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ANFIS used as a Maximum Power Point Tracking Algorithm for a Photovoltaic System

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ABSTRACT

Photovoltaic (PV) modules play an important role in modern distribution networks; however, from the beginning, PV modules have mostly been used in order to produce clean, green energy and to make a profit. Working effectively during the day, PV systems tend to achieve a maximum power point accomplished by inverters with built-in Maximum Power Point Tracking (MPPT) algorithms. This paper presents an Adaptive Neuro-Fuzzy Inference System (ANFIS), as a method for predicting an MPP based on data on solar exposure and the surrounding temperature. The advantages of the proposed method are a fast response, non-invasive sampling, total harmonic distortion reduction, more efficient usage of PV modules and a simple training of the ANFIS algorithm. To demonstrate the effectiveness and accuracy of the ANFIS in relation to the MPPT algorithm, a practical sample case of 10 kW PV system and its measurements are used as a model for simulation. Modelling and simulations are performed using all available components provided by technical data. The results obtained from the simulations point to the more efficient usage of the ANFIS model proposed as an MPPT algorithm for PV modules in comparison to other existing methods.

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1. INTRODUCTION

The efficiency of PV modules in various situations is already known across industries and trades. However, since sunlight, as the source for generating electricity from PV modules, depends on weather conditions, PV modules may have lower efficacy. This results in low electricity generation from solar power. Three factors affect the effectiveness of electricity generation from solar power: solar exposure of the module, module temperature and PV system properties. The first two factors are beyond human control and are highly unstable because they change from one second to another, depending on the weather conditions and season. Consequently, these properties result in PV systems being an unreliable source of electricity. This paper addresses the above problem and presents the ANFIS method used as the MPPT algorithm from which are many presented in previous papers [2]. In this paper, developed ANFIS algorithm was simulated in the actual PV system and applied in practice [4]. ANFIS is proposed as the MPPT algorithm and modelled in Matlab. The control aspect of the PV system using the ANFIS algorithm is addressed in the papers: comparing it with QUARTUS II [2], mathematical model of PV panels using ANFIS [3], proposing ANFIS

as MPPT [4], proposition ANFIS as energy losses predicament [5], peak load predicament [6], and wind power plant MPPT [8-11]. However, none of them was implemented in the actual PV plant system. Therefore, none of them have results compared against results collected from PV plant. Numerous articles have demonstrated the flexibility of the ANFIS method, although not directly related to PV systems, but were instead: compared against the Neural Network in laboratory conditions [7], used in the role of Expert system for steel grading [8], and integrated bidirectional subsystem MPPT [17]. The articles that have focused on the comparison of the ANFIS method with some other Artificial Intelligence (AI) methods such as the Neural Networks (NN), Genetic Algorithm (GA), proved that ANFIS is the most suitable for use in uncertain systems [17] and without a doubt presented ANFIS as the most suitable algorithm for MPP tracking. Previous work also presents ANFIS as multilevel cascade inverter for PV systems [18] concluding the quality of the methods in predicting MPP in a simulated environment. In the past four years, numerous articles and reports addressed the simulations of PV cells and consequently of PV modules, and served as the basis for developing authentic models for further research. Type-2 Fuzzy logic controller [10], PV MPPT controller with I-V and P-V curve results [12], comparison with the Fuzzy logic controller [13], standalone complex PV system with MPPT controller [14], trained ANFIS and Fuzzy logic controller according to Perturb and Observe (P&O) algorithm [16]. The papers that dealt with ANFIS in detail, considering all layers and training methods, opened the path to use ANFIS as the method to resolve all insufficiently defined problems with a high rate of uncertainty in conclusions [2-4], [21]. The MPPT algorithm is, in general, already integrated in DC-AC inverters, so that all algorithms for managing control systems are locked and cannot be modified, and which are known: Perturb and Observe (P&O) and Incremental Conductance (InCond), or both, are installed in the MPPT algorithm. Many researchers have embedded the ANFIS algorithm in the filed-programmable gate array (FPGA) [2], [6].

This paper deals with ANFIS as an MPPT algorithm in an actual 10 kW PV system used for electricity generation, which has the role of a distributed generation (DG) source of energy, i.e. it feeds all generated energy into the distribution system operator [1]. The specifications of the actual PV system installed on the roof, which are important for the simulation, are presented in Section 2. Taking samples from the inverters, 'teaching' and training the algorithm in ANFIS structure, its block diagram and modelling of the actual system is presented in Section 3. Basics of ANFIS architecture and algorithm, simulations with the data from the actual measurements, the comparison of the obtained results and discussion are contained in Section 4. Section 5 contains the conclusion drawn from the simulation results.

2. SAMPLING AND SYSTEM MODELLING

2.1. PV System

The properties of the PV system taken into account in the process of designing the model include THD_U (Total Harmonic Distortion of Voltage), which is addressed in the article referred to under references, DC Voltage characteristics based on PV modules model provided by in-field measurement, P-V and I-V graphs provided by calculations of string connected PV modules. THD is installed in a three-level PWM signal generator where the impact on voltage distortion is defined. The set THD_U is 1.48% presented in Figure 1 for voltage frequency scan.

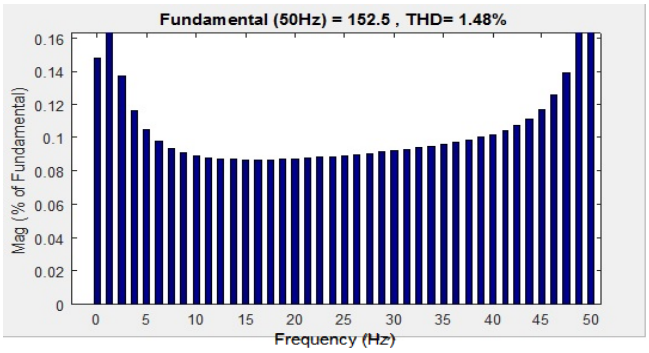


Figure 1. Total harmonic voltage distortion - THD_U.

The analysis of the field measurements in the PV system established that there was no reactive power exchange between the PV system and the distribution network, so no simulation of a reactive power

source (Q) was used. The measuring point from which the data for subsequent analysis was taken is the identical location of the actual PV system at the point of power exchange between the PV array and the distribution network. The size of the sample for analysis is $Ts=10^{-6}$ so that the sinusoid is clearly visible, as well as all transients in the operation of the DC-DC stabilizer. All components used in the simulation are set up on the basis of the actual results of the system output, so that transients are presented as realistically as possible. As in Section 2, the modules in the simulation are arranged accordingly: in 4 rows for each inverter and of the same type as in the actual PV system. P-V and I-V module specifications are shown in Figure 2.

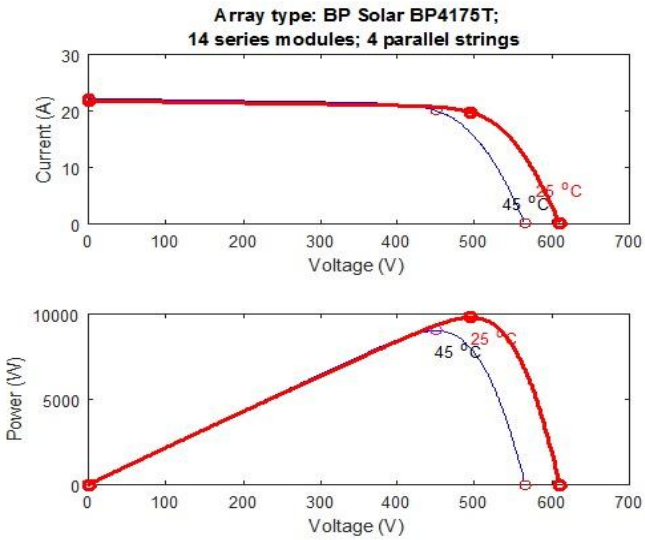


Figure 2. P-V and I-V characteristics of the entire PV system

In order to limit the inverter power output, a three-phase 10 kVA AC-AC transformer was installed on the array, immediately at the outlet of the PV system to the distribution network. The consumer representing the distribution network as an energy-using device was simulated using the RLC line parameters P= 15 kW, Q_L=0 kVAr, Q_C=0 kVAr. Since Q_L and Q_C do not participate in the consumption from the PV system, as there is no reactive power exchange, their value was set as 0 kVAr. The frequency of the PV system during the entire simulation was in the range 49.96 Hz – 50.05 Hz, which complies with the HRN EN 50160 electric power quality standard. Adjustment to the mains voltage of the distribution network was simulated with the constant 230 V voltage on the inlet to the PWM signal generator.

2.2. ANFIS Algorithm

Neuro-fuzzy method is important in the designing of fuzzy expert systems. In any case, the right selection of the number, type, rules and parameters of the fuzzy system Membership Functions (MFs) is vital for acquiring the minimum performance. Trial and error is the method to achieve the minimum performance. This fact emphasizes the weight of settings of the fuzzy systems. ANFIS is a Sugeno network within the adaptive systems facilitating learning and training. That framework makes models more systematic and uses expert knowledge so that user does not have to be an expert. For better understanding the ANFIS architecture, consider the following fuzzy system which has two rules, two inputs, and therefore is a first order Sugeno model:

Rule 1: If (x is A_1) and (y is B_1) then ($f_1 = p_1x + q_1 + r_1$) (1)

Rule 2: If (x is A_2) and (y is B_2) then ($f_2 = p_2x + q_2 + r_2$) (2)

Literature proposes several types of reasoning of Sugeno fuzzy systems [11]. Based on type of fuzzy reasoning and if-then rules, there are three types of fuzzy inference systems mostly used:

a. Depending on rule's strength, the overall output is the weighted average of each rule's crisp output (the product or minimum of the degrees of match with the premise part) and MFs. The output membership function used in this example is a monotonic function.

b. The output of fuzzy system is obtained by applying "maximum" operation to the certified fuzzy outputs (each is equal to the minimum of scoring result and the output membership function of each rule). Diverse schemes have been presented to obtain the final (crisp) output based on the main fuzzy output; some of them are centroid of area (CoA), bisector of area (BoA), mean of max (MoM), etc. [11].

c. Takagi-Sugeno "if-the" rules are used for the purposes of this paper. Linear combination of fuzzy input variables plus a constant term are used for output of each rule, and the ultimate output is the average weight of output from every rule. One of the ANFIS architectures is the implementation of these two rules as shown in Figure 3. A circle represents a fixed node, as presented in Figure 3, a square indicates an adaptive node (the parameters are changing during training with back propagation or hybrid method of learning).

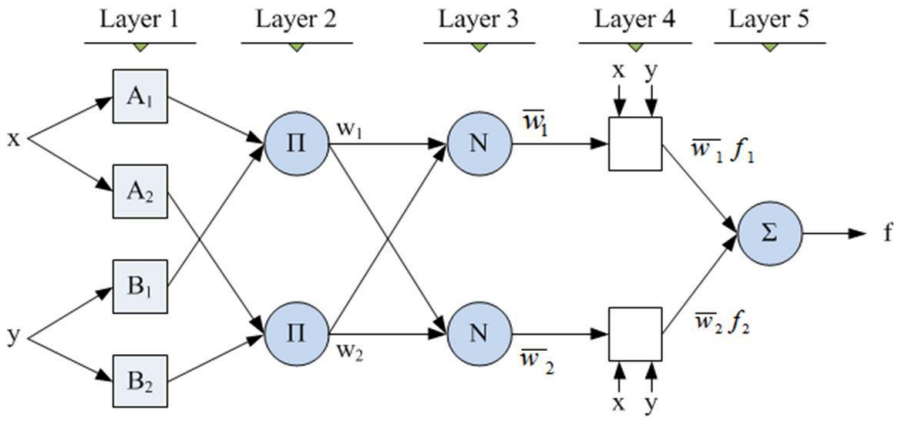


Figure 3. ANFIS architecture

Layer 1: Nodes in this layer are adaptive nodes. The output of each node is the degree of membership of the input of the fuzzy membership functions represented by the node. Expressions for obtaining those outputs are:

$$O_{1,I} = \mu_{Ai}(x) \quad i=1,2 \tag{3}$$

$$O_{1,I} = \mu_{Bi}(x) \quad i=3,4 \tag{4}$$

where, A_i and B_i are any suitable fuzzy sets in parametric form, and $O_{1,i}$ is the output of the node in the i-th layer. This paper uses trapezoidal shape MFs.

Layer 2: The nodes in this layer are fixed (not adaptive) and therefore are called a Neural Network layer. They are signed with Π to indicate that they play the role of a multiplier function of inputs. Outputs from this node are presented in expression (5).

$$O_{2,i} = W_i = \mu_{Ai}(x)\mu_{Bi}(y) \quad i=1,2 \tag{5}$$

Layer 3: The nodes in this layer are also fixed nodes. They are signed with N to indicate that they perform a normalization of the scoring strength from the previous layer. Output from this node is given in (6).

$$Q_{3,1} = \overline{W} = \frac{w_i}{W_1+W_2} \; ; i = 1,2 \tag{6}$$

Layer 4: All the nodes in this layer are adaptive nodes, and therefore this layer is a Fuzzy logic layer. The output of each node is simply the product of the normalized scoring strength and a first order polynomial function. Output from each node from this layer is presented in (7).

$$O_{4,I} = \overline{W_i}\, f_i = \overline{W_i}\,(p_i x + q_i y + r_i) \quad i=1,2 \tag{7}$$

Layer 5: This layer has one node signed with S to indicate simple summarization in this layer.

$$Q_{3,1} = \sum_i \overline{W}_i \cdot f_i = = \frac{\sum_i W_i \cdot f_i}{\sum_i \dot{W}_i}\ ; i = 1,2 \tag{8}$$

The ANFIS architecture is not unique. Combination of some layers can be still produce the same output instead. In ANFIS architecture, there are two adaptive layers (Layers 1 and 4, Fuzzy layers). Layer 1 has three alterable parameters (a_i, b_i and c_i) referring to the input of MFs. These parameters are called premise parameters. Layer 4 also has three alterable parameters (p_i, q_i and r_i) referring to the first order polynomial function. These parameters are consequent parameters. The task of the training or learning algorithm for this architecture is to tune all the alterable parameters to make the ANFIS output match the training data as much as they can.

3. MPPT WITH THE ANFIS ALGORITHM

Representation of the entire modelled actual PV System presented in Figure 4 with its components marked.

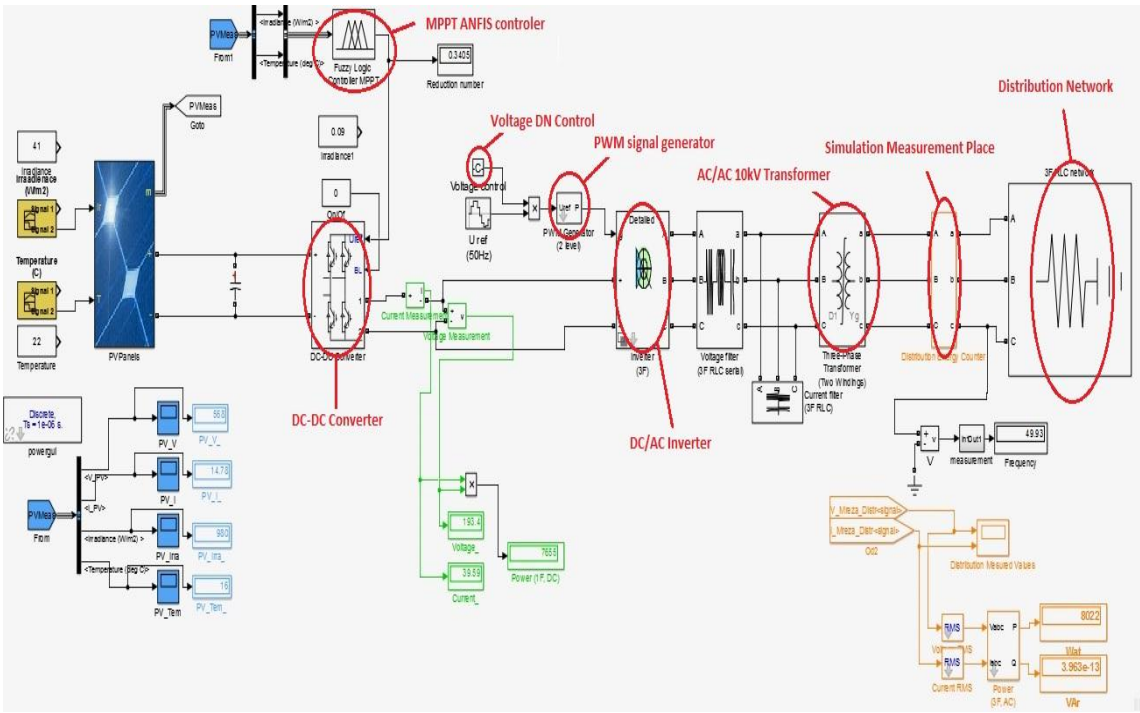


Figure 4. Actual modelled PV system diagram

Marked with a red ellipse is the DC-DC converter with the purpose of regulating output DC voltage according to the ANFIS MPPT controller marked with another red ellipse. ANFIS controller works according to input values of Temperature (^oC) and sun irradiance (W/m^2) based on trained .fis file. Another detail is voltage control for outside voltage regulation based on user input working with the PWM signal generator. The above mentioned are input for DC/AC inverter based on diode switching gear with set up dip and swell voltage regulation. The next red ellipse is the AC/AC 10 kW power transformer used for power limiting output and voltage regulation on AC side. The last two red ellipses are the measurement place for output results and the Distribution network with simulated RLC consumer.

The explanation for creating and the levels comprising the ANFIS cognitive method has been described in numerous earlier articles in bibliography [8], [10-13], [15], [17] and [18-22]. The creation of the ANFIS MPPT algorithm was applied with the data recorded directly from the power exchange point between

the PV system and the distribution network. The following data were used:

a. Hours of solar exposure (irradiance),
b. Ambient temperature per hour,

Humidity is not considered in this paper. The output power from the system was measured with regard to the collected values for solar exposure and temperature. The input to the ANFIS algorithm comprises the data about the solar exposure of PV modules and ambient temperature, and the output is a nonlinear coefficient as a control signal for the DC-DC stabilizer which maintains voltage in PV modules in the maximum efficiency range. These points are indicated in Figure 4. Based on the data concerning solar exposure and temperature, the ANFIS algorithm with its output directly through the DC-DC stabilizer affects the voltage in PV modules, thus modifying the output power of the PV system. Data on the best sunlit days for 2015 and 2016 were used to train the ANFIS algorithm, so that all situations in between are within the scope of ANFIS. Training was performed without the impact of the measured values from the actual PV system; instead, the simulation was used as the basic model. Training was performed using the following parameters: 10 training epochs, 6 trapezoidal membership functions. A Hybrid Optimization Model was used, with error $Er=10^{-6}$, shown in Figure 7 are results of the ANFIS MPPT algorithm training. It can be noticed in Figure 7 that the greatest level of efficiency is when ambient temperature is in the 15°C - 20°C range, with solar irradiation over 900 W/m^2. It is important to note that the temperature that was used as input for the training of the ANFIS MPPT algorithm is in fact ambient temperature, and solar exposure is irradiation according to the weather reports. The output power from the PV system as "output" variable is shown in Figure 5. The ANFIS trained system with Sugeno inference algorithm using two-inputs and one-output is shown in Figure 6. The membership functions for both inputs and output regarding values are shown in Figure 7. One can notice in Figure 7 the shape of a trapezoid for individual membership functions and that is due to users' custom shifting. It's possible to change shape but the results are considerably different. View with membership functions of trained system is shown in Figure 8, 2-input, 1-output ANFIS with layers and membership functions in one image. The number of generated rules for the entire ANFIS trained system is 72. Also, it is possible to generate more, but complexity of the system makes training last much longer.

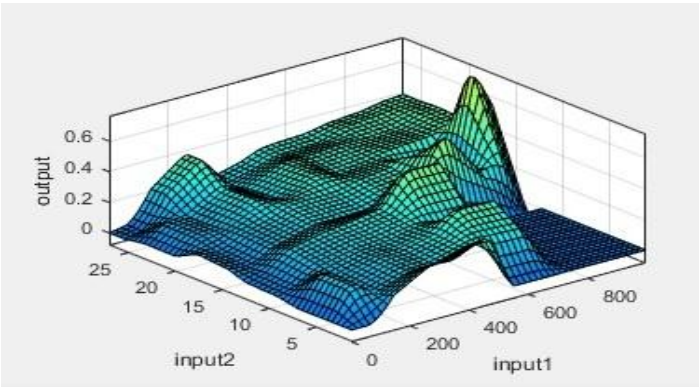


Figure 5. Surface of the functioning of the MPPT algorithm

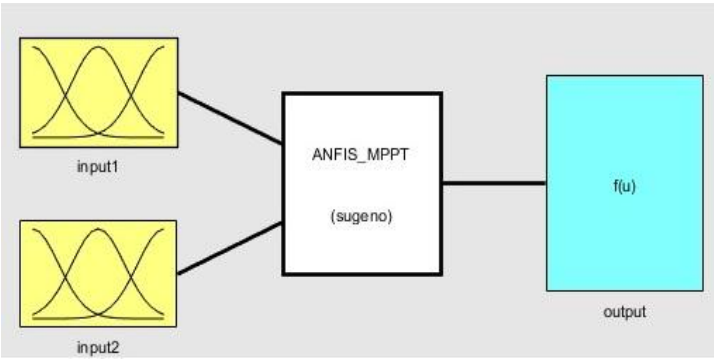


Figure 6. Two inputs with the Sugeno Inference Model and system output

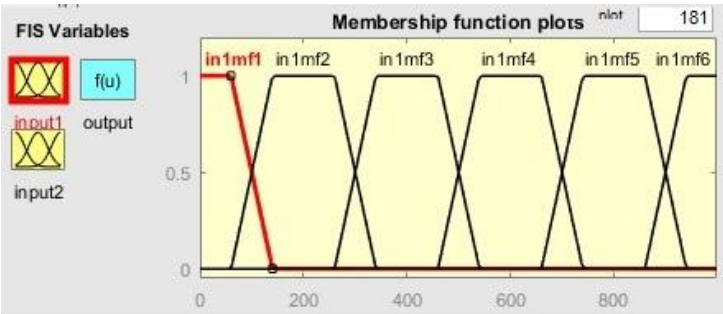


Figure 7. Solar exposure with 6 trapezoidal membership functions

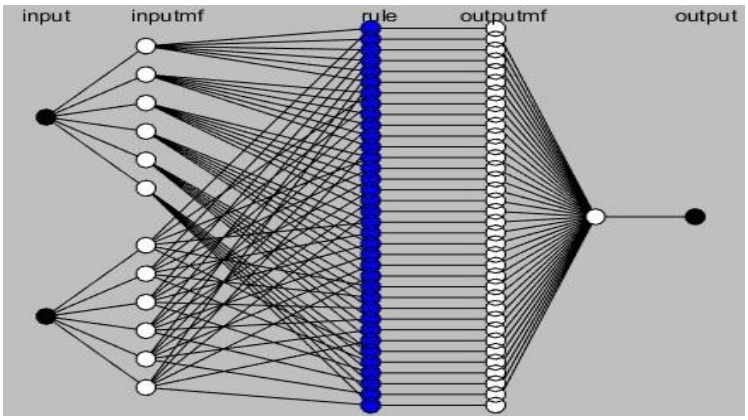


Figure 8. ANFIS MPPT system diagram with layers

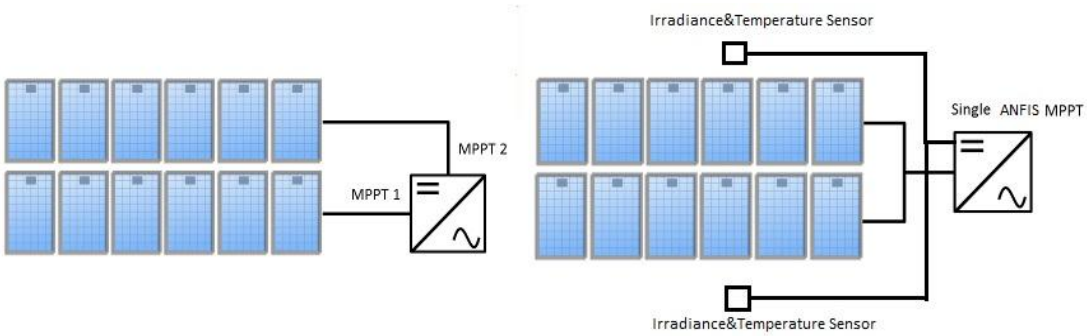


Figure 9. Left – conventional dual-MPPT system, right – ANFIS MPPT algorithm with two sensors

The MPPT algorithm, which is built in the inverters in Table 2, was not used to train the ANFIS MPPT algorithm. This means that the ANFIS MPPT algorithm "learns" independently from the existing MPPT algorithm in inverters, and the final result of its activity provides the output to the DC-DC stabilizer which regulates DC voltage of the modules. The company, which produces installed inverters, uses a Dual-MPPT system to connect modules. This system requires that two separate connections be used to connect PV modules facing different directions: east and west. This results in greater efficiency of all modules.

The Dual MPPT connection system to the same row of PV modules ensures separate operation in the case of defect on an individual module, thus maintaining the maximum efficiency of the entire PV array. Using a single ANFIS MPPT algorithm to which all PV modules are connected regardless of their tilt angle or azimuth, it is possible to switch from one row of modules to the other using the universal solar irradiance meter. This would have the same effect as a Dual-MPPT system, without having to change the DC/AC inverter, but requires two additional inputs, as shown in Figure 9. Since training of the ANFIS MPPT algorithm is unique for each PV array, this would cover all the costs of additional material, while such costs are unavoidable in the case of the classic MPPT algorithms in a Dual-MPPT system.

4. CASE SAMPLE AND SIMULATION RESULTS

The 9.59 kW solar photovoltaic modules for electricity generation are installed with a 30° tilt angle on the south slope of the roof of a house in Španско, a neighborhood in Zagreb. The system works parallel with the distribution network, and it is used to supply electricity to the appliances in the family house, while any excess electricity is fed into the power grid. During the period when the solar modules do not generate sufficient electricity, power to the appliances is supplied by electricity from the grid. Having regard to the fact that peak energy generation of the installed PV system is during mid-day, it meets approximately 50 % of own demand while the remainder is fed into the electric power distribution network [1]. The photovoltaic system consists of 56 modules mounted on the roof of a house, distributed in four rows with a 30° tilt angle, with three rows comprising 14 modules, where the rated power per module is 170 W, and one row comprising 14 modules with rated power per module of 175 W.

The entire PV system contains 56 PV modules with total power of 9.59 kWp. The specifications of the installed modules presented in Table 1. Eleven (11) modules are connected in series to individual inverters (overall three such inverters). The remaining 9 modules are connected in series and the added 14 new modules are also connected in series to the fourth inverter. The rated power of the three inverters is 3000 VA respectively, and one inverter has the power of 4200 VA [1].

Table 1. PV modules data

Technical data	PV strings 1, 2, 3	PV string 4	
Maximum power P_{max}	170	175	W
Maximum power voltage U_{mp}	36	35,4	V
Maximum power current I_{mp}	4,72	4,9	A
Short-circuit current I_{sc}	5	5,5	A
Open circuit voltage U_{oc}	44,2	44,3	V
Maximum system voltage	600	600	V
Dimensions	1593 x 790 x 50		mm
Mass	15.4	15.4	kg
Number of modules	42	14	pcs

The PV system comprises three installed solar inverter units of 3000 VA, and one unit of 4200 VA, whose specifications are listed in Table 2 [1].

Table 2. Inverter strings data.

Technical data	PV string inverter	PV string inverter	
Input			
Maximum PV Ppv	4100		W
Maximum DC power $P_{DC, max}$	3250	4400	W
Maximum DC voltage $U_{DC, max}$	600	750	V
PV voltage, MPP-range U_{PV}	232-550	125-750	V
Maximum current $I_{PV. Max}$	12	11	A
DC noise voltage U_{SS}	<10	<10	%
Maximum No. in a series (parallel)	3	2	
Output			
Maximum AC power $P_{AC, max}$	3000	4200	W
AC rated power $P_{AC, nom}$	2750	4000	W
Total current harmonic distortion	<4	<4	%
Operating range, grid voltage U_{AC}	198-260	198-260	V
Rated range, grid voltage	180-265	180-265	V
AC power frequency f_{AC}	49,8-50,2	49,8-50,2	Hz
Rated power frequency	45,5-54,5	45,5-54,5	Hz
Feed-in phase cos φ	1	1	

Simplified block diagram of the PV system connection to the low voltage distribution network, is shown in Figure 10. According to Figure 1, marketed place of measurement, “Energy meter”, from which the gathered data are used in this paper, is in place between plant and distribution network.

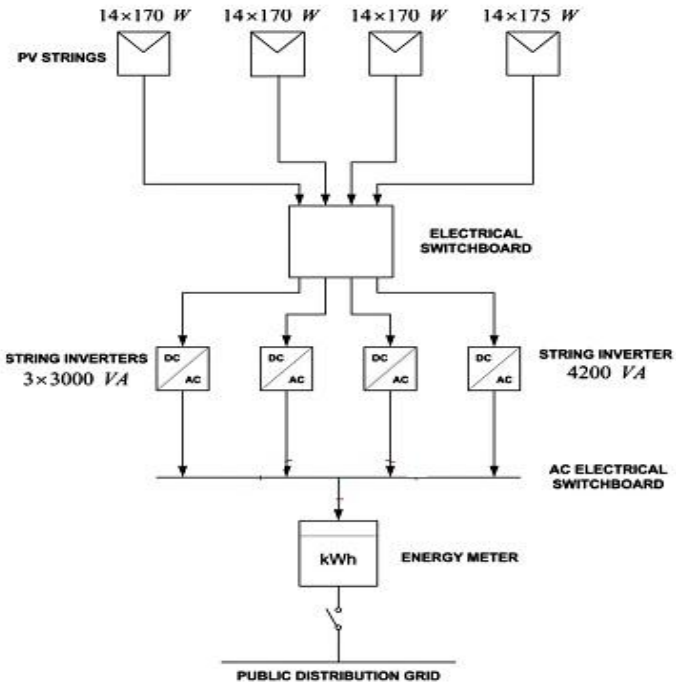


Figure 10. Block diagram of PV modules and inverters.

An algorithm for maximum Power Point Tracking imbedded in PV string inverters is not provided by the manufacturer and the assumption is that inverters are using one of most popular methods: Perturb & Observe or Incremental Conductance. Some manufacturers implement both methods combined in one or more MPPT controllers, but in this case it uses more than one controller for string modules at a different angle. The PV system that was considered in this paper, on the roof of house is oriented to the east with 30° azimuth, presented in Figure 11.

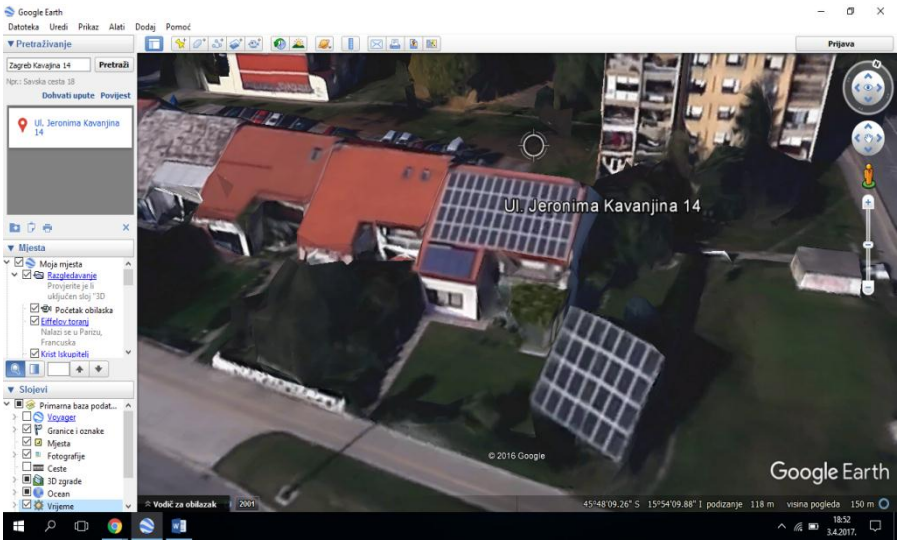


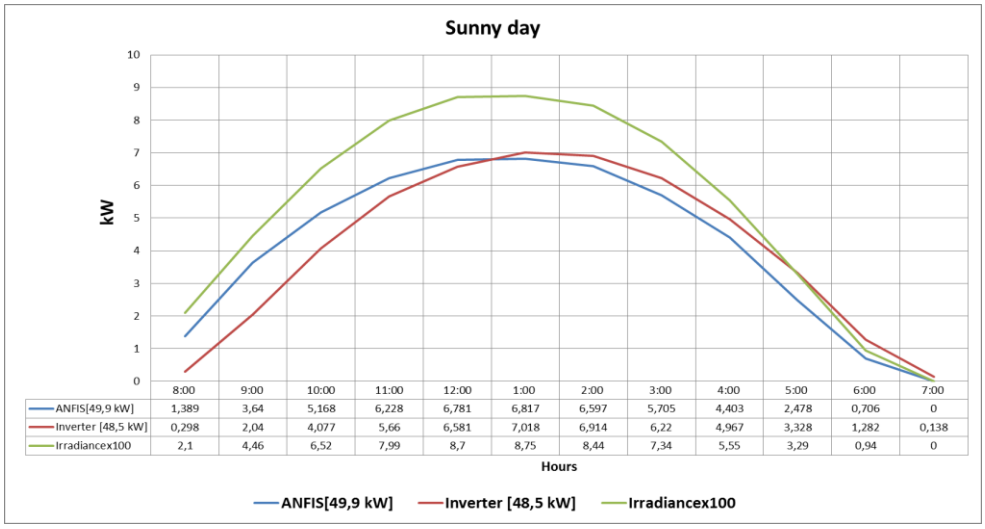
Figure 11. PV system installed on the house roof (Google Maps)

Following the training of the ANFIS MPPT algorithm, a simulation was launched with the activated ANFIS MPPT algorithm as shown in Figure 1. The input data concerning solar exposure and temperature were taken from the weather forecast for that day. The results obtained in the simulation were compared to

the measured power values on the actual PV system from the online portal to which the PV system is linked. The testing was conducted over a period of 18 chosen days. Due to the extensiveness of the obtained results, only 12 days are presented. The results over 12 days are presented in Table 4 and Table 5. The generated day power curve of simulation is shown in Figure 12 and Figure 13. Together with the measured power of the inverter and irradiance. As can be seen, the ANFIS MPPT performs better than the installed MPPT algorithm. Sunny day sample based on on-site measurements and compared against the results from designed model is presented in Figure 12 together with sunlight irradiance. Same analogy for cloudy days is presented in Figure 13 also with sunlight irradiance. Based on presented graphs, both Figure, 12 and Figure 13, show results as presented in Table 3.

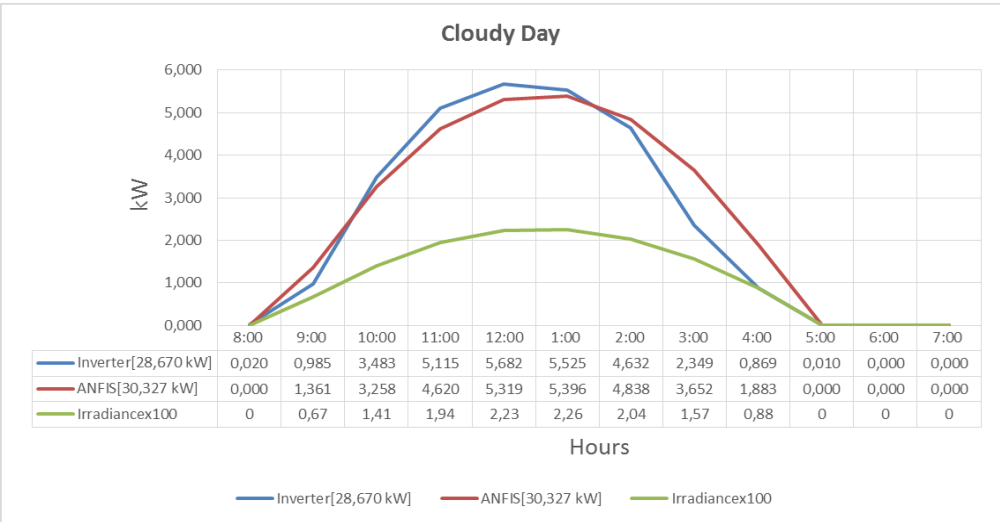
Table 3. Sunny day and cloudy day results

			Difference	
	ANFIS	Inverter	kW	%
Sunny day	49.91 kW	48.52 kW	1.38	2.78
Cloudy day	30.32 kW	28.67 kW	1.65	5.46



	8:00	9:00	10:00	11:00	12:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00
ANFIS[49,9 kW]	1,389	3,64	5,168	6,228	6,781	6,817	6,597	5,705	4,403	2,478	0,706	0
Inverter [48,5 kW]	0,298	2,04	4,077	5,66	6,581	7,018	6,914	6,22	4,967	3,328	1,282	0,138
Irradiancex100	2,1	4,46	6,52	7,99	8,7	8,75	8,44	7,34	5,55	3,29	0,94	0

Figure 12. Comparison of the power curve for a sunny day of sampling and results from model



	8:00	9:00	10:00	11:00	12:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00
Inverter[28,670 kW]	0,020	0,985	3,483	5,115	5,682	5,525	4,632	2,349	0,869	0,010	0,000	0,000
ANFIS[30,327 kW]	0,000	1,361	3,258	4,620	5,319	5,396	4,838	3,652	1,883	0,000	0,000	0,000
Irradiancex100	0	0,67	1,41	1,94	2,23	2,26	2,04	1,57	0,88	0	0	0

Figure 13. Comparison of the power curve over a cloudy day of sampling and results from model

Table 4. 12-day sampling test results

Date	Method/Units	6:00 AM – 09:00 AM;	Percentage difference [%]
1.4.2016	ANFIS [kW]	62.892	18.27
	Inverter [kW]	51.397	
1.5.2016	ANFIS [kW]	65.800	2.49
	Inverter [kW]	64.157	
1.7.2016	ANFIS [kW]	61.010	7.51
	Inverter [kW]	56.426	
1.10.2015	ANFIS [kW]	51.299	3.,30
	Inverter [kW]	34.728	
6.2.2016	ANFIS [kW]	53.152	16.38
	Inverter [kW]	44.444	
10.9.2016	ANFIS [kW]	57.573	17.45
	Inverter [kW]	47.524	
13.6.2016	ANFIS [kW]	63.787	41.72
	Inverter [kW]	37.170	
13.9.2016	ANFIS [kW]	57.573	15.24
	Inverter[kW]	48.795	
14.1.2016	ANFIS[kW]	48.172	64.88
	Inverter [kW]	16.916	
18.3.2016	ANFIS[kW]	61.275	6.28
	Inverter [kW]	57.424	
24.1.2016	ANFIS [kW]	48.172	33.75
	Inverter [kW]	31.913	
29.6.2016	ANFIS [kW]	63.787	7.06
	Inverter [kW]	59.278	

Table 5. Sum total of sampling results over 12 days

12 days test		Difference	
ANFIS [kW]	Inverter [kW]	kW	%
694.492	550.172	144.320	20.78

From the results shown, it is obvious that the ANFIS MPPT performs better by 20.78 % than the conventional algorithm in inverters to obtain the point of maximum efficiency of PV modules. This results should not be taken for granted, because this experiment did not take into consideration non measurable situations like cleaning of PV panels, birds and other animals making shadows, unpredictable malfunctions in equipment, etc. The actual meteorological conditions that could not be tested in the simulation, and which affect the behavior of the PV system, should be taken into consideration. Besides, account should be taken of the greater complexity of the actual system, which comprises the position of the inverter (its heating up, exploitation period), cross-section of DC distribution wiring, energy-consuming devices connected before the meter of the output power from the PV system to the distribution network. As can be seen in Figure 8, the actual PV system is turned slightly to the west compared to the simulated system, which is ideally positioned between the east and west. This difference can be easily eliminated with a mathematical operation, so that the simulation results remain the same.

5. CONCLUSION

This work proves that ANFIS as a method meets the requirements of a PV system to use the MPPT algorithm. It should be underlined that the benefits of ANFIS as an MPPT method are multiple: sampling is not aggressive because it measures the values unrelated to the output of the PV system, voltage and electricity (U and I), a very smooth and fast response to voltage fluctuations, it is irrelevant which materials the PV system is made from, mobility from one system to another subject to additional training, universal for any type of inverter as stated in Section 3, simple implementation of the Dual-MPPT method with additional training. The importance of research done in this paper is a comparison of a real life example MPPT controller with the ANFIS modelled system, and concrete results that are presented in Table 4 and Table 5. As required by the presented results, there is a next step in this research. The next step in research is to train the ANFIS MPPT algorithm over several additional days of sampling and to apply it as a Dual-MPPT algorithm in a simulation. In addition, this conclusion has to be demonstrated by actually connecting the ANFIS MPPT algorithm to the actual PV system.

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