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Improvement of Rooftop Solar Panels Efficiency using Maximum Power Point Tracking Based on an Adaptive Neural Network Fuzzy Inference System

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Abstract: Rooftop solar panels are a strategy for achieving Indonesia's renewable energy goals, but their non-linear characteristics make them difficult to control, especially in the face of extreme weather changes. An effective controller is needed to optimize the power output of solar panels. This study proposes a Maximum Power Point Tracking (MPPT) controller based on an Adaptive Neural network Fuzzy Inference System (ANFIS) to address this control problem. The capacity of the rooftop solar panels is 3,430-Watt peak (Wp) and they are connected to a 220-Volt (V) grid system. The system is designed, simulated, and analyzed using the Simulink model. The proposed ANFIS MPPT control for rooftop solar panels is compared to Perturb and Observe (P&O) MPPT and no MPPT systems. The simulation results show that in rapid changes in irradiation and extreme temperature, the efficiency of MPPT based on ANFIS is better than P&O MPPT and no MPPT by 0.4523 and 0.1115%, respectively.

Keywords: Adaptive Neural Network, Fuzzy Inference System, Efficiency, Rooftop Solar Panels, Maximum Power Point Tracking

Introduction

Indonesia has great potential for solar energy because of its location at the equator. All Indonesian regions are exposed to sunlight throughout the year and sunlight energy is straightly converted into electricity. Solar energy potential in Indonesia is 207.8 GWp, as reported by the Indonesian National Energy Council (DEN, 2019). Based on this report, the Ministry of Energy and Mineral Resources Republic of Indonesia released a regulation on how to build rooftop solar panels. This regulation ensures that the quality and optimal conversion of sunlight into electrical energy work effectively. Every electricity customer can utilize solar-based electricity for personal needs and sell it to the electricity grid. Electricity customers are allowed to install a rooftop solar panel capacity at the same as their customer capacity contract (ESDM, 2021). Zero-emission energy in Indonesia's target by 2050 (IESR, 2021) will be supported by this regulation. This regulation is also supported by the United State Institute for international development on technical assistance (USAID, 2020).

Erratic and extreme weather occur due to climate change phenomena, so this situation makes solar panels' performance decrease. Roof solar panels are affected directly by these weather changes because the solar panels are placed on the roofs of houses or buildings. Based on global solar atlas data, the West Nusa Tenggara Republic of Indonesia, the air temperature, average direct irradiation, and specific photovoltaic power output are as follows: 11.3-27.8°C; 1.53-5.25 kWh/m^2 and 2.82-4.62 kWh/kWp, respectively (Group, 2022). These data show that solar radiation and temperature fluctuate and affect rooftop solar panel performances. One of the scenarios to increase panel efficiency is to stabilize the panel temperature by the circulating water method. This method can increase panel efficiency from 7.57 to 8.11% (Pido *et al*., 2018). Another option to increase the efficiency of rooftop solar panels is to use a tracking system technique.

There are two tracking system models so far, namely mechanical and electrical. However, the mechanical tracking system has been abandoned because it requires much energy to control the solar panels to follow the sun's movement direction. At the same time, the electric tracking system is being developed actively to produce optimal output from the photovoltaic system (Abdel-Salam *et al*., 2019). The electrical tracking system tracks the maximum power of the solar modules electronically. Solar modules have non-linear characteristics because they are made from semiconductor materials. The Maximum Power Point Tracking (MPPT) electric tracking system uses offline, online, and artificial intelligence techniques. The offline technique has the disadvantage of tracking results due to partial shade conditions, sudden irradiation changes and ramps, and other non-ideal conditions. Online technique such as Perturb and Observe (P&O) is proposed by Abdel-Salam *et al.* (2018) to overcome the disadvantages of offline techniques. The P&O technique provides stable conditions with efficiency and dynamic efficiency up to 96.98 and 91.9%, respectively. On the other hand, soft computing techniques (artificial intelligence techniques) are developed rapidly and are used to solve complex problems in MPPT field research. These techniques include Fuzzy Logic Control (FLC), Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), difference evolution and genetic algorithms, particle swarms, artificial bee colonies, grey wolf optimizers, and many others. The MPPT fuzzy logic control is applied to control the DC-DC converter through the duty cycle to get the maximum output power from the PV system (Eltamaly and Farh, 2020). It is reported that the FLC MPPT tracks environmental condition changes rapidly (Loukriz *et al*., 2013), and makes power and efficiency of PV systems increased for this condition (Chekired *et al*., 2014; Hasan *et al*., 2013; Kamarzaman and Tan, 2014; Messai *et al*., 2011). Another soft computing technique implemented for MPPT calculation is ANN because the ANN is very effective in solving non-linear problems. It is more accurate and efficient in tracking uniform conditions than other conventional MPPT techniques (Rai *et al*., 2011; Messalti *et al*., 2017; Laudani *et al*., 2014; Mancilla-David *et al*., 2014).

ANFIS is defined as a soft computing technique that combines FLC and ANN algorithms. The FLC-type with the harmonic search metaheuristic method can provide the best approach for generating optimal vector values in optimizing the fuzzy type-1 and interval type-2 controller membership function in non-linear problems (Patel, 2022). For the system under uncertainty conditions, the fuzzy type-1 and type-2 intervals are implemented to improve various algorithms in control fields (Patel and Shah, 2022a-f). Artificial Conditional Network (ACN) is a popular research topic due to their better ability to handle modeling and parameter uncertainties (Raval *et al*., 2023). A combination of the FLC and ACN methods is enhanced on each method's deficiencies. The Fuzzy Logic System membership function is generated by training based on the uncertainty of system parameter data using ANN. The ANFIS has been proven to increase the stability of a single-machine electric power system (Ginarsa and Zebua, 2014). The ANFIS control is applied to more than just a single machine. Moreover, this control maintains a large power system's stability (Muljono *et al*., 2018). A Power System Stabilizer (PSS) based on ANFIS control is implemented on integrated systems with renewable energy generation (Ginarsa *et al*., 2020). Transient condition in a High Voltage Direct Current (HVDC) system is corrected by the additional controller based on ANFIS (Ginarsa *et al*., 2022a-b). In the MPPT research field, the ANFIS is applied to adjust the boost converter duty cycle to increase the PV system efficiency (Alfian *et al*., 2022). Moreover, ANFIS-based MPPT design is also used to track change properly in solar irradiation and temperature in rooftop solar panel systems connected to single-phase grid systems (Nrartha *et al*., 2022). Artificial intelligence applications for solar panel control have been developed intensively by previous researchers. However, research topic change in radiation followed by an extreme change in temperature has not been investigated so far.

This study reports on the implementation of ANFIS as an MPPT to increase the efficiency of rooftop solar panels connected to a single-phase power grid system with varying irradiation dan followed by extreme changes in temperature. Materials and research methods are explained after the introduction, followed by a discussion of the research results. In the final section, a conclusion is given on the efficiency of the ANFIS MPPT technique compared to the no MPPT and MPPT Perturb and Observe (P&O) methods.

Materials and Methods

The Simulink tool 8.5 on MATLAB version R2015a is employed for the simulation. The solar module is Trina Solar TSM-250PA05.08. The rooftop solar panel consisted of 14 modules arranged in series to produce a voltage at a maximum power point of 434 V for a 3,498 Wp. The weight of each module is 8.6 kg and the total weight of the roof solar panel system is 260.4 kg. The area required for installation on the roof was 22.92 m^2. The module specifications are Table 1.

The rooftop solar panel is modeled at Simulink as a PV array with a configuration of 14 Trina Solar TSM-250PA05.08 modules connected in series. The system model was analyzed for the range of solar irradiance of 2-1000 W/m^2 and temperature 15-55°C. On the output side, the solar panels were loaded with varying resistive loads to obtain the characteristics/behavior for each combination of irradiation and temperature (Nrartha *et al*., 2022). The simulation results (irradiation, temperature, and voltage at maximum power point) were stored and used for ANFIS training data. The amount of data to train the ANFIS MPPT was 1000 pairs of inputs (irradiation and temperature) and output (voltage at maximum power point).

The fuzzy inference system on ANFIS MPPT uses sub-clustering with a range of influence of 0.5; squash factor of 1.25; accept a ratio of 0.5 and reject ratio of 0.15. The number of FIS membership functions for irradiation and temperature each has six membership functions. The input membership function is of type gaussmf, while the output membership function is linear. Then ANFIS was trained using the hybrid optimization method with 1000 epochs. Figure 1(a-b) show irradiation and temperature membership functions. Figure 2(a-b) show the control surfaces and the structure of the ANFIS MPPT.

The next step is to validate the ANFIS training results with test data. The test data are 14 pairs of training data in the range 50-1000 W/m^2 and 25-55°C for irradiation and temperature. The test aims to ensure that the rules generated from the ANFIS MPPT learning outcomes produce the same results between the ANFIS MPPT and the test data. Comparison results are significant to ensure the quality control of ANFIS MPPT is effective.

Rooftop solar panels were connected to a 220 Volt electric power network model on Matlab/Simulink. An inverter device was installed on the rooftop solar panels output to convert the DC voltage/current to AC voltage/current in a single-phase grid system. The single-phase inverter was equipped with a controller. The Sinus PWM method was applied to control the inverter. The inverter specifications were the universal bridge with two arms, where the Rs, Cs, and Ron were 106 Ohms, in farads, and 10^{-3} Ohms, respectively. An Insulate Gate Bipolar Transistor was included as a switching component. The inverter was also equipped by PLL as a controller, current regulator, four pulses bipolar modulation for the PWM generator, and carrier frequency. The carrier frequency was operated on 63 × 50 or 3150 Hz (network frequency: 50 Hz). The load on the grid side was set at S = 5+ j2 kVA. Grid power is defined as the difference between load power and power from rooftop solar panels. Equations 1 and 2 are the energy equations for the DC and AC sides. Equation 3 is a formula to calculate efficiency:

$$E_{DC} = P_{DC} x t \tag{1}$$

where, P_{DC} and t are the DC output power of rooftop solar panels and operating time, respectively:

$$E_{AC\_PV} = I_{RMS\_PV} x V_{RMS_{PV}} x \cos(\theta) x t \tag{2}$$

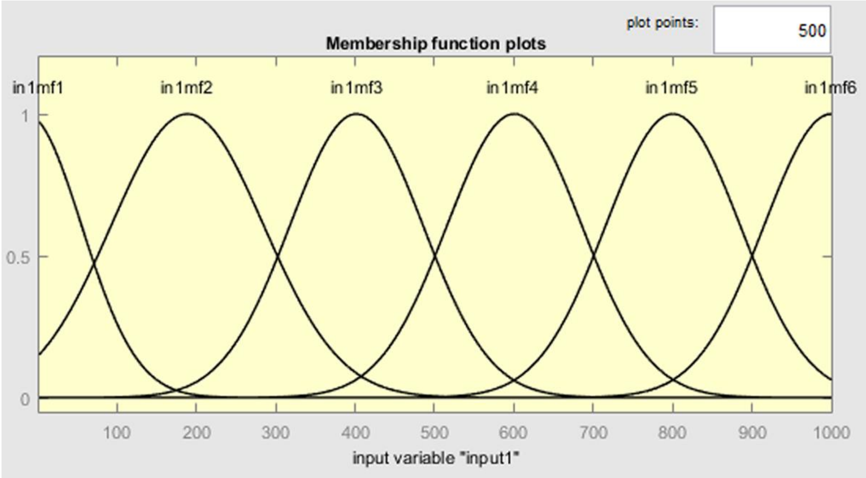
where, $\cos(\theta)$ is the load power factor:

$$\eta = \frac{E_{AC_{PV}}}{E_{DC}} x 100\% \tag{3}$$

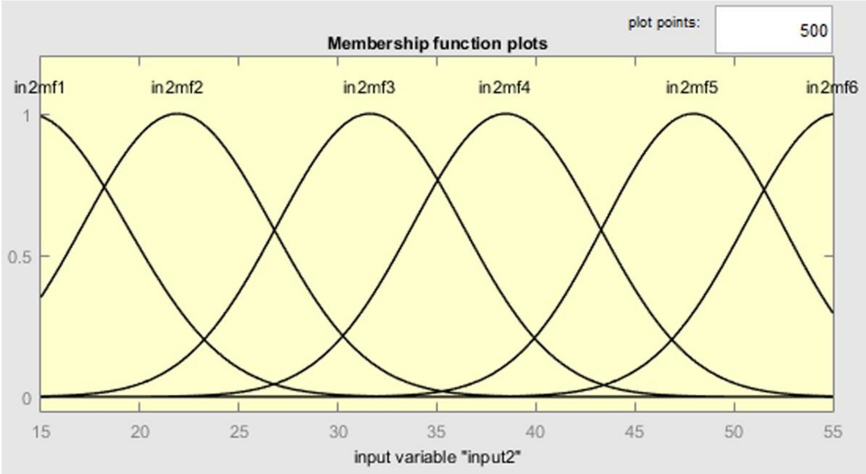
Figure 3 the rooftop solar panel network connected to a single-phase grid. Rooftop solar panels with no MPPT and P&O MPPT were used as benchmarks to compare the performance of rooftop solar panels with ANFIS MPPT.

Table 1: Trisna Solar TSM-250PA05.08 Specification (Trina Solar, 2011)

Module data	Value
Maximum power (W)	249.86
Cell per module (Ncell)	60.00
Open circuit voltage Voc(V)	37.60
Short-circuit current Isc (A)	8.55
The voltage at maximum power point Vmp (V)	31.00
Current at maximum power point Imp (A)	8.06
Temperature coefficient of Voc (%/°C)	-0.35
Temperature coefficient of Isc (%/°C)	0.06

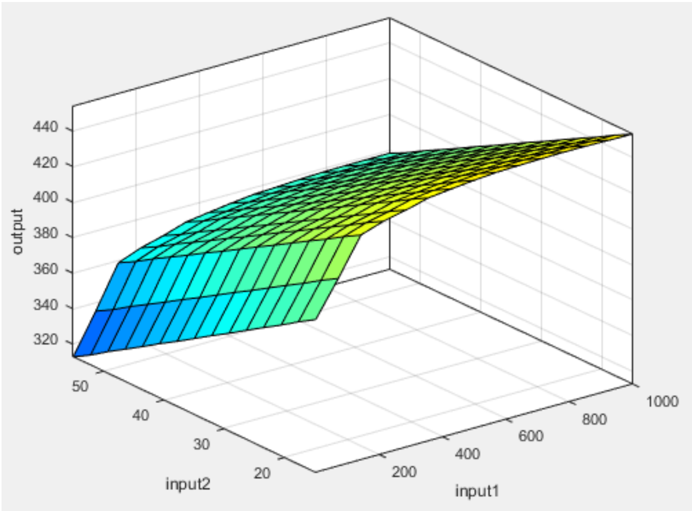


(a)

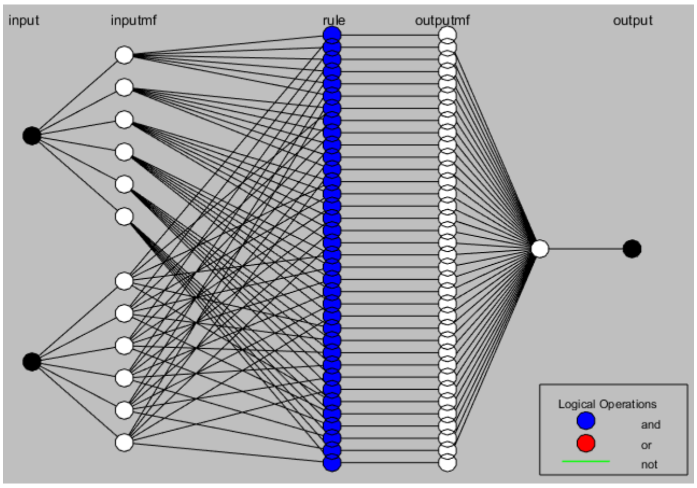


(b)

Fig. 1: Membership function of input, showing (A) Gaussmf membership function for irradiation and (B) Gaussmf membership function for temperature



(a)



(b)

Fig. 2: ANFIS MPPT control showing (A) The control surface and (B) The structure

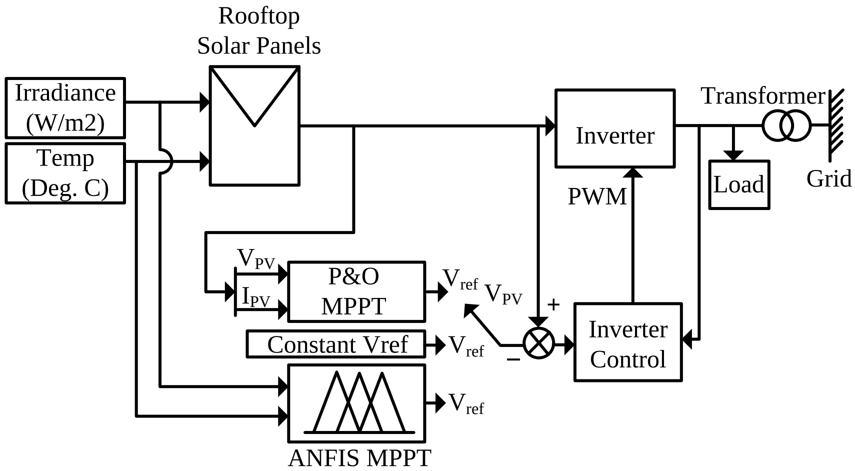


Fig. 3: Grid-connected rooftop solar panels for several MPPT control methods

Results and Discussion

The test results of the ANFIS MPPT model after training with input/output data are compared with the test data to determine its accuracy, Table 2. The maximum error of the ANFIS MPPT model is 2.02% at 50 W/m^2 and 55°C and the minimum error is 0.00% at 500 W/m^2 and 25°C; 900 W/m^2 and 25°C; 900 W/m^2 and 55°C; and 1000 W/m^2 and 55°C. It is founded that high-nonlinearity performance is shown by the rooftop solar panels, especially at low irradiation and temperature. More diverse training data is needed to find more detailed results.

The grid-connected solar panel model in simulink is Fig. 4. Three simulation scenarios were studied: Grid-connected solar panels with no MPPT, P&O MPPT, and ANFIS MPPT. The input values in the inverter control block are replaced with 1, 2, or 3 for systems with no MPPT, P&O MPPT, and ANFIS MPPT to change the scenario. Figure 5 shows varying irradiation and constant temperature. Irradiation varied from 250, 750; 1000; 800; 400; and 200 W/m^2 and temperature at 25°C. The change of irradiation from one to the next is with a slope of +/- 8000.

Figure 6 shows the operating results of grid-connected rooftop solar panels for variable irradiation at a constant temperature. Figures 6(a, d) show that the three methods have almost the same output power and the current flowing from the rooftop solar panel to the load for each change in irradiation. The comparison results of energy and efficiency are Table 3. Energy yields on the DC and AC sides of the roof solar panels during operation for each MPPT method are calculated using Eq. 1 and 2. The efficiency values are obtained from Eq. 3.

The result in Table 3 shows that the most energy is provided by the DC side of the rooftop solar panel with the grid-connected P&O MPPT. But on the AC side, the biggest energy from rooftop solar panels occurred on ANFIS MPPT. The efficiency was achieved at 36.562, 36.569, and 36.586% for systems with no MPPT, P&O MPPT and ANFIS MPPT, respectively. The efficiency of the ANFIS MPPT was at 0.0664% compared to the no MPPT and 0.0474% compared to the P&O MPPT. The ANFIS MPPT results are better than the other competing methods. Figure 6(b) shows the reference voltage (V_{ref}) output of each MPPT. The V_{ref} fluctuation of the MPPT P&O control is larger than the others. So, the voltage in the AC network is more fluctuate for MPPT P&O, Fig. 6(c).

The solar panel's temperature increases with increasing solar irradiation and vice versa. The following simulation is a change in irradiation followed by a change in solar panel temperature. The irradiation changes were the same as in the previous simulation. Irradiation changes were followed by the temperature of rooftop solar panels at 25, 35, 50, 40, 35, and 27°C. The varying irradiation and extreme temperature changes are shown in Fig. 7. The irradiation gradient is the same as the previous simulation, while the temperature gradient is +/-80.

The output results of rooftop solar panels for variations in irradiation and temperature. Figure 8(a) shows the DC output power of ANFIS MPPT is better than the method with no MPPT and P&O MPPT. Similarly, Fig. 8(d) shows that the current supplied by the rooftop solar panels to the electrical load for the ANFIS MMPT method is more significant than the other methods comparison results are Table 4.

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The result in Table 4 shows that the ANFIS MPPT method for rooftop solar panels produces greater energy on the DC and AC sides than other methods. In terms of efficiency, the ANFIS MPPT method is the most. The efficiency of the no MPPT, P&O MPPT, and ANFIS MPPT methods was 36.505, 36.629, and 36.670%. So ANFIS MPPT is 0.452% better than the method with no MPPT and 0.112% than the P&O MPPT method.

Variations of irradiation and temperature, as Fig. 7, the method with no MPPT produces a constant V_{ref}. However, in the P&O MPPT ANFIS MPPT method, V_{ref} changes depending on the panel temperature. The MPPT ANFIS method provides a more stable and faster V_{ref} change than the MPPT P&O method, Fig. 8(b). Figure 8(c) is the voltage change on the side of the AC network due to a change in V_{ref}. Changes in V_{ref} as a control voltage for voltage detection at maximum power (such as the system modeling) were investigated earlier (Eltamaly and Farh, 2020). The maximum voltage (V_m) at maximum power was found not constant with changes in irradiation and V_m decreased at a higher panel temperature.

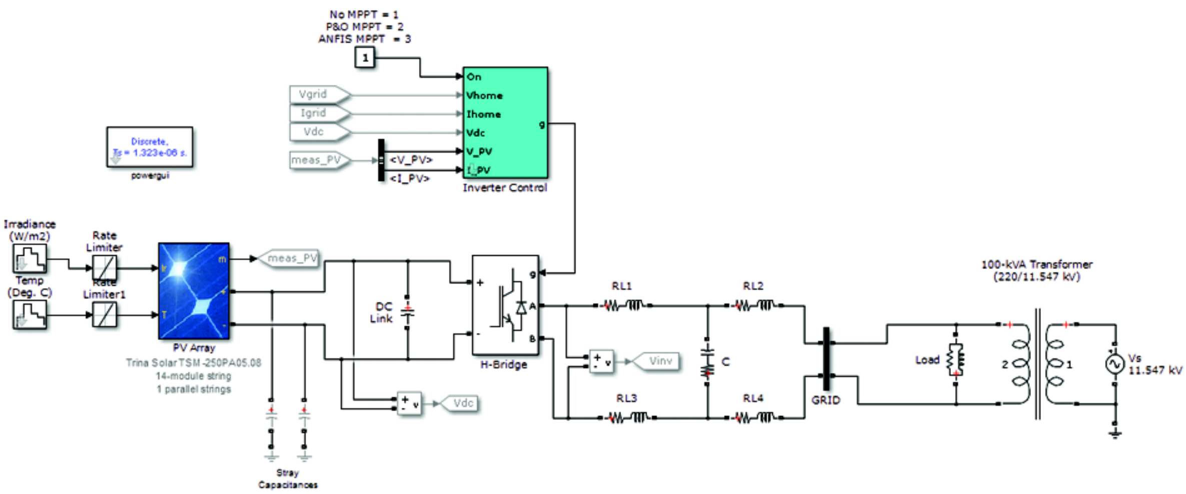

Fig. 4: Simulink model of grid-connected rooftop solar panels with 3 types of MPPT

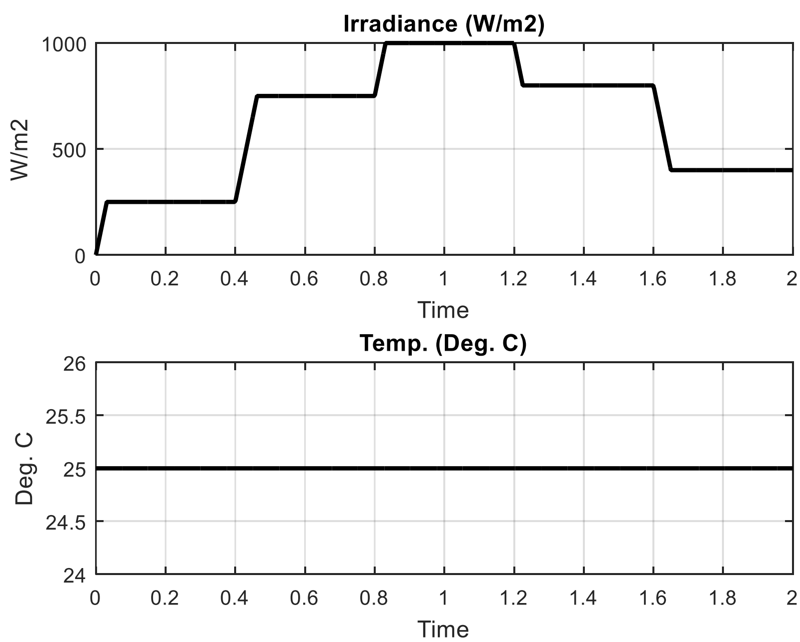

Fig. 5: Variable irradiation and constant temperature

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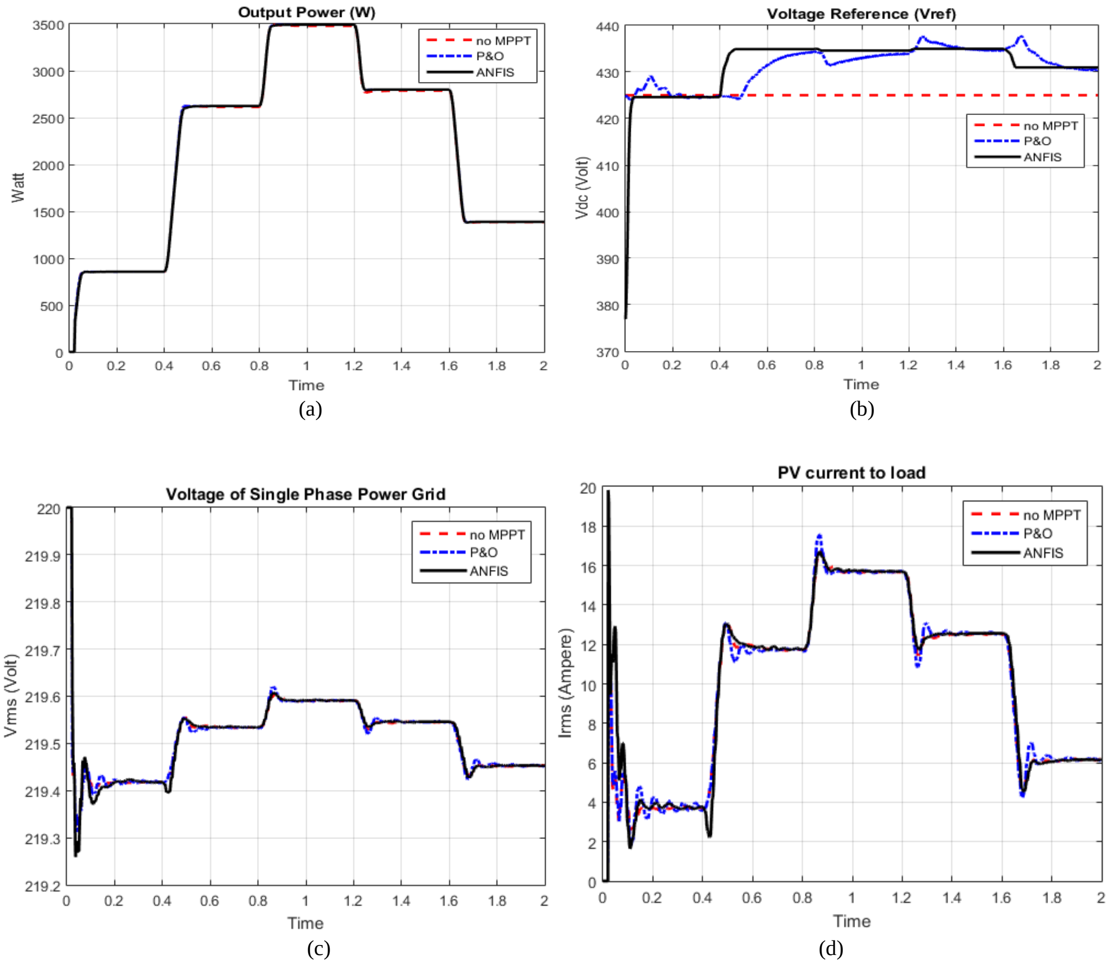

Fig. 6: Rooftop solar panel output for variable irradiations at a constant temperature, showing (A) DC output power, (B) Reference voltage, (C) Grid voltage, and (D) Load current from the rooftop solar panel

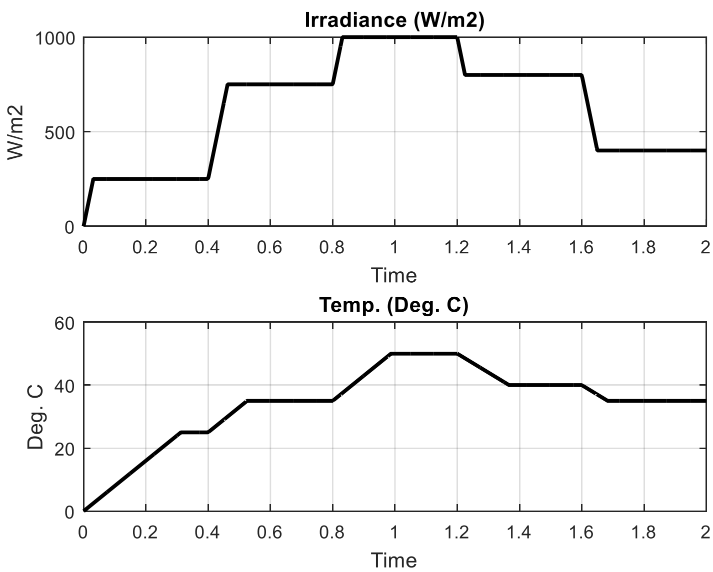

Fig. 7: Varying irradiation and temperature

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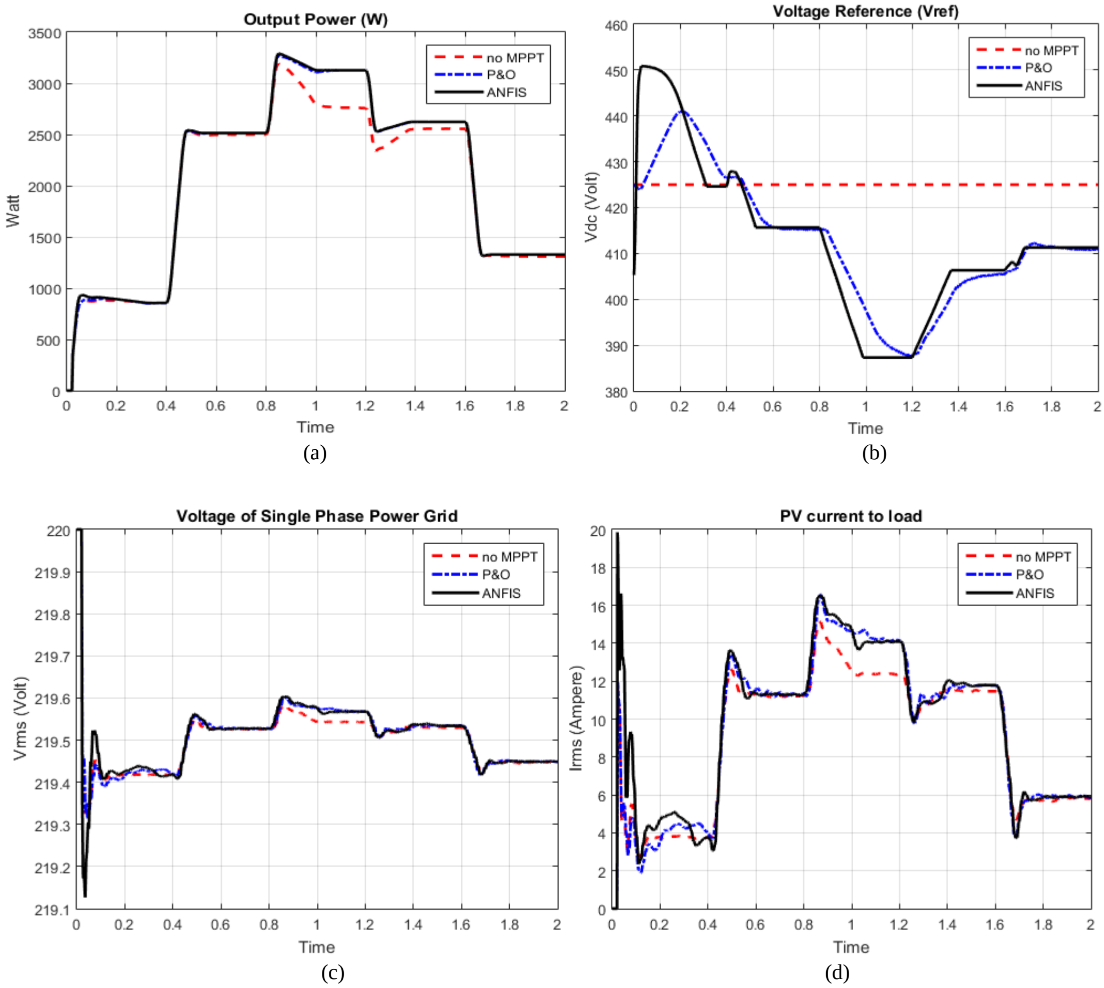

Fig. 8: The output of the rooftop solar panel for varying irradiation and temperature showing (A) DC output power, (B) Reference voltage, (C) Grid voltage, and (D) Load current from the rooftop solar panel

Table 2: Comparison of ANFIS MPPT vs test data

I_{rr} W/m^2	Temp. (°C)	V_{ref} (Volt)	V_m (Volt)	Error (%)
50	25	389	397.0	2.02
50	55	326	334.5	2.54
100	25	408	410.0	0.49
100	55	347	349.0	0.57
300	25	427	427.5	0.12
300	55	368	368.5	0.14
500	25	433	433.0	0.00
500	55	375	374.5	0.13
700	25	435	434.5	0.12
700	55	377	377.5	0.13
900	25	435	435.0	0.00
900	55	378	378.0	0.00
1000	25	435	434.5	0.12
1000	55	378	378.0	0.00

Note:
I_{rr} Irradiance
V_{ref} ANFIS MPPT
V_m Data at MPPT

Table 3: Comparison of energy and efficiency at irradiation fluctuation and constant temperature

Energy	No MPPT	P&O MPPT	ANFIS MPPT
DC side (10^8 J)	1.774	1.781	1.780
AC side (10^8 J)	0.649	0.651	0.651
Efficiency (%)	36.562	36.569	36.587

Table 4: Comparison of energy and efficiency at varying irradiation and temperature

Energy	No MPPT	P&O MPPT	ANFIS MPPT
DC side (10^8 J)	1.593	1.661	1.663
AC side (10^8 J)	0.581	0.609	0.610
Efficiency (%)	36.505	36.629	36.670

Conclusion

Applying the ANFIS MPPT method to rooftop solar panels connected to a single-phase network can increase the efficiency of rooftop solar panels. At fluctuating irradiation and constant temperature, the increase in efficiency of the ANFIS MPPT method reached 0.0664 and 0.0474% against the method with no MPPT and P&O MPPT. At fluctuating irradiation and extreme temperature, the efficiency increases of the ANFIS MPPT method reached 0.4523 and 0.1115% compared to the methods with no MPPT and P&O MPPT. The efficiency of ANFIS MPPT is better in all operating conditions compared to the no MPPT and P&O MPPT methods.

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Author’s Contributions

I Made Ari Nrartha: Responsible for the writing, problem formulation, and simulation of on-grid rooftop solar panel systems, for systems with no MPPT, with MPPT P&O and MPPT ANFIS, respectively.

I Made Ginarsa: Responsible for the writing, literature review, and initial research survey.

Agung Budi Muljono: Responsible for ANFIS control designed.

Sultan: Responsible for ANFIS train and validation.

Ida Ayu Sri Adnyani: Responsible for analysis of results.

Muhammad Roil Bilad and Muhammad Abid: Validation, manuscript writing, and revision.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

References

Abdel-Salam, M., El-Mohandes, M. T., & Goda, M. (2018). An improved perturb-and-observe-based MPPT method for PV systems under varying irradiation levels. *Solar Energy*, *171*, 547-561. https://doi.org/10.1016/j.solener.2018.06.080

Abdel-Salam, M., EL-Mohandes, M. T., & Goda, M. (2019). *History of Maximum Power Point Tracking* (pp. 1-29). https://doi.org/10.1007/978-3-030-05578-3_1

Alfian, M. R., Nrartha, I. M. A., & Zubaidah, T. (2022). ANFIS-based MPPT Controller Design on Boost Converter to Improve Photovoltaic System Performance. *Dielektrika*, *9*(2), 1-10. https://doi.org/10.29303/dielektrika.v9i2.310

Chekired, F., Mellit, A., Kalogirou, S. A., & Larbes, C. (2014). Intelligent maximum power point trackers for photovoltaic applications using FPGA chip: A comparative study. *Solar Energy*, *101*, 83-99. https://doi.org/10.1016/j.solener.2013.12.026

DEN. (2019). Indonesia Energy Out Look 2019. *Journal of Chemical Information and Modeling*, *53*(9), 1689-1699.

Eltamaly, A. M., & Farh, H. M. H. (2020). *PV Characteritics, Performance and Modelling* (pp. 31-63). Springer Nature. https://doi.org/10.1007/978-3-030-05578-3_2

ESDM, M. (2021). *Pembangkit Listrik Tenaga Surya Atap yang Terhubung pada Jaringan Tenaga Listrik Pemegang Izin Usaha Penyediaan Tenaga Listrik Untuk Kepentingan Umum* (p. 34). https://drive.esdm.go.id/wl/?id=5XQv80ogkSp0tLQsY4wJNUPVSPpcgGtz

Ginarsa, I. M., & Zebua, O. (2014). Stability improvement of single machine using ANFIS-PSS based on feedback-linearization. *Telkomnika (Telecommunication Computing Electronics and Control)*, *12*(2), 315–324. https://doi.org/10.12928/TELKOMNIKA.v12i2.1977

Ginarsa, I. M., Nrartha, I. M. A., Muljono, A. B., Sultan, S., & Nababan, S. (2022a). *Additional Control Based on ANFIS Algorithm to Improve Transient Current of Converter-Side in HVDC Transmission System*. *January*, 383-390. https://doi.org/10.1007/978-981-16-2123-9_29

Ginarsa, I. M., Nrartha, I. M. A., Muljono, A. B., Sultan, S., & Nababan, S. (2022b). Strategy to reduce transient current of inverter-side on an average value model high voltage direct current using adaptive neuro-fuzzy inference system controller. *International Journal of Electrical and Computer Engineering (IJECE)*, *12*(5), 4790-4800. https://ijece.iaescore.com/index.php/IJECE/article/view/26395/15906

Ginarsa, I. M., Nrartha, I. M. A., Sultan, S., Muljono, A. B., & Nababan, S. (2020). Perbaikan Stabilitas Dinamik Sistem Tenaga Terintegrasi Pembangkit Listrik Tenaga Mikro Hidro dan Diesel Menggunakan PSS Berbasis ANFIS. *Jurnal Sains Teknologi & Lingkungan*, *6*(2), 249. https://doi.org/10.29303/jstl.v6i2.197

Group, W. B. (2022). *Global Solar Atlas* (p. 6). https://globalsolaratlas.info/map?c=-8.5946,117.575684,8&r=IDN

Hasan, M., Mekhilef, S., & Henk, M. (2013). Photovoltaic System Modeling with Fuzzy Logic Based Maximum Power Point Tracking Algorithm. *International Journal of Photoenergy*. https://doi.org/10.1155/2013/762946

IESR. (2021). *Indonesia Energy Transition Outlook 2022. Tracking Progress of Energy Transition in Indonesia: Aiming for Net-Zero Emissions by 2050*. Institute for Essential Services Reform (IESR).

Kamarzaman, N. A., & Tan, C. W. (2014). A comprehensive review of maximum power point tracking algorithms for photovoltaic systems. *Renewable and Sustainable Energy Reviews*, *37*, 585-598. https://doi.org/10.1016/j.rser.2014.05.045

Laudani, A., Fulginei, F. R., Salvini, A., Lozito, G. M., & Mancilla-David, F. (2014). Implementation of a neural MPPT algorithm on a low-cost 8-bit microcontroller. *2014 International Symposium on Power Electronics, Electrical Drives, Automation and Motion*, 977-981. https://doi.org/10.1109/SPEEDAM.2014.6872101

Loukriz, A., Abdelhamid, L., & Sabir, M. (2013). *Comparison of P&O and fuzzy MPPT Methods for Photovoltaic System.* Conference: ICPEA.

Mancilla-David, F., Riganti-Fulginei, F., Laudani, A., & Salvini, A. (2014). A Neural Network-Based Low-Cost Solar Irradiance Sensor. *IEEE Transactions on Instrumentation and Measurement*, *63*(3), 583-591. https://doi.org/10.1109/TIM.2013.2282005

Messai, A., Mellit, A., Guessoum, A., & Kalogirou, S. A. (2011). Maximum power point tracking using a GA optimized fuzzy logic controller and its FPGA implementation. *Solar Energy*, *85*(2), 265-277. https://doi.org/10.1016/j.solener.2010.12.004

Messalti, S., Harrag, A., & Loukriz, A. (2017). A new variable step size neural networks MPPT controller: Review, simulation and hardware implementation. *Renewable and Sustainable Energy Reviews*, *68*, 221-233. https://doi.org/10.1016/j.rser.2016.09.131

Muljono, A. B., Ginarsa, I., Nrartha, I. M., & Dharma, A. (2018). Coordination of Adaptive Neuro Fuzzy Inference System (ANFIS) and Type-2 Fuzzy Logic System-Power System Stabilizer (T2FLS-PSS) to Improve a Large-scale Power System Stability. *International Journal of Electrical and Computer Engineering*, *8*(1), 76-86. https://doi.org/10.11591/ijece.v8i1.pp76-86

Nrartha, I. M. A., Ginarsa, I. M., Muljono, A. B., Sultan, S., & Adnyani, I. A. S. (2022). ANFIS based MPPT Design for Rooftop Solar Panels Connected to Single Phase Power Grid. *The First Mandalika International Multi-Conference on Science and Engineering 2022*.

Patel, H. R. (2022). Fuzzy-based metaheuristic algorithm for optimization of fuzzy controller: Fault-tolerant control application. *International Journal of Intelligent Computing and Cybernetics*, *15*(4), 599-624. https://doi.org/10.1108/IJICC-09-2021-0204

Patel, H. R., & Shah, V. A. (2022a). Comparative Analysis Between Two Fuzzy Variants of Harmonic Search Algorithm: Fuzzy Fault Tolerant Control Application. *IFAC-Papers OnLine*, *55*(7), 507-512. https://doi.org/10.1016/j.ifacol.2022.07.494

Patel, H. R., & Shah, V. A. (2022b). Fuzzy Logic Based Metaheuristic Algorithm for Optimization of Type-1 Fuzzy Controller: Fault-Tolerant Control for Nonlinear System with Actuator Fault∗∗The author(s) received funding for the ACODS-2022 registration fees from Dharmsinh Desai University, Na. *IFAC-Papers OnLine*, *55*(1), 715-721. https://doi.org/10.1016/j.ifacol.2022.04.117

Patel, H. R., & Shah, V. A. (2022c). Shadowed Type-2 Fuzzy Sets in Dynamic Parameter Adaption in Cuckoo Search and Flower Pollination Algorithms for Optimal Design of Fuzzy Fault-Tolerant Controllers. In *Mathematical and Computational Applications* (Vol. 27, Issue 6). https://doi.org/10.3390/mca27060089

Patel, H. R., & Shah, V. A. (2022d). Simulation and Comparison Between Fuzzy Harmonic Search and Differential Evolution Algorithm: Type-2 Fuzzy Approach. *IFAC-Papers OnLine*, *55*(16), 412-417. https://doi.org/10.1016/j.ifacol.2022.09.059

Patel, H. R., & Shah, V. A. (2022e). Type-2 fuzzy logic applications designed for active parameter adaptation in metaheuristic algorithm for fuzzy fault-tolerant controller. *International Journal of Intelligent Computing and Cybernetics*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/IJICC-01-2022-0011

Patel, H. R., & Shah, V. A. (2022f). A metaheuristic approach for interval type-2 fuzzy fractional order fault-tolerant controller for a class of uncertain nonlinear system*. *Automatika*, *63*(4), 656-675. https://doi.org/10.1080/00051144.2022.2061818

Pido, R., Himran, S., & Mahmudin, M. (2018). Analisa Pengaruh Pendinginan Sel Surya Terhadap Keluaran dan Efisiensi. *Teknologi*, *19*(1), 31-38. file:///C:/Users/User/Downloads/7858-18490-1-SM.pdf

Rai, A. K., Kaushika, N. D., Singh, B., & Agarwal, N. (2011). Simulation model of ANN based maximum power point tracking controller for solar PV system. *Solar Energy Materials and Solar Cells*, *95*(2), 773-778. https://doi.org/10.1016/j.solmat.2010.10.022

Raval, S., Patel, H. R., Patel, S., & Shah, V. A. (2023). *Passive Fault-Tolerant Control Scheme for Nonlinear Level Control System with Parameter Uncertainty and Actuator Fault BT-Applications of Fuzzy Techniques* (S. Dick, V. Kreinovich, & P. Lingras (eds.); pp. 229-242). Springer International Publishing.

Trina Solar. (2011). *TSM-PC05A The Honey Module* (p. 2). https://www.energymatters.com.au/images/trina-solar/trina-pc05a-250w.pdf

USAID. (2020). *Panduan Perencanaan dan Pemanfaatan PLTS Atap di Indonesia*.