

MAXIMIZING EFFICIENCY OF A PHOTOVOLTAIC WATER PUMPING SYSTEM USING THE MPPT-BASED FUZZY LOGIC CONTROLLER

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Abstract

In order to facilitate the most suitable approach for maximizing the overall efficiency of a standalone photovoltaic water pumping system (PVWPS), providing a more accurate and efficient model is necessary prior to installation. In this paper, after implementing the PVWPS model, the fuzzy logic controller (FLC) based on the maximum power point tracking (MPPT) technique is proposed to detect the maximum PV power output by regulating the switching duty ratio of the interface converter to match the PV generator and motor pump as the load. The FLC design is derived from the genetic optimization, and thus the complexity is significantly reduced by 24%. In the test, the PVWPS with MPPT controllers was carried out under weather variations at a constant head pumping (20 m) and a daily average water supply of 20,000 L/day. As a result, the proposed MPPT-FLC offers PV energy utilization efficiency of up to 91% by means of maximizing the motor speed, and consequently increasing the water discharge per watt of the installed PV array. Furthermore, the global efficiency of the PVWPS can increase up to 3.4%, which is 6%, 10%, and 15% more efficient than the existing controllers: the conventional FLC, the neural network-based controller, and the perturb and observe method, respectively.

Keywords: PV energy utilization efficiency, maximum power point tracking, fuzzy logic controller, photovoltaic water pumping system

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Introduction

In recent decades, the applications of photovoltaic (PV) systems have been increasingly popular, especially of the stand-alone PV water pumping system (PVWPS) (Rao *et al.*, 2018). The PVWPS plays an important role in minimizing the dependence on diesel/gasoline, in reducing the costs of modern irrigation, and in reducing greenhouse gas. However, a high initial cost, on average 70% of the life cycle cost or about 8 times that of a fossil-powered WPS (Odeh *et al.*, 2006), is one of the disadvantages. In addition, a very low global system efficiency, usually varying from 2% to 5% due to the types of PV technology (Daud and Mahmoud, 2005), is the main drawback. Therefore, in most of the PVWPSs, the PV size is optimized (Langridge *et al.*, 1996). Furthermore, in operation, the PV efficiency drops dramatically as the operating temperature of the PV panels rises during the day. Thus, the cooling techniques based on water spraying on the panel surface (Abdolzadeh and Ameri, 2009) and the installation of collectors beneath the PV panels (Habibollahi *et al.*, 2015) are used to cool down the cell temperature, resulting in increased total efficiency by 1%.

Besides the PV sizing and cooling technique, matching the PV source to the load by an interfacing convertor-controller is adopted to ensure that the operating point is located at the maximum power point (MPP) at all times, for example, the current-locked loop based on irradiation-independent optimum matching as a linear feedback controller (Alghuwainem, 1994). Unfortunately, the MPP is unique on the nonlinear current-voltage curve and greatly varies with irradiance and temperature conditions. To handle uncontrollable weather conditions and maintain efficient load matching, various maximum power point tracking (MPPT)-based controllers are applied to the PV systems. In the existing PVWPS, the hill-climbing MPPT-based methods, including the perturb and observe (P&O) method (Harrag *et al.*, 2017) and the incremental conductance (IC) (Kumar *et al.*, 2014), are widely used because of their

relative low cost and ease of implementation. However, they are inefficient in operation, especially with wrong tracking under rapidly changing weather. In contrast, the artificial intelligence (AI)-based nonlinear and adaptive MPPT controllers, such as neural network-based controllers (NNC) (Bouselham *et al.*, 2017), fuzzy logic controllers (FLC) (Chaouali *et al.*, 2017; Izzuddin *et al.*, 2018; Talbi *et al.*, 2018) and others, outperform the and IC methods at the expense of high complexity.

The principal aim of this work is to maximize the efficiency of the PVWPS by maximizing the PV generator's efficiency. To draw the maximum PV power output, the MPPT-FLCs are used as the load matching in the PVWPS. To obtain the optimal controller, the FLC design is derived by a multi-objective genetic algorithm (MOGA) - a stochastic optimization. The PVWPS analyzed in this paper includes a 1 kW PV array coupled to a motor pump through an interface converter to regulate the PV output voltage/power. Throughout the work, the water source is a well, and total dynamic head (TDH) is assumed to be 20 m. The water is required to deliver a daily average of 20 m³, so that the flow rate (Q) is varied in the range between 1-5 m³/h according to the variations of the PV power output. The performances of the proposed MPPT-FLC/MOGA, in terms of the global efficiency of the PVWPS and the energy utilization efficiency, are compared with those of the conventional FLC (i.e., fuzzy parameters designed by the expert and trial-and-error), NNC, and P&O. The PVWPS model and MPPT controllers are implemented and demonstrated in Matlab software, and the system performances are analyzed through the simulated results.

Methods

In the following, the PVWPS is described. The main block diagram of the PVWPS (Figure 1) comprises 4 parts: the PV array, DC-DC buck converter, permanent magnet DC (PMDC)

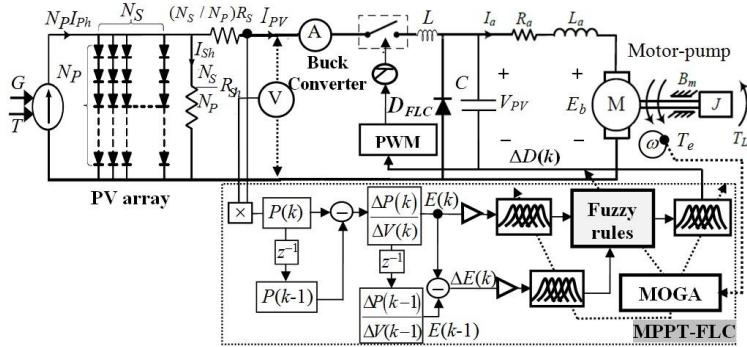


Figure 1. Schematic diagram of the PVWPS with the proposed MPPT-FLC derived by the MOGA optimization

motor driving the centrifugal pump, and the proposed MPPT-FLC.

PV Generator and Modeling of the PV Array

In application, the PV array in Figure 1 consists of N_s and N_p connected in series and parallel PV modules, respectively, in order to increase power and voltage/current. An equivalent circuit of the PV cell, usually represented by the single diode model (De Blass *et al.*, 2002), is essential to simulate the PV current-voltage (I_{PV} - V_{PV}) and power-voltage (P_{PV} - V_{PV}) characteristics. In this model, the PV cell represented by a current source is described by 5 parameters: the photo-current (I_{ph}), diode saturation current (I_{sd}), series resistance (R_s), shunt resistance (R_{sh}), and the ideality factor of the diode (n), which are deduced from the PV parameter estimation method (Wongsathan and Seedadan, 2017).

The output current of the PV array (I_{PV}) related to the output PV voltage (V_{PV}) is implicitly expressed as

$$I_{PV} = N_p I_{ph} - N_p \times I_{sd,0} \left(\frac{T}{T_0} \right)^3 \times \exp \left[\frac{qE_g}{nk_B} \left(\frac{1}{T_0} - \frac{1}{T} \right) \right] \times \left[\exp \left[\frac{qV_{temp}}{nk_B T} \right] - 1 \right] - \frac{V_{temp}}{R_{sh} / N_p}, \quad (1)$$

where $I_{ph} = (I_{sc} + K_I (T - T_0))(G/G_0)$, $V_{temp} = (V_{PV}/N_s) + (I_{PV} R_s / N_p)$, K_B is Boltzmann's constant, q is the electron charge, G is the solar irradiance in W/m^2 , T is the ambient temperature in Kelvin (K), I_{sc} is the short circuit current at standard test conditions (STC, $T_0 = 298$ K and $G_0 = 1,000$ W/m^2), K_I is the temperature coefficient of I_{sc} , $I_{sd,0}$ is the saturated diode current, and E_g is the band gap energy (eV). In this work, a commercial polycrystalline silicon module (model type ND - 130T1J, Sharp Corp., Osaka, Japan) with its electrical specifications (Table 1) is employed as the case study. The PV module is tested under the pseudo-solar irradiance which is set up to validate the simulations in Figure 2(a).

At the STC, the PV parameters are obtained as $I_{ph} = 8.01$ A, $I_s = 8.77$ μA , $R_s = 0.016$ Ω , $R_{sh} = 690.7$ Ω , and $n = 1.877$. In order to increase the voltage for driving the utilized motor, the PV modules are connected in series and then N_s is sufficiently selected as 8 ($\approx 1,000$ W/130 W). For providing the information to the controller design, the preliminary results of the I_{PV} - V_{PV} and P_{PV} - V_{PV} characteristics under

Table 1. Electrical specifications of the utilized PV module at the STC

Parameters	Value
Maximum power output (P_{MMP})	130 W
Voltage at the maximum power point (V_{MMP})	17.4 V
Current at the maximum power point (I_{MMP})	7.5 A
Open circuit voltage (V_{OC})	22 V
Short-circuit current (I_{SC})	8 A

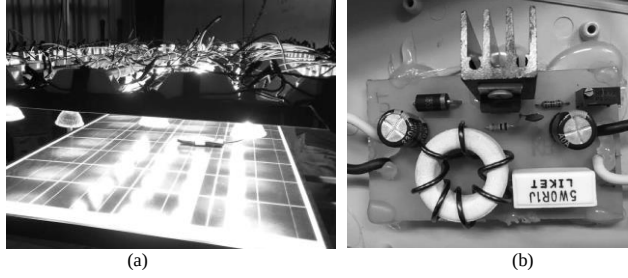


Figure 2. a) The measures of PV current and voltage of the utilized PV module under pseudo-irradiance and b) the buck converter prototype board implementation

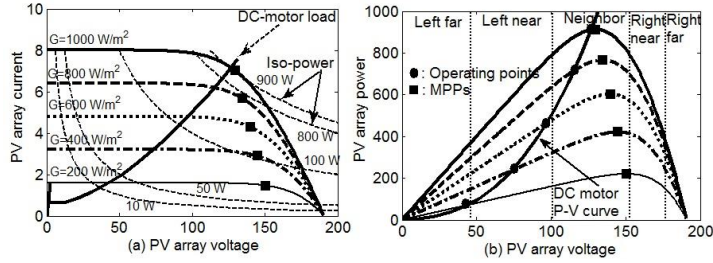


Figure 3. a) The I_{PV} - V_{PV} characteristics and b) the P_{PV} - V_{PV} characteristics of the utilized PV array against motor load characteristics with the partitioned regions for the MPPT-FLC design

the variation in irradiance (200-1,000 W/m²) at $T = 20^\circ\text{C}$ are depicted in Figures 3(a) and 3(b), respectively.

The PV generator efficiency (η_{PV}) can be expressed as

$$\eta_{PV} = \frac{P_{PV}}{G \times S_{PV}}, \quad (2)$$

where S_{PV} is the effective PV surface area (for the utilized PV array, $S_{PV} = (1.50 \times 0.7) \times 8 \text{ m}^2$).

Buck Converter and the Design

The buck converter is employed to step down the PV voltage to a rated motor voltage by controlling the switch duty cycle (D) according to the pulse width modulation (PWM) signal generated by the MPPT controller. For designing the buck converter, the ripple current and voltage are assumed to be 5%, and the PWM switching frequency is set to 200 kHz. The maximum input and output voltages are 200 V and 120 V, respectively.

Through the method referred to in Florescu and Oprea (2012), the minimum inductance (L_{min}) and conductance (C_{min}) have been estimated to be 250 μH and 20 μF , respectively. After setting the buck converter parameters, the prototype circuit of the buck converter has been implemented for the test, Figure 2(b).

The efficiency of the buck converter relates to the product of the armature voltage V_a as the output voltage and the armature current I_a of the PMDC motor with respect to the PV power output is expressed as

$$\eta_{Con} = \frac{V_a I_a}{V_{PV} I_{PV}} \quad (3)$$

Motor Pump

In this study, the centrifugal pump is employed due to the minimal starting torque requirement. To drive the pump, a

PMDC motor which could be easily matched with the PV array, is chosen. From the circuit diagram in Figure 1, the dynamic equation of the motor is given by

$$V_a = I_a R_a + L_a \frac{dI_a}{dt} + E_b, \quad (4)$$

where $E_b = K_e \omega$ is the back electromotive force (emf), K_e is the back emf constant, ω is the angular speed of the rotor, R_a is the armature resistance, and L_a is the armature inductance. The balance of the electromagnetic torque (T_e) and load torque (T_L) is expressed as

$$T_e = K_t I_a = J \frac{d\omega}{dt} + B\omega + T_L, \quad (5)$$

where K_t is the torque constant, J is the moment of inertia, B is the viscous torque constant, and C is the torque constant for rotational losses. At the steady state, i.e., $\frac{dI_a}{dt} = 0$ and $\frac{d\omega}{dt} = 0$, the PV power, $P_{PV}(G, T) = I_a^2 R_a + I_a E_b$, is supplied to the motor. When replacing $T_e = \frac{E_b I_a}{\omega}$ in Equation (5) and solving I_a , then

$$P_{PV}(G, T) = \frac{R_a}{K_t^2} (B^2 \omega^2 + 2B\omega T_L + T_L^2) + B\omega^2 + T_L \omega. \quad (6)$$

The driving torque of the centrifugal pump is given by $T_L = K_L \omega^L$, where K_L and L are the constant load torque. For $L = 1.8$, by substituting T_L into Equation (6), then the relation between $P_{PV}(G, T)$ and ω is expressed as

$$P_{PV}(G, T) = \left(\frac{K_L^2 R_a}{K_t^2} \right) \omega^{3.6} + \left(\frac{2BK_L R_a}{K_t^2} + K_L \right) \omega^{2.8} + \left(\frac{B^2 R_a}{K_t^2} + B \right) \omega^2 \quad (7)$$

The electrical and mechanical specifications of the utilized PMDC motor and centrifugal pump are shown in Table 2. The power matching between the PV array and the motor pump without any interfacing converter-controller is shown in Figure 3(b). It is seen that the operating points of the motor deviate away from the MPPs, especially under low irradiance. Moreover, the motor would not start operating unless the irradiance reaches 200 W/m², Figure 3(a), and thereby the motor may operate under a locked condition for a long time, causing heat that leads to a shortening of its life. To handle this problem, a device called a linear current booster is applied only at the start in the early morning.

The efficiency of the motor pump (η_{M-P}) related to the hydraulic power ($P_h = \rho \times g \times Q \times TDH$) is given by

$$\eta_{M-P} = \frac{P_h}{P_{PV}}, \quad (8)$$

where ρ is the water density, and g is the gravitational constant. Therefore, the total efficiency, including η_{PV} (Equation 2), η_{Con} (Equation 3), and η_{M-P} (Equation 8), can be expressed as

Table 2. The electrical and mechanical specifications of the PMDC motor and centrifugal pump

Parameters	Value
Rated motor voltage (V_a)	120 V
Rated motor current (I_a)	9 A
Rated motor speed (ω)	200 rad/s
Armature resistance (R_a)	1.5 Ω
Armature inductance (L_a)	0.2 H
Voltage constant (K_t)	0.67 V/(rad/s)
Torque constant (K_L)	0.67 Nm/A
Motor friction (A_m)	0.2 Nm
Moment of inertia (J)	0.0236 Kg m ²
Viscous friction coefficient (B)	0.0024 Nm/(rad/s)
Load torque constant (K_e)	0.0004 Nm/(rad/s)

$$\eta_T = \eta_{PV} \eta_{Con} \eta_{M-P} \quad (9)$$

As aforementioned, $TDH = 20$ m, $Q = 1/3,600\text{-}5/3,600$ m³/sec, and $P_{PV} = 100\text{-}950$ W, and then η_{M-P} varies between 25% and 31%. Assuming η_{Con} is at 100%, to increase the total efficiency, the PV efficiency η_{PV} is maximized.

MPPT-FLC Design and Optimization

On designing the FLC based on the Mamdani fuzzy inference system (FIS) in Figure 1, at the sampling time k , $E(k) = \frac{\Delta P_{PV}}{\Delta V_{PV}}$ and its difference

$\Delta E(k)$ are used as inputs, and the incremental duty cycle $\Delta D(k)$ is the output. In step 1 (fuzzification), the crisp inputs are converted to fuzzy values μ (Equation 10) through 5 different triangular membership functions (TMF) each (Figure 5) composed of negative small and big (NS and NB), zero (Z), and positive small and big (PS and PB), which correspond to the 5 partitioned regions of the obtained $P_{PV}\text{-}V_{PV}$ curves, as shown in Figure 3(b):

$$\mu(x; a, b, c) = \max \left(\min \left(\frac{x-a}{b-a}, \frac{c-x}{c-b} \right), 0 \right), \quad (10)$$

where $\mu \in [0, 1]$, x is the crisp value, and a , b , and c are the triangular parameters.

In step 2 (inference rule), the 25 compositional If-Then rules (Table 4) are generated to dictate the fuzzy output. The j^{th} rule is defined, for example: if $E(k)$ is PS and $\Delta E(k)$ is NB , then $\Delta D_j(k+1)$ is PS . The fuzzy output of the j^{th} rule is determined as $\mu(\Delta D_j) = \max\{\min\{\mu(E), \mu(\Delta E)\}\}$. Lastly, in step 3

(defuzzification), the fuzzy outputs of the R_{FLC} -significant rule are mapped to the crisp output using a centre of gravity which is expressed as

$$\Delta D = \frac{\sum_{j=1}^{R_{FLC}} \Delta D_j \mu_C(\Delta D_j)}{\sum_{j=1}^{R_{FLC}} \mu_C(\Delta D_j)} \quad (11)$$

where $R_{FLC} \in [1, 25]$. For the complexity in terms of multiplication counts in each FIS iteration, the FLC provides $(6R_{FLC} + 1)$ -multiplication, including $(4R_{FLC})$ - and $(2R_{FLC} + 1)$ -multiplication in computing Equations (10) and (11), respectively. It is seen that the complexity of the MPPT-FLC depends on R_{FLC} .

Through the FLC/MOGA optimization, the universe of discourse (UOD) of the inputs and output is identified first. The N_{pop} chromosome as the tentative solution possessing a certain length of genes (parameters) with N_{bit} -length binary coding is randomly generated and normalized within the specified UODs. In the encoding scheme (Table 3), all the system parameters, including TMF parameters (a 's, b 's, and c 's), R_{FLC} , genetic parameters (crossover rate P_C and mutation rate P_M), and other relevant parameters (C_1 and C_2 in Equation (12)), are represented into 1 chromosome that allows the simultaneous optimization. The 25-rule set is randomly generated within $\{0, 1\}$ in which '1' means consideration of and '0' means omitting the according rules. During the offline training, after setting the initial values of the PV operating point (V_{PV} , I_{PV}), E , ΔE , D , ΔD , and ω to 0, whereas $R_{FLC} = 25$, the i^{th} chromosome is taken into the Mamdani-FIS and evaluates the outputs $\Delta D_{k,i}$ in Equation (11). The duty ratio is updated by $D_{k+1,i} = D_{k,i} + \Delta D_{k,i}$. Then,

Table 3. Chromosome representation for the parameters of TMF, fuzzy rules, genetic operator, and the objective function in the MOGA optimization

FLC-MOGA	Inputs		Output	Fuzzy rules	GA parameters	Relevant parameters
Variable	E	ΔE	ΔD	R_{FLC}	P_C and P_M	C_1 and C_2
Gene	(a, b, c)	(a, b, c)	(a, b, c)	$\{0, 1\}$	P_C, P_M	C_1, C_2
Gene No.	1-15	16-30	31-45	46-70	71-72	73-74

the new PV operating points and the corresponding motor speed $\omega_{k+1,i}$ are generated. The error between $\omega_{k+1,i}$ and the maximum speed $\omega_{\max}(G, T)$ is cumulatively summed up. All chromosomes are set with their ranking through the fitness (F) of the multi-objective function composed of control accuracy in terms of the sum of absolute error (SAE) of the motor speed and rule reduction and given by

$$F_{i,iter} = \frac{C_{1,i}}{\sum_{k=1}^{N_{SP}} \lambda^{N_{SP}-k} |\omega_{\max}(G,T) - \omega_{k+1,i}|} + C_{2,i} \frac{R_{FLC,i,iter-1}}{R_{FLC,i,iter}}, \quad (12)$$

where N_{SP} is the maximum samples per iteration ($iter$), λ is the forgetting factor, and the parameters C_1 and C_2 are the weighted constants which are properly selected to balance the SAE and rule reduction terms.

The parent chromosome based on the high fitness values is selected by the roulette wheel method to generate the offspring toward the genetic operators (crossover and mutation). The evolution is repeated until the maximum iteration (N) is achieved.

Simulation Results and Discussion

For the MPPT-FLC's design, the UODs are identified as follows: $E \in [-20, 20]$, $\Delta E \in [-20, 20]$, $\Delta D \in [-0.5, 0.5]$, $P_C \in [0.5, 0.99]$, $P_M \in [0.01, 0.2]$, $C_1 \in [1,500, 2,000]$, and $C_2 \in [1, 15.7]$. The other parameters of the MOGA are set as $N = 100$, $N_{SP} = 100$, $N_{pop} = 10$, and $N_{bit} = 12$. The convergence of the best chromosome (solution) is shown in Figure 4, and R_{FLC} varies between 14-21 rules. At the 50th iteration, the chromosome has converged to the optimal solution with a final value of R_{FLC} of 19, resulting in a 24% reduction in computational complexity. Therefore, the optimized MPPT-FLC yields a 115-multiplication in computing at each FIS iteration. The significant 19 rules obtained from the MOGA optimization are shown in 2-D in Table 4 and compared with all 25 rules of the conventional FLC. The best shapes of the TMFs corresponding to the fine-tuned parameters a , b , and c from the MOGA

are shown in Figure 5(b), whereas those selected by the expert are shown in Figure 5(a).

To verify the performances of the proposed MPPT-FLC and to quantify how it increases the system's efficiency, in the test it is compared with the other existing controllers: the conventional FLC, NNC, and P&O. The MPPT controllers are carried out under the 7 different weather conditions of varying G and T , as shown in Figure 6. The control results of the transient and steady-state responses are

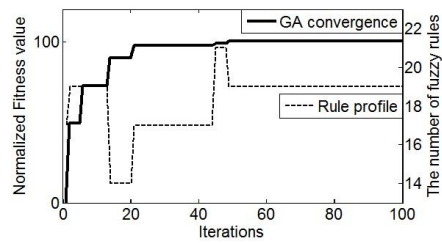


Figure 4. The convergence of the best chromosome with the profile of the number of significant fuzzy rules

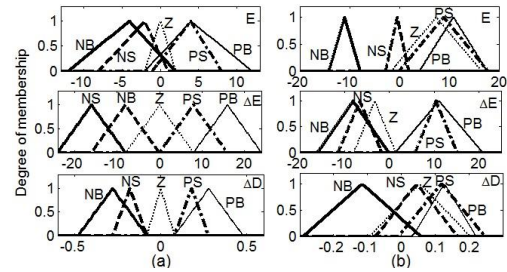


Figure 5. The shapes of the TMFs from a) conventional design and b) the MOGA optimization

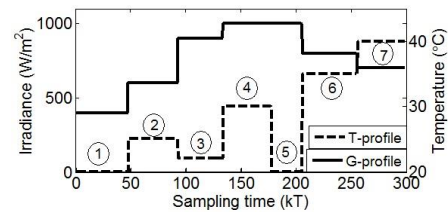


Figure 6. Set up weather conditions of the irradiance and temperature

shown in Figure 7. It is seen that the proposed FLC gives the fastest response without overshoot and achieves the highest stabilized accuracy. Furthermore, it is able to follow the MPP in the right direction even under the rapidly changing G and T (in the 6th condition) and skips the local maximums, whereas the NNC offers a slow response under low irradiance ($kT = 0-50$) and high temperature ($kT = 200-300$). In addition, the FLCs and NNC provide a smoother post-transient waveform as compared to the P&O controller that has high oscillations that cause wasted energy. Moreover, it is clear that the P&O controller tracks the MPP in the wrong direction under rapid weather changes ($kT = 200-250$), due to the lack of adaptive control. Considering the motor speed (Figure 8), the generated and optimal speeds have a good matching under weather variations. However, the proposed FLC sharply provides the maximum motor speed corresponding to the highest tracked power, leading to the maximum pumped water discharge output.

To further compare the performance of the MPPT controllers, the PV energy utilization efficiency related to the power obtained from the MPPT controllers $P_{MPPT}(t)$ with respect to the maximum power $P_{MPP}(t)$ over the time interval $[t_i, t_f]$ is considered and expressed as

$$\eta_{utilize} = \int_{t_i}^{t_f} \frac{P_{MPPT}(t)}{P_{MPP}(t)} dt. \quad (13)$$

From the comparison in Figure 9 and also in Table 5, the proposed FLC, conventional FLC, NNC, and P&O on average provide 91%, 85%, 81%, and 77% of energy utilization efficiency, respectively.

The main results, including maximum PV power, flow rate, motor speed, and system efficiencies obtained from the conventional and proposed FLCs, are detailed in Table 5. For the proposed FLC, the total efficiency varies between 0.4%-3.4% with an average value of 2%, which is 0.5% more efficient than

Table 4. Fuzzy rule base of the MPPT-FLCs obtained from the conventional design and the MOGA optimization

ΔE	Conventional design					MOGA optimization				
	NB	NS	Z	PS	PB	NB	NS	Z	PS	PB
NB	PB	Z	NS	Z	NB	PB			NS	NS
NS	PB	PS	NS	Z	NB	PB		PB	Z	NB
Z	PS	PS	Z	NS	NB		NB	PB	NS	
PS	Z	PB	PS	NS	NS	NS	PB		NB	NS
PB	Z	PB	PS	NB	Z	Z	NB	NS	PB	NB

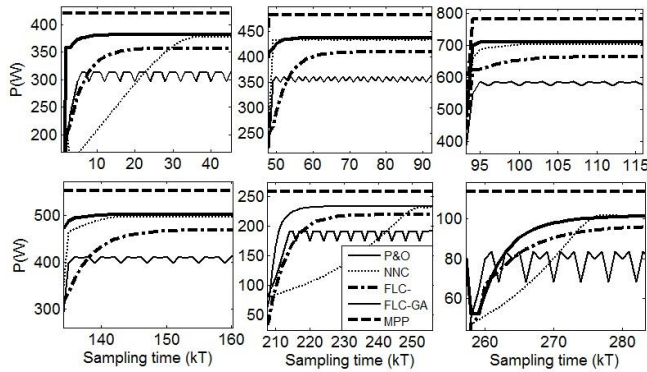
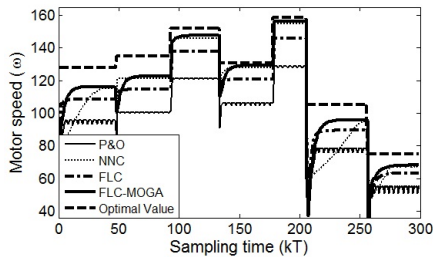
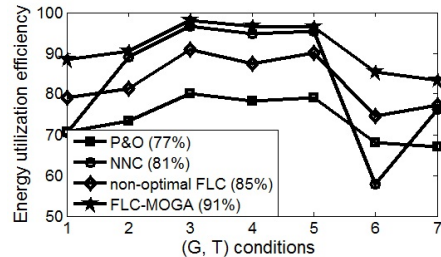


Figure 7. Control results of the tracking power obtained from the MPPT controllers under various weather conditions

Table 5. Performances of the PVWPS with the MPPT-based conventional FLC and proposed FLC/MOGA

G	T	P_{MPP}	P_{MPPT}	ω	Q	η_{PV} Equation (2)	η_{M-P} Equation (8)	η_T Equation (9)	$\eta_{utilize}$ Equation (13)
The conventional MPPT-FLC									
400	20	420	357	112.8	1.51	10.63	21.2	2.2	85.0
600	25	481.8	410	113.1	2.16	8.13	26.0	2.1	85.1
900	22	782.4	665	138.6	3.32	8.80	24.3	2.1	91.3
1000	28	551.7	468.8	121.1	2.56	5.58	26.4	1.5	84.9
1000	20	955.8	775	128.9	4.04	9.23	19.8	1.8	81.1
800	35	257.8	218	89.8	1.14	3.24	25.4	0.8	84.5
700	40	113.6	96.2	65.7	0.45	1.64	23.6	0.4	84.7
Average			427.1	110	2.1	6.7%	24%	1.5%	85%
The proposed MPPT-FLC/MOGA									
400	20	420	370	117	1.57	11	22.9	2.5	88.0
600	25	481.8	435	120	2.30	8.6	29.4	2.5	90.2
900	22	782.4	710	148	3.55	9.4	27.8	2.6	90.7
1000	28	551.7	503	130	2.75	6	30.4	1.8	91.1
1000	20	955.8	950	158	4.95	11.3	29.7	3.4	99.3
800	35	257.8	233	96	1.22	3.5	29.1	1.0	90.3
700	40	113.6	101	69	0.47	1.7	25.9	0.4	88.9
Average			471.7	119.7	2.4	7.3%	28%	2%	91%

**Figure 8. Output motor speed of the MPPT controllers under given weather variations****Figure 9. Comparison of the energy utilization efficiency of the MPPT controllers under the given weather conditions of irradiance G and temperature T**

the rest. Therefore, the motor speed and the water discharge of the proposed FLC are higher than those of the rest by 8.8% and 14.3%, respectively. The details of the NNC and P&O are not shown here, but they give a total efficiency lower than the FLCs and vary between 0.4%-2.5% and 0.2%-1.9%, with an average value of 1.6% and 1.2%, respectively. Furthermore, it is seen that the proposed MPPT-FLC presents good performances under a low temperature condition. For a very high temperature and even low or medium irradiance conditions, the performance is degraded. In this regard, integrating the cooling technique

into the MPPT controller can help increase the mean efficiency.

Conclusions

In this paper, the MPPT-based FLC derived by the MOGA optimization is proposed and applied to the PVWPS. The complexity of the FLC, in terms of the number of fuzzy rules, is significantly reduced while maintaining the MPPT performances and, consequently, the system parameters are fine-tuned to meet the control stability easily. When carried out under

varying irradiance and temperature conditions, the proposed MPPT-FLC/MOGA outperforms the other existing controllers in terms of increased response time and stabilized accuracy as well as global efficiency and energy utilization efficiency improvements. Therefore, the motor speed, as well as the pumped water discharge, is maximized. Continuing this work, the PVWPS with the MPPT-FLC is currently under practical installation so in the near future it will be modified and extended to other PV applications, if the results are satisfactory.

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