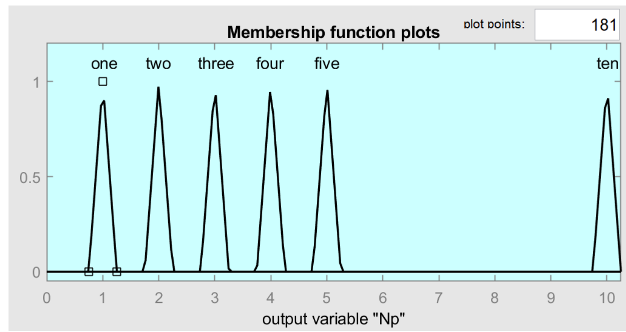


Fig. 7. Membership function for the input to the fuzzy logic



a)



b)

Fig. 8. Membership function for the output a) Ns, recommended number of PV cells in series b) Np, recommended number of PV cells in parallel

IV. Results And Discussion

The number of the PV cells that should be connected in series vs. parallel recommended by the Simulink Matlab-based fuzzy logic model for maximum power transfer is shown in Fig. 9 and Fig. 10. The simulated data shown in Fig. 9 and Fig. 10 is generated using a fuzzy logic-based model, and actual data is an optimal solution developed by brute force analysis. Based on the recommended configuration by the fuzzy logic system, the Raspberry Pi will generate the data packet for reconfiguring the CMOS embedded PV module. Using this fuzzy logic system, the maximum power generated by the CMOS embedded PV module is shown in Fig. 11.

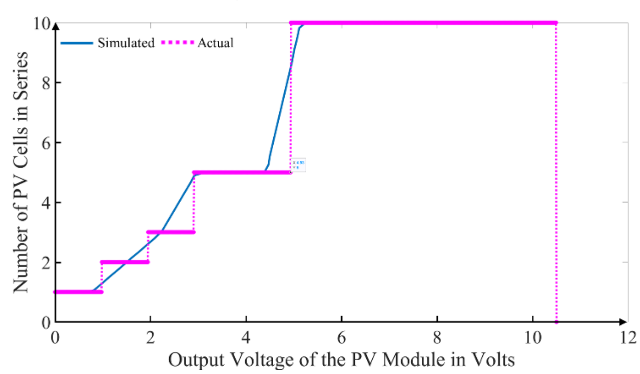


Fig. 9. The number of PV cells should be connected in series for maximum power transfer recommended by the fuzzy logic model

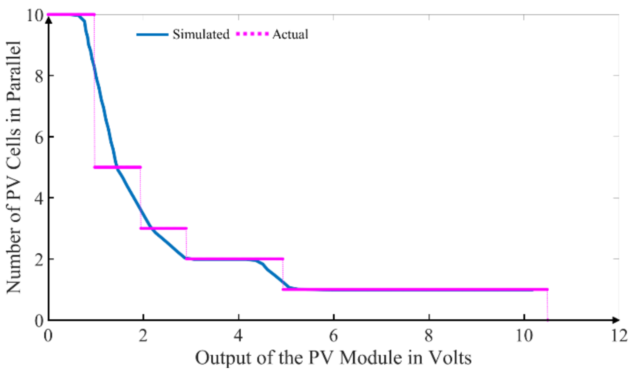


Fig. 10. The number of PV cells should be connected in parallel for maximum power transfer recommended by the fuzzy logic model

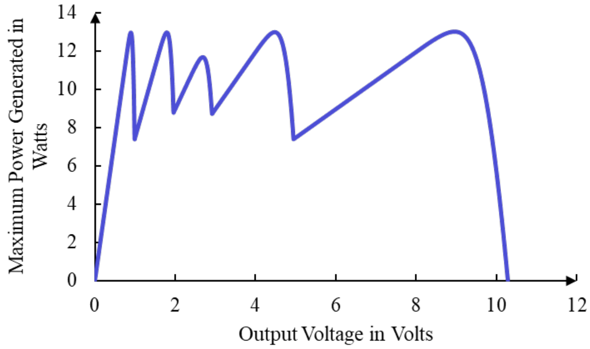


Fig. 11. Maximum power generated by the CMOS embedded PV module

The fuzzy logic model presented in this paper is elementary since it only considers the PV module's output voltage as an input function. Partial shading conditions and operating temperature affect the performance of the PV module. The PV panel deployed in the forest gets affected due to the shading caused by surrounding trees and plants. Additionally, the operating temperature of the PV panel will not stay constant throughout the day. Hence, a robust fuzzy logic system must consider temperature, partial shading condition, solar irradiation, output current, and voltage.

V. Future Work

This paper presents a fuzzy logic-controlled PV panel to power the sensor networks for fire detection. This system can match the load with the power generated by the PV module, which ensures maximum power transfer. The simulated data generated by the fuzzy logic system to recommend the optimal arrangement (number of PV cells in parallel x number of PV cells in series) matches with the actual configuration for maximum power. The technique presented in this paper can also be used to power micro-autonomous drones.

The fuzzy logic model presented in this paper to control the CMOS embedded PV module is very simplistic. A separate published paper will report a more realistic fuzzy logic system that considers operating temperature, number of shaded PV cells, solar irradiation, output current, and voltage.

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References

[1] S. Sannigrahi *et al.*, "Connection between forest fire emission and COVID-19 incidents in West Coast regions of the United States," *arXiv preprint arXiv:2106.03130*, 2021.

[2] "Welcome to CAL FIRE." https://www.fire.ca.gov/ (accessed Jul. 06, 2021).

[3] M. D. Mastrandrea, M. Inman, and D. Cullenward, "Assessing California's progress toward its 2020 greenhouse gas emissions limit," *Energy Policy*, vol. 138, p. 111219, Mar. 2020, doi: 10.1016/j.enpol.2019.111219.

[4] A. I. Miranda, M. Coutinho, and C. Borrego, "Forest fire emissions in Portugal: A contribution to global warming?," *Environmental Pollution*, vol. 83, no. 1–2, pp. 121–123, 1994.

[5] P. Barmpoutis, P. Papaioannou, K. Dimitropoulos, and N. Grammalidis, "A Review on Early Forest Fire Detection Systems Using Optical Remote Sensing," *Sensors*, vol. 20, no. 22, Art. no. 22, Jan. 2020, doi: 10.3390/s20226442.

[6] V. Di Biase and G. Laneve, "Geostationary Sensor Based Forest Fire Detection and Monitoring: An Improved Version of the SFIDE Algorithm," *Remote Sensing*, vol. 10, no. 5, Art. no. 5, May 2018, doi: 10.3390/rs10050741.

[7] D. Kinaneva, G. Hristov, J. Raychev, and P. Zahariev, "Early forest fire detection using drones and artificial intelligence," in *2019 42nd International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, 2019, pp. 1060–1065.

[8] S. Sudhakar, V. Vijayakumar, C. S. Kumar, V. Priya, L. Ravi, and V. Subramaniyaswamy, "Unmanned Aerial Vehicle (UAV) based Forest Fire Detection and monitoring for reducing false alarms in forest-fires," *Computer Communications*, vol. 149, pp. 1–16, 2020.

[9] C. Yuan, Z. Liu, and Y. Zhang, "Aerial images-based forest fire detection for firefighting using optical remote sensing techniques and unmanned aerial vehicles," *Journal of Intelligent & Robotic Systems*, vol. 88, no. 2, pp. 635–654, 2017.

[10] C. Yuan, Z. Liu, and Y. Zhang, "Fire detection using infrared images for UAV-based forest fire surveillance," in *2017 International Conference on Unmanned Aircraft Systems (ICUAS)*, 2017, pp. 567–572.

[11] A. A. A. Alkhatib, "A Review on Forest Fire Detection Techniques," *International Journal of Distributed Sensor Networks*, vol. 10, no. 3, p. 597368, Mar. 2014, doi: 10.1155/2014/597368.

[12] R. Mahto, "Fault Resilient and Reconfigurable Power Management Using Photovoltaic Integrated with CMOS Switches," *Electrical and Computer Engineering ETDs*, Jul. 2016, [Online]. Available: https://digitalrepository.unm.edu/ece_etds/259

[13] R. V. Mahto, D. K. Sharma, D. X. Xavier, and R. Raghavan, "Improving performance of photovoltaic panel by reconfigurability in partial shading condition," *JPE*, vol. 10, no. 4, p. 042004, Feb. 2020, doi: 10.1117/1.JPE.10.042004.

[14] R. Mahto, P. Zarkesh-Ha, and O. Lavrova, "Reconfigurable power management for monolithic CMOS-on-Photovoltaic under partial and complete shading," in *2016 IEEE International Reliability Physics Symposium (IRPS)*, Apr. 2016, pp. 3C-4-1-3C-4–7. doi: 10.1109/IRPS.2016.7574525.

[15] K. Sood, R. Mahto, H. Shah, and A. Murrell, "Power Management of Autonomous Drones using Machine Learning," in *2021 IEEE Conference on Technologies for Sustainability (SusTech)*, Apr. 2021, pp. 1–8. doi: 10.1109/SusTech51236.2021.9467475.

[16] L. Castaner and S. Silvestre, *Modelling photovoltaic systems using PSpice*. John Wiley and Sons, 2002.

[17] R. Mahto, P. Zarkesh-Ha, and O. Lavrova, "Reconfigurable photovoltaic integrated with CMOS for a fault tolerant system," in *2016 IEEE 43rd Photovoltaic Specialists Conference (PVSC)*, Jun. 2016, pp. 2578–2581. doi: 10.1109/PVSC.2016.7750114.