Optimized Fuzzy Controller for MPPT of Grid-connected PV Systems in Rapidly Changing Atmospheric Conditions

Majid Dehghani, Mohammad Taghipour, Gevork B. Gharehpetian, and Mehrdad Abedi

***Abstract*—Due to nonlinear behavior of power production of photovoltaic (PV) systems, it is necessary to apply the maximum power point tracking (MPPT) techniques to generate the maximum power. The conventional MPPT methods do not function properly in rapidly changing atmospheric conditions. In this study, a fuzzy logic controller (FLC) optimized by a combination of particle swarm optimization (PSO) and genetic algorithm (GA) is proposed to obtain the maximum power point (MPP). The proposed FLC uses the ratio of power variations to voltage variations and the derivative of power variations to voltage variations as inputs and uses the duty cycle as the output. The range of changes in fuzzy membership functions and fuzzy rules are proposed as an optimization problem optimized by the PSO-GA. The proposed design is validated for MPPT of a PV system using MATLAB/Simulink software. The results indicate a better performance of the proposed FLC compared to the common methods.**

***Index Terms*—Photovoltaic (PV), maximum power point tracking (MPPT), fuzzy, particle swarm optimization (PSO), genetic algorithm (GA), incremental conductance, perturb and observe.**

I. Introduction

According to the U.S. Department of Energy, the demand for electricity is expected to increase 30% by 2035 as a result of new consumption models, e. g. smart plug-in electric vehicles and smart homes [1]. To decrease the greenhouse gas emission, the attention has been drawn to the electricity generation of renewable energy resources as ecofriendly and nonpolluting power generation units [2]. Photovoltaic (PV) systems, wind turbine units, and fuel cells are renewable energy resources widely used in different power systems.

Among all the renewable energy resources, solar power is worldwide fastest-growing energy source, which is renewable and clean with affordable availability [3], [4]. It is used as an economic source of energy in many applications, including power supply for rural areas, battery charging, and water pumping [5], [6].

There are two main limiting issues associated with PV systems, i. e., high installation cost and low energy conversion efficiency [7], [8]. To address the first issue, the emerging PV technologies are less expensive using more efficient semiconductors for electricity production. To increase the energy conversion efficiency, all components of the PV system must be optimized. The maximum power point tracking (MPPT) controller can be used to obtain the maximum output power of the PV system under different atmospheric conditions [9], [10].

The perturbation and observation (P&O) method is a typical technique used for MPPT due to its simplicity and easy implementation [11]-[14]. However, there are many fluctuations around the maximum power point (MPP) using this method, which results in significant loss of energy, especially in large-scale PV systems [15]. An incremental conductance (INC) method was proposed in [16] to overcome these problems. This method uses constant measurement steps, which makes it possible to track the MPP by measuring the ratio between instantaneous conductance and INC values of the PV system power.

Recently, the design of a suitable controller for MPPT has attracted lots of attention [17]-[21]. In [22], the P&O method was proposed for the operation of the PV-based water pumping system and theoretical and practical results were compared. In [23], a comparison between different MPPT strategies of commonly used methods such as P&O and INC with fuzzy control method was provided. In [24], two MPPT methods were presented based on fuzzy and neural control systems, and the results of proposed methods were compared. In [25], an INC method was used for MPPT in PV arrays. In [26], a new method of MPPT technique was proposed to use the particle swarm optimization (PSO) method. These methods only use one pair of sensors to control PV arrays, which leads to lower prices, higher overall efficiency and simplicity in implementation. However, these methods do not properly function under rapidly changing atmospheric conditions.

The application of artificial intelligence techniques for MPPT such as neural networks [27], [28], intelligent algorithms [29]-[31] and fuzzy logic controllers (FLCs) [32]-[35] has significantly improved the tracking performance under

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different conditions compared with conventional methods. Unlike linear controllers, the FLCs are intelligent systems that have no sensitivity to the variation of topology, parameters and operation conditions. These features make the FLC attractive for system designers. The main challenges associated with the design of FLCs are the type selection of fuzzy inference system, the shape and range of changes in fuzzy membership functions and fuzzy rules. To overcome these challenges, the shape and range of changes in fuzzy membership functions and fuzzy rules must be optimized.

Heuristic methods such as genetic algorithm (GA) [36], PSO [37] and neural networks [38] have been suggested in the literature to optimize the parameters of FLCs. The methods based on neural networks require a large amount of historical data to train the network for acceptable results. Due to its random nature, GA cannot provide a single and accurate solution for the problem. It also requires complex and time-consuming calculations for the convergence. Compared with GA, PSO is easier to be implemented and is less dependent on the initial population. However, it easily falls into local optimum in high-dimensional space and has a low convergence rate in the iterative process.

To overcome the above-mentioned problems, this paper proposes a combination of PSO and GA (PSO-GA) to optimize the fuzzy system of MPPT controller. This combination covers the weaknesses of each individual algorithm, leads to optimized parameters in FLCs, and improves the speed and accuracy of the system. The main scheme is to optimize the shape, membership functions and fuzzy rules of fuzzy method using PSO-GA. The GA is used to find an approximate solution using mutation and crossover operators. The PSO is used to reach the exact solution. The performance of the proposed MPPT controller is compared with P&O method, INC method, FLC-GA, and FLC-PSO with rapid changes of radiation and temperature. The proposed method can reduce the steady-state oscillation and increase the response speed and accuracy compared with other methods.

The rest of this paper is organized as follows. The PV system model is described in Section II. Section III describes different MPPT methods such as P&O, INC, and FLC. The proposed PSO-GA fuzzy controller is explained in Section IV. The simulation results are included in Section V followed by the conclusion in Section VI.

II. Model of PV System

A PV cell is modelled using the single diode equivalent circuit. In this model, the open-circuit voltage and short-circuit current are considered as two important parameters. The short-circuit current depends on the irradiance, while the open-circuit voltage is affected by the type of cell material and temperature. More details about single-diode equivalent circuit of PV cell and its equations can be found in [39], [40].

III. MPPT Techniques

Figures 1 and 2 show the characteristics of a PV system in different irradiance and temperature levels, respectively. Both solar irradiance and temperature have the influence on the MPP of PV module. Since the environmental conditions are constantly changing and *P*-*V* curve has nonlinear characteristics, an MPPT controller is required to track the modified MPP whenever a variation in temperature and/or irradiance occurs [41].

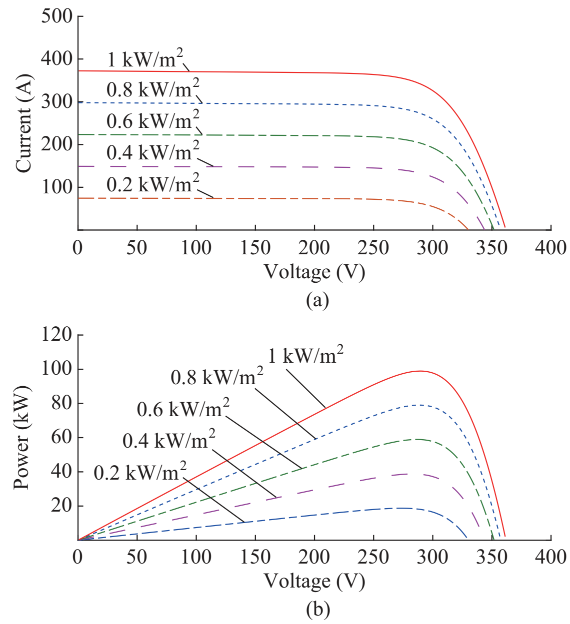

Fig. 1. *I*-*V* and *P*-*V* characteristics in variable irradiances. (a) *I*-*V* characteristics. (b) *P*-*V* characteristics.

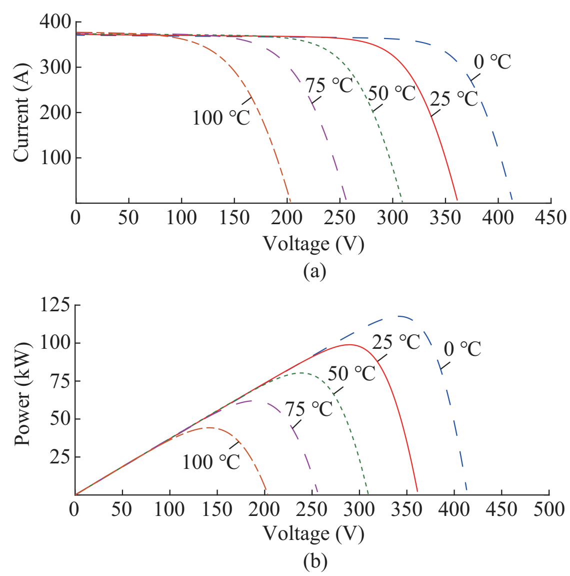

Fig. 2. *I*-*V* and *P*-*V* characteristics in variable temperatures. (a) *I*-*V* characteristics. (b) *P*-*V* characteristics.

Different MPPT methods such as P&O, INC and fuzzy systems are used to track the MPP of PV system. A brief overview of those methods is presented in this section.

A. P&O Method

The P&O method compares the previously delivered power with the one after disturbance by periodically varying the voltage of panel to reduce the oscillation around the MPP [42]. In this method, the voltage disturbance of PV system is implemented in a specific direction, e.g., increasing voltage magnitude, and then the output power variation ($\Delta P = P_{present} - P_{past}$) is measured, where $P_{present}$ and P_{past} are the present and past output power, respectively. If ΔP is positive, the operation point will move towards the MPP in the same direction (increasing the voltage magnitude). If ΔP is negative, the operation point will move away from the MPP and it must move in the opposite direction (decreasing the voltage magnitude) [43].

B. INC Method

The basis of this method is to measure the derivative of PV output power with its voltage [16]. The equation which describes the output power of a PV system is given by:

$$P_{MPP} = V_{MPP} I_{MPP} \tag{1}$$

where P_{MPP}, V_{MPP}, and I_{MPP} are the output power, voltage, and current of MPP, respectively. At the MPP where the slope of curve ($\mathrm{d}P/\mathrm{d}V$) is zero, differentiating (1) with respect to the voltage, we can obtain:

$$\frac{\mathrm{d}P}{\mathrm{d}V} = I + V\frac{\mathrm{d}I}{\mathrm{d}V} = 0 \tag{2}$$

$$\frac{\mathrm{d}I}{\mathrm{d}V} = \frac{\Delta I}{\Delta V} = -\frac{I_{MPP}}{V_{MPP}} \tag{3}$$

Therefore, the basic equations of this method can be written as:

$$\frac{\mathrm{d}P}{\mathrm{d}V} = 0 \rightarrow \frac{\Delta I}{\Delta V} = -\frac{I}{V} \rightarrow \text{Operation point is at MPP} \tag{4}$$

$$\frac{\mathrm{d}P}{\mathrm{d}V} > 0 \rightarrow \frac{\Delta I}{\Delta V} > -\frac{I}{V} \rightarrow \text{Operation point is at left side of MPP} \tag{5}$$

$$\frac{\mathrm{d}P}{\mathrm{d}V} < 0 \rightarrow \frac{\Delta I}{\Delta V} < -\frac{I}{V} \rightarrow \text{Operation point is at right side of MPP} \tag{6}$$

C. FLC

The FLC consists of three main parts. The first part is a fuzzy maker that converts input variables which contain true values into a fuzzy or linguistic set. The second part is the fuzzy inference that combines if-then fuzzy rules based on the principles of fuzzy logic. In the third part, the fuzzy variables are converted back to real values by using defuzzification layer to apply them to the main control system.

IV. Proposed MPPT Control Based on PSO-GA and FLC

Unlike conventional MPPT controllers, intelligent controllers such as FLCs are robust with sudden atmospheric changes. In this section, the MPPT controller is optimized using the fuzzy system and PSO-GA. The proposed controller is an off-line controller and the computation costs are not investigated. The design phase of this controller includes fuzzy design because we want to set the duty cycle (D) of DC-DC converter using fuzzy rules. For this purpose, the fuzzy inputs and outputs must be defined and their definition scope and membership functions must be determined. In this paper, the ratio of power variations to voltage variations and the variation ratio of power variations to voltage variations (the derivative of the first one) are considered as the inputs of the fuzzy system. Also, since the goal of controller design is to set D, it is considered as the output of the fuzzy system. Thus, the fuzzy system consists of two inputs and one output. The membership functions considered for the input and output are triangular membership functions. The range of variations of these variables is covered by 3 membership functions for the inputs and 9 membership members for the outputs. It should be noted that in all the above cases, the range of variables defined in the phase system is symmetrically covered by triangular membership functions.

The most of MPPT methods operate based on the P-V characteristic of PV module. In FLC, the controller inputs E and $\mathrm{d}E$ given by (7) and (8) are the rate of power variations to voltage variations and the variation of E at time t, respectively. The output of the controller is also the duty cycle.

$$E(t) = \frac{P_{PV}(t) - P_{PV}(t-1)}{V_{PV}(t) - V_{PV}(t-1)} \tag{7}$$

$$\mathrm{d}E(t) = E(t) - E(t-1) \tag{8}$$

where $P_{PV}(t)$ and $V_{PV}(t)$ are the output power and voltage of PV module, respectively.

A. Definition of Membership Function

In the first step, the definition range and membership functions of all fuzzy inputs and outputs are identified. There are 5 variables defined for each input membership function and 17 variables defined for the output membership function, all of which are identified through optimization process. Figure 3 shows an example of a membership function with 5 parameters ($x(1)$ to $x(5)$) where the symbols are defined as negative (N), zero (Z), and positive (P). The location of these parameters should be optimized for the best result.

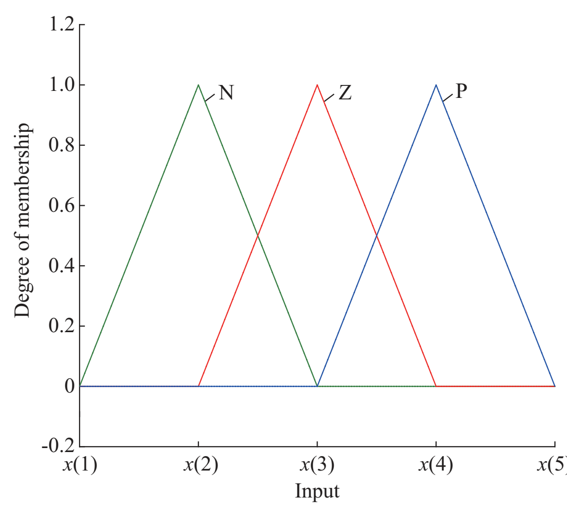

Fig. 3. Sample of FLC membership function.

B. Design of Fuzzy Rules

In the second step which is the most important stage of the fuzzy controller design, the fuzzy rules should be designed. Since the fuzzy inputs are divided into three membership functions, fuzzy rules will contain nine rules, as listed in Table I, where $x(28)$ to $x(36)$ are considered as optimization variables for fuzzy rules, and their optimal values should be determined. In this stage, 10 optimization variables are used to determine the membership functions of the inputs, 17 variables are used to determine the values of membership function of outputs, and 9 variables are used to determine the fuzzy rules.

TABLE I
SUMMARY OF FLC RULES

D			E
dE is P	dE is Z	dE is N	
$x(30)$	$x(29)$	$x(28)$	N
$x(33)$	$x(32)$	$x(31)$	Z
$x(36)$	$x(35)$	$x(34)$	P

C. Definition of Objective Function

The last step is the definition of objective function. The goal is to optimize (minimize) the error level of fuzzy inputs E and dE. In this paper, the integral square error (ISE) criterion is used as the cost function.

$$J(\Delta E)=\int_{0}^{T_{sim}}\left(\Delta E^{2}+\Delta \mathrm{d}E^{2}\right)\mathrm{d}t \tag{9}$$

where T_{sim} is the simulation time; and ΔE and $\Delta \mathrm{d}E$ are the ratio of power mismatch to voltage mismatch and its derivation which should be optimized, respectively.

D. Optimization Algorithms

In this section, PSO-GA is used to optimize the fuzzy system for MPPT controller in PV system. The GA cannot provide a precise solution for the problem due to its random nature. It requires complex and time-consuming calculations for convergence. In contrast, the PSO can reach the exact solution by comparing its position with surrounding positions, and the global positions of all the particles. However, it may fall into the local optimum in high-dimension space, if used inappropriately. The GA results in various solutions using crossovers and mutations, which can cover the weakness of the PSO. Also, the PSO can cover the weakness of the GA by accelerating the computation speed and increasing the accuracy. For this reason, PSO-GA is proposed, which has the speed and accuracy of PSO and the diversity of GA.

In the first step, the initial solution is randomly generated over the search space. The initial position of the particle x_0 is also generated from a uniform distribution in the range $[x_{\min}, x_{\max}]$, where $x_{\min}$ and $x_{\max}$ are the lower and upper bounds of the variables, respectively.

In the second step, the PSO is applied on the initial population. The position and velocity of each particle are determined based on individual particle experiences and other particle experiences. The algorithm ranks the results and saves the best and worst solutions to be used for the fast convergence. The initial population is evaluated and the population is ranked based on the values of P_{best} and g_{best}. The P_{best} is the best solution in every iteration, and g_{best} is the best solution in all iterations.

In the third step, the GA is applied on the remaining particles with low rank. In each iteration, the GA generates a new population using crossover and mutation operations. Finally, the population generated by GA and PSO is combined for the next iteration. This combination is used as initial solution for the next iteration. The algorithm will stop after specific number of iterations. The flowchart of the proposed algorithm is depicted in Fig. 4.

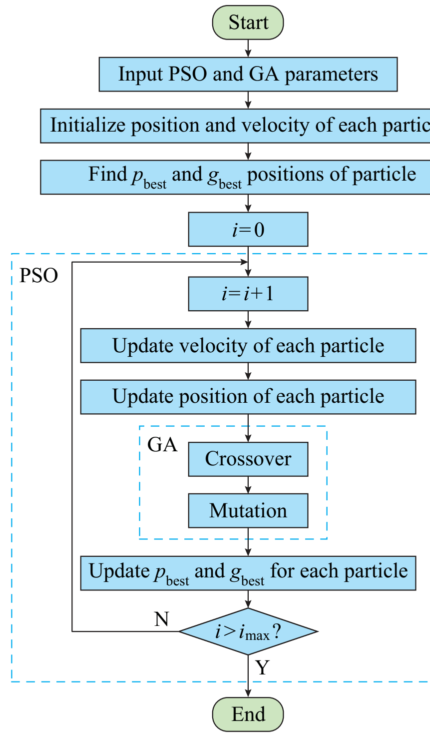

Fig. 4. Flowchart of PSO-GA.

E. Optimization

In this study, the PSO-GA is used to optimize the performance of FLCs. This section focuses on optimizing the objective function using the PSO-GA. In this paper, the parameters of the fuzzy system are set using the initial values. The input values of the fuzzy system are obtained using (7) and (8). Using (9), the objective function value is obtained during the simulation. In the next step, the operators of PSO-GA are applied to the fuzzy system parameters. Then, the objective function value is redefined using (9). In each step, the objective function value is compared with the previous value of the objective function and the better (lower) one is considered as the output of this step. These steps will continue until the stopping criteria are met. The objective function is plotted in terms of the number of iterations in Fig. 5. As shown in Fig. 5, the PSO-GA converges after about 20 iterations. To be safe, 40 iterations are considered as the stopping criteria for the proposed algorithm.

After the optimization by PSO-GA, the optimal parameters are obtained for the design of fuzzy system. Given the values of the optimal parameters for the input and output membership functions, the optimal results of membership functions are obtained as shown in Fig. 6, where the symbols are defined as negative big (NB), negative medium (NM), negative small (NS), positive small (PS), positive medium (PM), and positive big (PB).

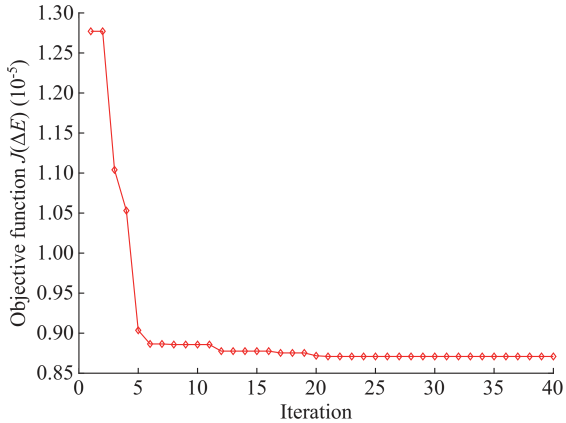

Fig. 5. Results of PSO-GA.

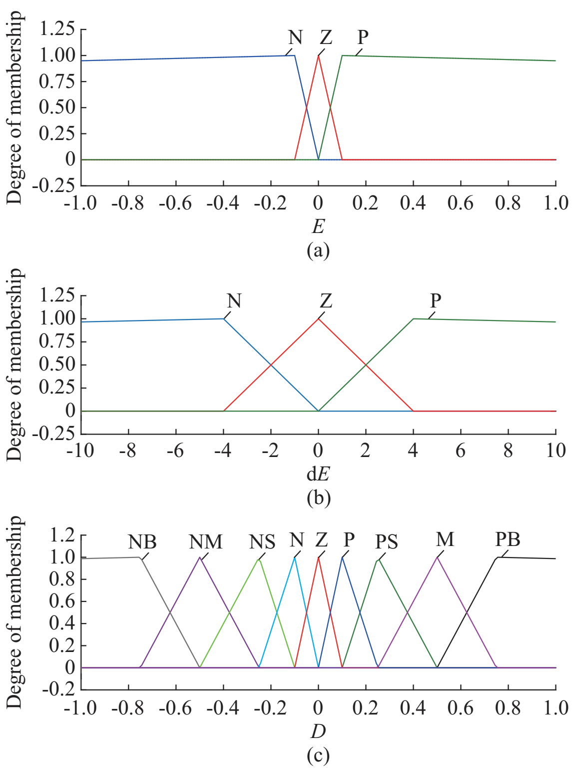

Fig. 6. Optimal results of membership functions of FLC with parameter E, dE or D. (a) E. (b) dE. (c) D.

Using the variables $x(28)$ to $x(36)$, the fuzzy rules are obtained as listed in Table II.

TABLE II
RULES OF PROPOSED FLC

D			E
dE is P	dE is Z	dE is N	
PS	PM	PB	N
N	Z	P	Z
NB	NM	NS	P

V. SIMULATION RESULTS

A. Test System

The simulation of three-phase PV system is carried out in various scenarios. The P&O method based controller, INC method based controller, PSO-based optimized FLC, and GA-based optimized FLC are compared with the PSO-GA-based optimized FLC. Figure 7 shows the simulated structure of PV system in MATLAB software. The PV module is connected to a three-phase network through a DC-DC converter and an inverter. The system feeds 20 kW and 10 kW local loads and then the surplus power is injected to the network. This system is simulated in different scenarios as follows.

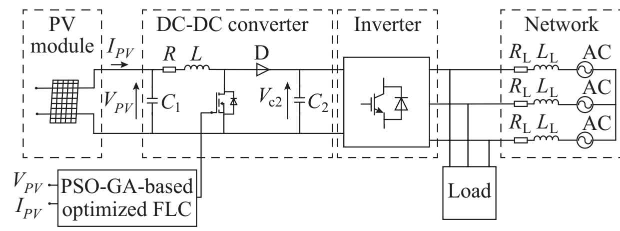

Fig. 7. PV system under study.

B. Case 1: Variable Temperatures and Constant Irradiance

In this case, at $t=1$ s, the temperature increases from 25 °C to 30 °C and at $t=1.5$ s, it changes to 35 °C and finally returns to initial temperature 25 °C at $t=2$ s. Figure 8 shows the output voltage variations of PV system. As shown in Fig. 8, the proposed PSO-GA-based optimized FLC reaches its optimal point at $t=0.2$ s, which clearly indicates its better performance compared to the INC method based and P&O method based controllers. The controllers based on INC method and P&O method reach their optimal points at $t=0.48$ s and $t=0.54$ s, respectively. The time of reaching the optimal points for PSO-based and GA-based optimized FLCs is the same as the proposed PSO-GA-based optimized FLC. However, they have different optimal points in comparison with the proposed controller.

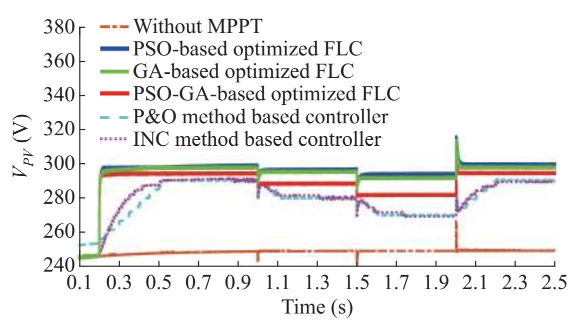

Fig. 8. Voltage variations with variable temperatures and constant irradiance.

Figure 9 shows the changes in the output power of the PV system. As shown in Fig. 9, the proposed controller can operate at the optimal point and generate active power of 98.7 kW, while other controllers can generate 96.03 kW (PSO-based optimized FLC), 95.09 kW (GA-based optimized

FLC), 94.52 kW (INC method based controller) and 90.13 kW (P&O method based controller).

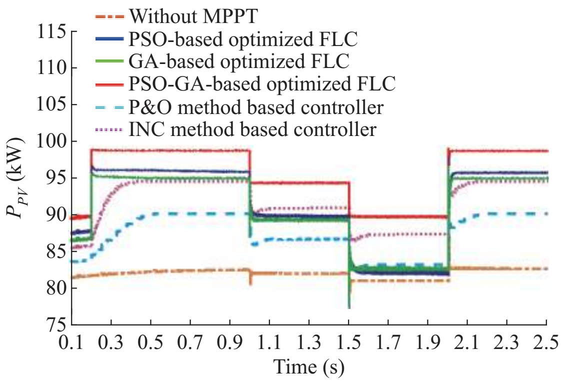

Fig. 9. Power variations with variable temperatures and constant irradiance.

According to Table III, the accuracy of the proposed PSO-GA-based optimized FLC is better than other controllers under different operation conditions. It can be seen that the output power of PV system with the proposed controller is higher than the output power of other controllers. It verifies the advantages of the proposed PSO-GA-based optimized FLC over other controllers. The average amount of the output power using the proposed controller increases 7%-8% compared to the P&O method based controller, 3%-4% compared to the INC method based controller, 3%-7% compared to GA-based optimized FLC, and 2%-8% compared to the PSO-based optimized FLC in different temperatures.

TABLE III
COMPARISON OF MPPT CONTROLLERS FOR VARIABLE TEMPERATURES AND CONSTANT IRRADIANCE

MPPT controller	Power output (kW)		
	25 °C	30 °C	35 °C
P&O method based controller	90.13	86.73	83.32
INC method based controller	94.52	90.91	87.32
GA-based optimized FLC	95.09	89.56	83.12
PSO-based optimized FLC	96.03	90.10	82.56
PSO-GA-based optimized FLC	98.70	94.47	89.94

C. Case 2: Variable Irradiances and Constant Temperature

In this case, the variable irradiances and constant temperature are considered. At $t=1$ s, the irradiance changes from 1000 W/m^2 to 800 W/m^2 and it again decreases to 600 W/m^2 at $t=1.5$ s. Figure 10 shows the output voltage variations of the PV system. As shown in Fig. 10, the proposed PSO-GA-based optimized FLC as well as PSO-based optimized FLC and GA-based optimized FLC has a good transition response and a very fast system reaction against the set point change. It can immediately restore the reference point and reach the MPP. While in other controllers, it takes about 0.3 s to reach the MPP.

Figure 11 shows the changes in the active power output of the PV system. As shown in Fig. 11, the active power is inversely proportional to the changes in irradiance. In this case, the proposed PSO-GA-based optimized FLC produces more active power compared to the other controllers with the lower irradiance. The proposed controller produces 58.64 kW active power with the lower irradiance, while other controllers have produced less active power (56.78 kW in PSO-based optimized FLC, 56.29 kW in INC method based controller, 56.14 kW in GA-based optimized FLC, and 53.68 kW in P&O method based controller). It indicates a remarkable improvement in the accuracy of the tracking of PV output power.

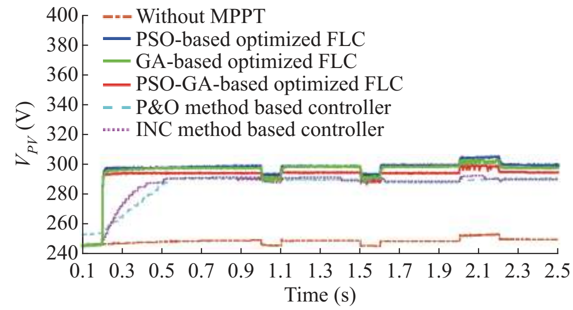

Fig. 10. Voltage outputs with variable irradiances and constant temperature.

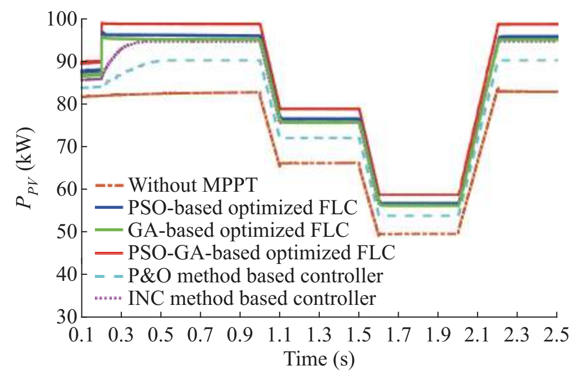

Fig. 11. Power outputs with variable irradiances and constant temperature.

Table IV summarizes the output power of the PV system for different controllers. It can be seen that the proposed controller produces more active power compared to others with different irradiances. According to Table IV, the average amount of power output of the proposed controller increases 2%-8% compared to other controllers.

TABLE IV
COMPARISON OF MPPT CONTROLLERS FOR VARIABLE IRRADIANCES AND CONSTANT TEMPERATURE

MPPT controller	Power output (kW)		
	1000 W/m^2	800 W/m^2	600 W/m^2
P&O method based controller	90.13	71.99	53.68
INC method based controller	94.52	75.47	56.29
GA-based optimized FLC	95.11	75.60	56.14
PSO-based optimized FLC	96.15	76.32	56.78
PSO-GA-based optimized FLC	98.85	78.69	58.64

D. Case 3: Simultaneous Change of Irradiance and Temperature

In this case, the irradiance and temperature change simultaneously and the proposed controller is compared with other controllers. At the beginning of the simulation, the irradiance is 700 W/m^2 and the temperature is 25 °C. At $t=1$ s, the irradiance increases to 1000 W/m^2 and the temperature reaches 40 °C. Figure 12 shows the output power of the PV system. The output power of the PV system is 85 kW in the proposed controller, which is more than other controllers.

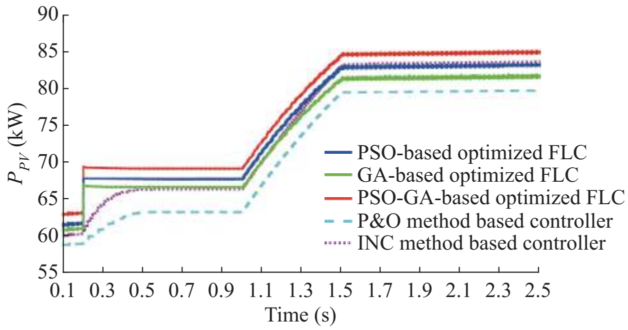

Fig. 12. Power outputs with variable irradiances and temperatures.

The output power of the PV system for Case 3 is shown in Table V. According to Table V, the active power produced by the proposed controller is higher than other controllers, which shows that the proposed controller has the best performance.

TABLE V
COMPARISON OF MPPT CONTROLLERS FOR VARIABLE IRRADIANCES AND TEMPERATURES

MPPT controller	Power output (kW)	
	700 W/m^2, 25 °C	1000 W/m^2, 40 °C
P&O method based controller	63.13	79.65
INC method based controller	65.52	83.24
GA-based optimized FLC	66.63	81.79
PSO-based optimized FLC	67.76	83.39
PSO-GA-based optimized FLC	69.19	84.91

VI. CONCLUSION

The selection of the type of fuzzy inference system, the shape and interval of changes in fuzzy membership functions and fuzzy rules have a significant impact on the controller performance. In this paper, a new FLC has been proposed for MPPT. The parameters of the FLC have been optimized using the PSO-GA. To investigate the performance of the proposed PSO-GA-based optimized FLC, the system has been tested with rapid changes of irradiance and temperature. The simulation results verify that the proposed controller outperforms the P&O method based controller, INC method based controller, GA-based optimized FLC, and PSO-based optimized FLC under different operation conditions. The proposed controller has a faster response rate and higher accuracy compared to other controllers. In addition, in terms of the accuracy, the proposed controller increases 2%-8% of the output power of the PV system compared to other controllers with different irradiances and temperatures, which results in better MPPT.

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