Study of Energy Control Strategies for a Standalone PV/FC/UC Microgrid in a Remote Area

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Abstract: Remote (or rural) area electrification is one of the main concerns, especially in developing countries. This paper presents a detailed investigation of different energy control strategies for a standalone microgrid in a remote area. In this microgrid, solar energy is considered as the primary energy source. Besides, taking into consideration stochastic nature of PV systems, a backup system that comprises a fuel-cell stack is hybridized, to avoid lack of energy and improve the reliability of the load. A battery bank and a supercapacitor pack are integrated as storage units along with an electrolyzer, as an alternative for energy storage. The electrolyzer absorbs the surplus energy production of the PV system if the battery bank reaches the maximum state of charge. Refueling the fuel-cell system with the stored hydrogen and meeting the average demand shortage, when the PV production is not sufficient, protects the battery bank against overcharge and deep discharge. In this paper, the main purpose is studying the energy control strategies that have high response time. These strategies, that are employed to control the energy flow, the fuel consumption, the dynamic performance, the microgrid efficiency, the battery/supercapacitors SOC, the energy sources/storage units life span and etc., include: the state machine control strategy, the rule-based fuzzy logic control strategy, the ANFIS-based control strategy, the equivalent consumption minimization strategy, the external energy maximization strategy, and the PI-type fuzzy logic control strategy. An effective approach is used to design the state machine control strategy and the rule-based fuzzy logic control. Additionally, the performance of all the energy control strategies, during different battery SOCs, is investigated. Finally, simulation results and the performance comparison of all the strategies are presented. Factors such as the fuel consumption, the fuel (and the fuel-cell) efficiency, and the battery (bank) state of charge, are used for assessment.

Keywords: fuel-cell, energy management, renewable energy, batteries, PV system, battery state of charge

1. Introduction

Nowadays renewable energy resources based power plants tend to replace their conventional (fossil fuels based) counterparts, as they are pollutant free, endless, economical and available [1]. Moreover, there are remote (or rural) areas all over the world, especially in developing countries, that do not have access to the main grid and still lack electricity power. As a result, off grid electrification through standalone microgrids is a beneficial solution, since extending the main grid is not always practical, cost-effective or affordable for rural residents [2, 3]. A microgrid usually comprises wind turbines and solar (PV) panels simultaneously or only one of them, depending on the climate characteristics of the geographical location where the microgrid is installed [4]. The main drawbacks of solar and wind energy sources is rapid fluctuations in the generated power and the risk of the load power loss when there is no wind or sunlight. Therefor considering the microgrid reliability and aiming to provide continuous energy to the load, a backup energy unit is required [4]. Taking into account considerable benefits of fuel-cells, such as high fuel efficiency, fuel availability, long life time, clean and silent operation, and low maintenance cost [5, 6, 7], a fuel-cell stack is one of the best choices.

Appreciating the significant merits of the fuel-cell technology, the slow dynamic response of the fuel-cell and the fueling problems, related to the production, storage, and transportation of the hydro gen must not be ignored. In addition, fuel-cells are unidirectional systems. Therefore, a battery (bank) is needed to control the energy flow in two directions and stabilize the DC bus voltage [8]. Furthermore, designing an energy management unit is another challenge to control the flow of the energy, the fuel consumption, the dynamic performance, the microgrid efficiency, the lifetime of the power sources, the battery/supercapacitors SOC and etc. [9, 4]. There are some studies related to the energy management of the microgrids in the literature. In short term analysis, with a time scale of seconds or minutes, a Mamdani-type rule- based fuzzy logic energy control strategy for a hybrid power system has been presented in [10]. It is discussed that designing experiences and knowledge about the components of the power system has an important role in the performance of this controller [9]. The authors in [11] compared the performance of Sliding Mode and PI controller in a microgrid, but it is shown that PI controller performance is dependent on the operating point [12, 13]. Therefore, PI controller with fixed parameters may not have effective performance, facing nonlinearity or parameter changes in the hybrid power system. [14]. The fuzzy logic controller does not need an exact mathematical model of the system and shows insensitivity to the system parameters variations [15]. Therefore, combination of linear PI controller with the fuzzy logic controller seems sound. Linear structure of the PI controller along with the fuzzy logic controller capabilities improves conventional PI controller performance. The fuzzy logic control of a DC microgrid was discussed in [16], in which the authors designed the fuzzy logic controller such that extends the battery lifetime. The authors in [17] presented energy management of a fuel-cell/ battery hybrid system using fuzzy logics for residential applications, in which they ruled daily AC electrical demand of a home during the 1400s of simulation for the energy management strategy performance assessment. A comparative study of different energy control algorithms consisting the "load following" and "the single-input single-outputs extremum seeking control" schemes was presented by the author in [8], for a hybrid renewable system comprising PV and wind energy as primary sources along with fuel-cell technology as the support system. To evaluate the hybrid system performance under a real load and random PV/WT power, the authors ruled a residential home load profile and a sunny day PV/WT power profile during 12 seconds of simulation. Moreover, Implementation of the state machine based control algorithm for a standalone hybrid system was presented in [18]. In addition, an ANFIS-Based control of a grid-connected hybrid power system is studied in [15]. The ANFIS-based controller employing the Sugeno-type fuzzy inference system is more reliable than the Mamdani-type applied fuzzy controller. In long term analysis, with a time scale of hour, different state machine power management strategies are employed in a pv/wind/fuel-cell hybrid system in [19]. This strategy needs an exact model of the system, and furthermore is sensitive to the errors or variations in the parameters measurement, in contrast to the fuzzy energy management strategy [20]. The Authors in [21] proposed the same strategy with a different approach for a hybrid boat energy control system in which they considered the battery lifetime characteristics during the states' definition stage. Although some of the problems of the classic strategies have been solved later, by introducing new algorithms, such as dynamic programming [22] and model predictive control [23], but they added to the amount of the computations [9]. There was not any comparative study of the optimally or sub optimally designed energy control strategies for standalone microgrids. This application needs more attention, but has not been studied extensively in the literature [24]. This motivated the authors of this paper to study the energy control strategies that are common either in microgrid studies or other applications, such as hybrid vehicles or more electric aircraft power systems, that can be applied to standalone microgrids, and investigate which strategy works better for a microgrid, especially a standalone one in a remote area. This paper is organized as follows: First, the state machine control strategy is presented and then the rule-based fuzzy logic control strategy is discussed. Regarding the lifetime issue of the battery bank, an effective approach is used to design the states and the rules of the state machine control strategy and the rule-based fuzzy logic control strategy, respectively, which is similar to the one that is proposed in [21] for a hybrid boat energy management system. Simulation results verify the successful operation of the discussed approach. Then, the ANFIS-based control strategy, the equivalent consumption minimization strategy, the external energy maximization strategy, which is introduced by the authors in [25] for a fuel-cell hybrid emergency power system of more electric aircraft, and finally the PI-type fuzzy logic control strategy is studied. Next, the simulation results are presented and finally, the performance comparison of all the strategies, under different operating conditions, is presented. Criteria such as the fuel consumption, the dynamic performance, the fuel (and the fuel- cell) efficiency, and the battery (bank) state of charge, are used for comparison. The hybrid system parametrization is presented in the appendix

2. Energy Management Strategies

Energy control system influences the fuel economy, the lifetime of the energy sources, the fuel efficiency, the dynamic performance, the overall efficiency of the microgrid, and etc. [21-25]. An overall energy control scheme between the main energy sources/ storage units and the backup system is necessary. This strategy helps to meet the (energy) demand requirements, such as high quality and reliable energy serving, while the design requirements and desired objectives are satisfied. These later requirements include: optimization of the hydrogen consumption, pollution emissions minimization, decreasing stress on the energy sources/ storage units, extending useful battery life time, and etc. [26, 27]. This paper focuses on the centralized energy management unit. As observed in Fig. 1, the data of all the energy sources/ storage units are sent to the main control center and the control signals of the local controllers are determined subsequently, based on all the design requirements and desired objectives [25, 28]. In this section, six energy management strategies are studied in detail.

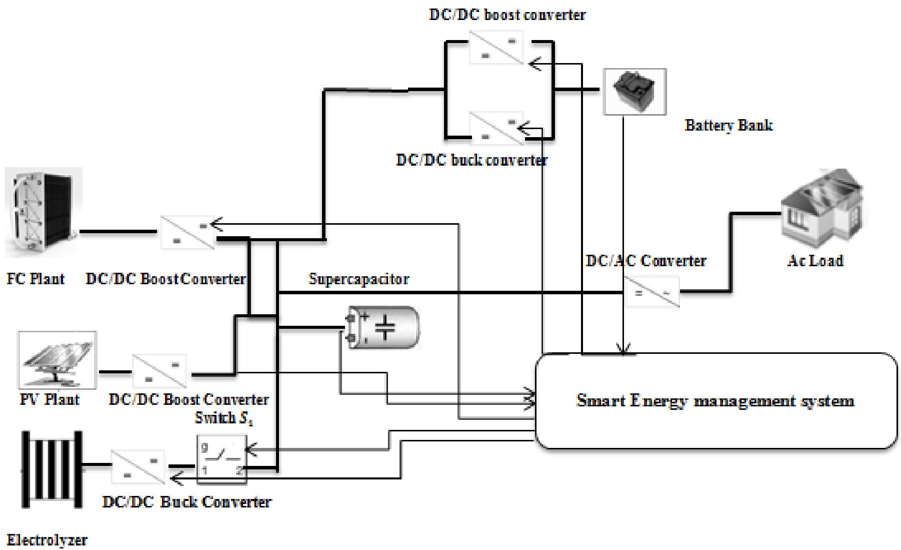


Fig. 1. A typical PV/FC/UC hybrid Power System.

2.1. State Machine Control Strategy

This scheme is based on a series of states that are defined based on the knowledge and past experience of the designer, to describe the overall behavior of the hybrid power system [9]. Therefore, more knowledge of the system components results in a more accurate and robust controller. Its sensitivity to the variations or errors in the measured signals besides requiring an exact mathematical model of the system is the main drawbacks of this strategy [20, 29]. In this paper, the state machine control strategy is based on fifteen states to determine the desired reference for the fuel-cell output power, as shown in Table 1. The fuel-cell power is decided based on the load power, the battery state of charge, and the PV production. Three levels are considered for the battery SOC: low, medium, and high. Battery bank power is calculated, considering the power balance constraint between total power production and consumption ($P_{load} = P_{PV} + P_{fc} + P_{batt}$, If $P_{load} > P_{pv}$). As observed, the supercapasitors power is not considered in the constraint, because they meet the load power in transient time intervals. In other words, the energy demand will be shared between the PV system, the fuel-cell and the battery bank, at the steady state. We followed an approach similar to the one employed in [21], which is described below, to design the states.

1) If (initial battery) SOC is high (SOC > 85%), the battery will be discharged, to help the fuel-cell provide the load power shortage, which is not supplied by the PV production. The battery bank lifetime characteristics issue has an important role in the states' definition. The battery bank minimum state of charge (SOC_{min}) and maximum state of charge (SOC_{max}) adjust the operation of the fuel-cell and the electrolyzer, respectively. Generally, a minimum level is considered for the fuel-cell output power for efficient operation. If $P_{net} \leq P_{fcmin}$, which means that the energy demand shortage is less than the fuel-cell minimum output power level, the fuel-cell will generate P_{fcmin} and the remaining amount ($(P_{net} - P_{fcmin}) < 0$) is delivered to the battery bank. If the remaining amount is positive, the battery bank will be discharged to meet the load demand shortage. If the battery SOC is high and the fuel-cell provides its maximum power, the energy demand shortage higher than $'P_{fcmax} + P_{optdischarg}'$ will discharge the battery bank faster to meet the load power.

2.2. Rule-based Fuzzy Logic Energy control Strategy

In this paper, the rule-based fuzzy logic strategy has three inputs: the battery state of charge, the load power, the PV power generation and one output: the fuel-cell power. Three levels are considered for the battery SOC, as the state machine control strategy. As observed, the battery SOC is divided into three ranges: "low", "medium" and "high". The PV production is divided into four fuzzy subsets: "very low", "low", "medium", and "high" and finally, five fuzzy subsets are considered for the fuel-cell and the demanded power: ""very low", "low", "medium"," high" and "very high". An approach similar to the one that is used in the state machine control strategy is employed, to design the fuzzy rules. Two main objectives for developing the rules are: First, providing the load with continuous and reliable energy in every condition and second, preventing the battery bank from overcharge and deep discharge. Table 2 shows the if-then rule-base and Fig. 2 shows the membership functions. In this section, the Mamdani- type fuzzy interface system and centroid defuzzification method are utilized. Fig. 3 shows the rule-based fuzzy logic energy management system surface.

2.3. ANFIS- Based Energy Control Strategy

This scheme consists of five layers, based on the combination of the Sugeno-type fuzzy inference system and neural networks. It includes a backpropagation algorithm alone or a hybrid method (least-squares backpropagation) to tune the parameters of the membership functions and the structure of the associated fuzzy inference system based on a given set of the input/output data [15, 30].

Table 1. State Machine Control Strategy

SOC	P_{load}	P_{fc}	P_{batt}
SOC >85	$P_{load} \leq P_{PV}$	0	P_{net}
	$P_{net} \leq P_{fcmin}$	P_{fcmin}	$(P_{net} - P_{fcmin}) \leq 0$
	$P_{fcmin} < P_{net} \leq P_{fcmin} + P_{optdischarg}$	P_{fcmin}	$(P_{net} - P_{fcmin}) > 0$
	$P_{fcmin} + P_{optdischarg} < P_{net} \leq P_{fcmax} + P_{optdischarg}$	$P_{net} - P_{optdischarg}$	$P_{optdischgarg}$
	$P_{net} > P_{fcmax} + P_{optdischarg}$	P_{fcmax}	$P_{net} - P_{fcmax}$
50<SOC<85	$P_{load} \leq P_{PV}$	0	P_{net}
	$P_{net} \leq P_{fcmin}$	P_{fcmin}	$(P_{net} - P_{fcmin}) \leq 0$
	$P_{fcmin} < P_{net} \leq P_{fcopt} - P_{battopt}$	P_{net}	0
	$P_{fcopt} - P_{battopt} < P_{net} \leq P_{fcopt} + P_{battopt}$	$\mathbf{P_{fcopt}}$	$P_{net} - P_{fcopt}$
	$P_{fcopt} + P_{batt\,opt} < P_{net} \leq P_{fcmax}$	P_{net}	0
	$P_{net} > P_{fcmax}$	P_{fcmax}	$P_{net} - P_{fcopt}$
SOC<50	$P_{load} \leq P_{PV}$	0	P_{net}
	$P_{net} \leq P_{fcmin}$	P_{fcmin}	$(P_{net} - P_{fcmin}) \leq 0$
	$P_{fcmin} < P_{net} \leq P_{fcmax} + P_{optcharg}$	$P_{net} - P_{optcharg}$	$P_{optcharg}$
	$P_{net} > P_{fcmax} + P_{optcharg}$	P_{fcmax}	$P_{net} - P_{fcmax}$

$P_{net} = P_{load} - P_{PV}$

Table 2. Rule-based Fuzzy Logic Control Strategy Rule-base

SOC	P_{PV} / P_{load}	VL	$P_{fc_{ref}}$ L	M	H
L	VL	L	VL	VVL	VVL
	M	M	L	VL	VVL
	M	H	M	L	VL
	H	H	H	M	L
M	VL	VL	VVL	VVL	VVL
	L	L	VL	VVL	VVL
	M	M	L	VL	VVL
	H	H	M	L	VL
H	VL	VVL	VVL	VVL	VVL
	L	VL	VVL	VVL	VVL
	M	L	VL	VVL	VVL
	H	M	L	VL	VVL

In this paper, the hybrid (least-squares backpropagation) algorithm is used to tune the membership functions and the structure of the inference fuzzy system. Fig. 6(b) shows the ANFIS-based control strategy. The amount of the data that is collected from the state machine control strategy in random the battery SOCs, the PV generation and the load power cases, which are used for the training, checking and testing, are presented in Table 3. The input and output variables were changed from zero to the maximum value, to collect a fair input/output data set. This procedure merges the capabilities of the neural networks, and the fuzzy logic strategy with the state machine control approach. The membership functions, after training, are shown in Fig. 3. The training error is below 5%. .

2.4. Equivalent Consumption Minimization Strategy

PV power generation is free of cost. As a result, the costs are assigned to the fuel consumption of the fuel-cell

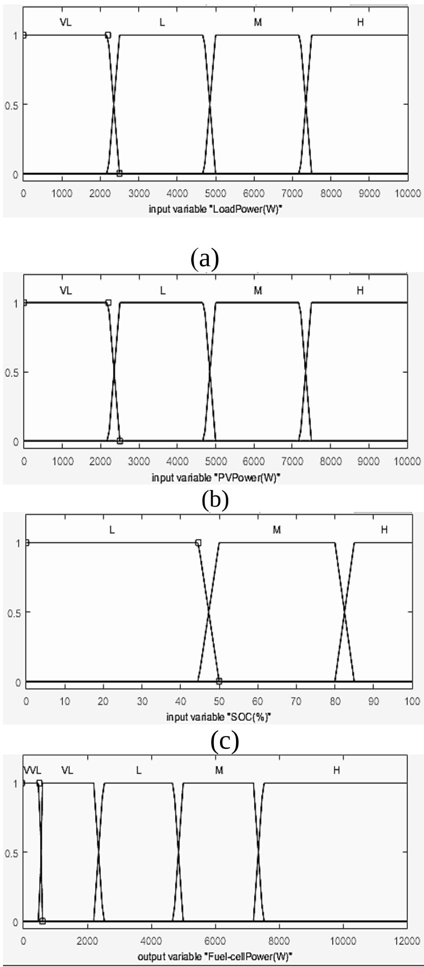


Fig. 2. Membership functions. (a) Load power (b) PV power (c) Battery state of charge. (d)) Fuel-cell power.

and the equivalent (fuel) consumption of the battery unit. Once again, aiming to minimize the cost function (F),

which is formulated as equation 1, a local optimization technique is used.

$$F = \text{ECMSfunction} = E_{fc} + (EQ_1).\ E_{batt} + (EQ_2).\ E_{sc} \quad (1\text{-}1)$$

Where EQ_1 and EQ_2 are the equivalent factors and E_{fc}, $(EQ_1).\ E_{batt}$ and $(EQ_2).\ E_{sc}$ are the fuel consumption of the fuel-cell, the battery bank equivalent fuel consumption and the supercapacitors equivalent fuel consumption, respectively. As mentioned before, the supercapacitors try to satisfy the energy demand in transient time intervals and the load power will be shared between the PV system, the fuel-cell and the battery bank, at the steady state. Then, the supercapacitors equivalent fuel consumption can be overlooked. Additionally, the fuel-cell hydrogen consumption and the battery equivalent fuel consumption are pertained to the fuel-cell power and the battery power, respectively [31]. Therefore the cost function can be rewritten as:

$$F = P_{fc} + (EQ_1).\ P_{batt} \quad (1\text{-}2)$$

2.4.2. Constraints

Power balance constraint (between total power generation and consumption), that must be considered, is:

$$P_{net} = P_{load} - P_{pv} = P_{fc} + P_{batt} \quad (2)$$

The equivalent factor EQ_1 can be defined as [31]:

$$EQ_1 = 1 - 2 * \mu * \frac{(SOC - 0.5(SOC_{max} + SOC_{min})}{SOC_{max} + SOC_{min}} \quad (3)$$

Where μ is a constant that controls the battery state of charge (It is equal to 0.65 in this paper). The boundary conditions, that limit the fuel-cell power, the battery bank power, the battery state of charge and the equivalent factor to their allowed limits, are:

$$P_{fcmin} < P_{fc} < P_{fcmax} \quad (4)$$

$$P_{charg\,max} < P_{batt} < P_{discharg\,max} \quad (5)$$

$$SOC_{min} < SOC < SOC_{max} \quad (6)$$

$$0 < EQ_1 < 2 \quad (7)$$

Fig. 4 shows the state machine control, the rule-based fuzzy logic strategy and the ECMS.

2.5. EEMS

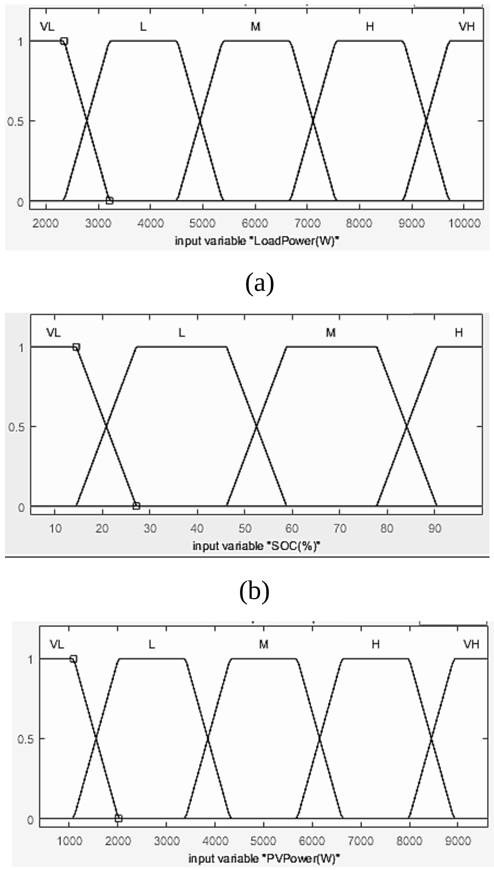
In this paper, there are four energy sources/storage units, but the output of the primary source, is dependent on weather patterns, hence is not predictable. Then, only the load power shortage that is not supplied by the PV system is met by the combination of the fuel-cell stack, the battery bank and the supercapacitors. Consequently, the EEMS can be applied to the proposed microgrid in this paper, too

2.5.1. Cost function

The cost function, which aims to maximize the external energy, is formulated as:

$$F = \text{EEMSfunction} = -P_{batt}\,\Delta T - 0.5 \times C \times \Delta V^2 \quad (8)$$

Where C, ΔT and ΔV are the supercapacitor nominal capacity, sampling time and the supercapacitor charge/discharge voltage, respectively.



(c)

Fig.3. Membership functions. (a) (b) Load power. Battery SOC. (c) PV power

Table 3. The Input Data Of The ANFIS-Based Energy Management Strategy.

Data Type	Number
Training	9044
Checking (To avoid overfitting problems)	1137
Testing (To avoid overfitting problems)	1171
Epochs	100

Similar to the equivalent consumption minimization strategy, a local optimization technique is used to minimize F.

2.5.2. Constraints

The boundary conditions, which must be considered to limit the battery bank power and DC bus voltage to their allowed limits, are:

$$P_{charg\,max} < P_{batt} < P_{discharg\,max} \quad (9)$$

$$V_{dcmin} < V_{dc} < V_{dcmax} \quad (10)$$

The inequality constraint is:

$$\frac{P_{batt}\,\Delta T}{V_{battnominal} Q} \leq SOC - SOC_{min} \quad (11)$$

2.6. PI-type Fuzzy Logic Control Strategy

This scheme is based on the combination of the rule- based fuzzy logic technique and linear PI controller [32-46]. Similar to conventional PI controller, it has two control gains, but these gains are not constant and can be self-tuned to have better tracking performance, in facing fast input signals ("error" and "rate of change of error") changes. Additionally, they can be tuned online for a better performance [13]. It can be employed in nonlinear systems, time-variant systems, and systems with large time constants [32, 33]. It does not need an exact mathematical model of the system [34] and has a better performance than classical PI controller [32]. PID-type and PI-type fuzzy logic controller are presented by authors for different applications, such as the active magnetic bearing system (control) or hybrid electric vehicles (speed control) [34,32, 35]. Taking into consideration the suitable performance of the PI-type fuzzy logic controller in reducing the steady state error to zero in addition to its capabilities discussed above, the structure that is shown in Fig.

Where Q is the battery bank nominal capacity.

Where $P_{load\ shortage}$ is the load power shortage. The supercapacitor charge/discharge voltage (ΔV) will be added to the DC bus voltage reference to force the supercapasitors to charge or discharge [25].

4 is proposed for the SOC control of the battery. The input signals of this strategy are "error" and "rate of change of error" and the output is the control signal (U), generated by the rule-based fuzzy logic control strategy. Generally, the Sugeno-type fuzzy controllers are faster and more reliable than the Mamdani-type fuzzy ones [34]. As a result, the Sugeno-type fuzzy inference system is more common for the PI-type fuzzy logic control strategy. Table 4 shows the fuzzy if- then rules, in which the rows colored in red show the desired performance of the rule based fuzzy controller during the transient stage. Moreover, the rows in black and blue show the desired performance during the settling state and the steady state, respectively [32]. Fig. 5 shows the membership functions and the surface of the fuzzy controller. Linguistic values in Table 4, for outputs, are: NL= -1, NM= -0.5, PM=0.5, PL=1 The parameters of all the energy management strategies, discussed before, are shown in Table 4. The energy management unit design requirements are shown in Table 5

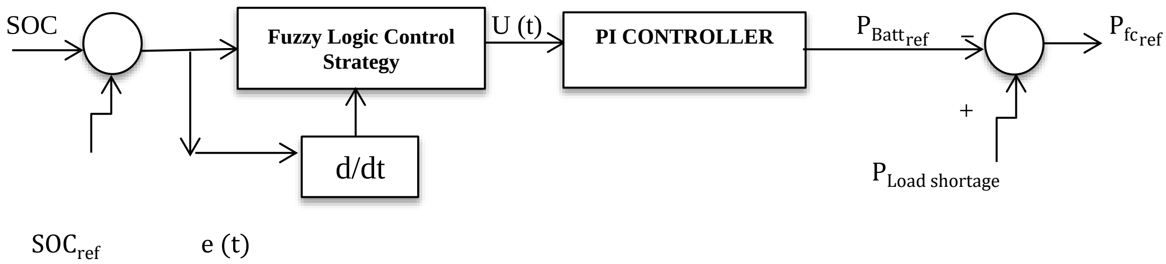


Fig. 4. PI-type fuzzy logic control strategy.

Table 4. PI-type Fuzzy Logic Control Strategy Rules

If e(t) is NL & $\Delta e(t)$ is NL	U(s)=NL
If e(t) is NL & $\Delta e(t)$ is NM	U(s)=NL
If e(t) is NL & $\Delta e(t)$ is L	U(s)=NL
If e(t) is NL & $\Delta e(t)$ is PM	U(s)=NM
If e(t) is NL & $\Delta e(t)$ is PL	U(s)=L
If e(t) is NM & $\Delta e(t)$ is NL	U(s)=NL
If e(t) is NM & $\Delta e(t)$ is NM	U(s)=NL
If e(t) is NM & $\Delta e(t)$ is L	U(s)=NM
If e(t) is NM & $\Delta e(t)$ is PM	U(s)=L
If e(t) is NM & $\Delta e(t)$ is PL	U(s)=PL
If e(t) is L & $\Delta e(t)$ is NL	U(s)=NL
If e(t) is L & $\Delta e(t)$ is NM	U(s)=NM
If e(t) is L & $\Delta e(t)$ is L	U(s)=L
If e(t) is L & $\Delta e(t)$ is PM	U(s)=PM
If e(t) is L & $\Delta e(t)$ is PL	U(s)=PL
If e(t) is PM & $\Delta e(t)$ is NL	U(s)=NL
If e(t) is PM & $\Delta e(t)$ is NM	U(s)=L
If e(t) is PM & $\Delta e(t)$ is L	U(s)=PM
If e(t) is PM & $\Delta e(t)$ is PM	U(s)=PL
If e(t) is PM & $\Delta e(t)$ is PL	U(s)=PL
If e(t) is PL & $\Delta e(t)$ is NL	U(s)=L
If e(t) is PL & $\Delta e(t)$ is NM	U(s)=PM
If e(t) is PL & $\Delta e(t)$ is L	U(s)=PL
If e(t) is PL & $\Delta e(t)$ is PM	U(s)=PL
If e(t) is PL & $\Delta e(t)$ is PL	U(s)=PL

Table5. Design Requirements

Parameter	**Value**
$P_{fcmin}, P_{fcmax}, P_{fcopt}$ (W)	0, 12544, 10285.7
$P_{optdischarg}, P_{battopt}, P_{optcharge}$ (W)	1440, 960, -1440
SOC_{max}, SOC_{min} (%)	85, 50
$V_{battnominal}, V_{dcmin}, V_{dcmax}$ (V)	60, 218, .222
$P_{charg\ max}$, $P_{discharg\ max}$ (W)	-2400, 4800

3. Simulation Results and Discussion

To investigate the performance of the energy control strategies, two case studies are taken into account as follows: pulsed load under step changes in the PV system output power and random load and PV power.

3.1. Pulsed load

Fig. 6 shows the load and the PV power versus time, which are assumed to be the same for all the strategies, in the first scenario. The step changes in the PV/Load power profiles are selected such that investigate the hybrid system behavior when makes face to different operating states during a day. The validation of the approach, which is discussed before for designing the state machine control strategy and the rule-based fuzzy logic energy management strategy, are shown in Figs. 7 and 8, for the microgrid that is shown in Fig.1. As observed, in the case of the state machine control strategy and the rule-based fuzzy logic energy management strategy, the fuel-cell follows the previously determined rules that aim to

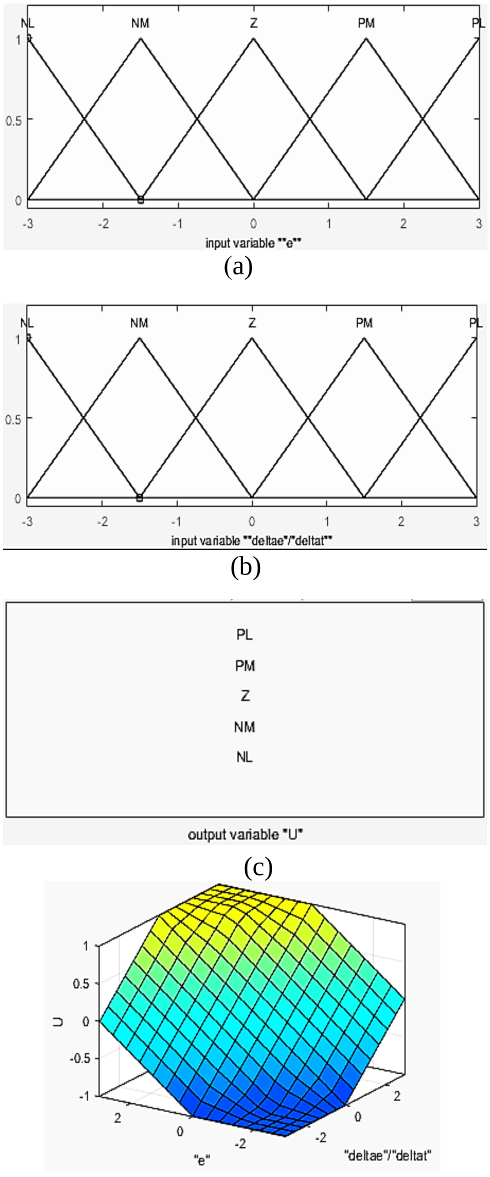


Fig. 5. (a) Membership functions of Δe(t) (b) Membership functions of e(t) (c) output variable (d) The surface of the fuzzy controller.

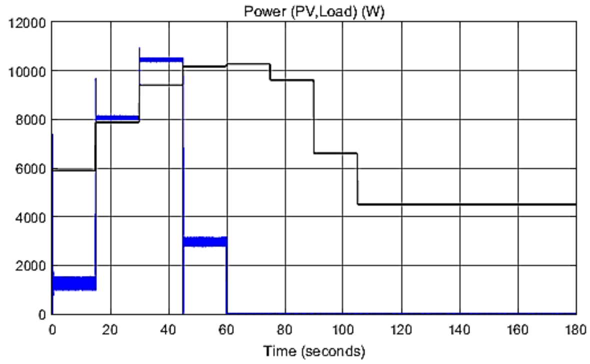
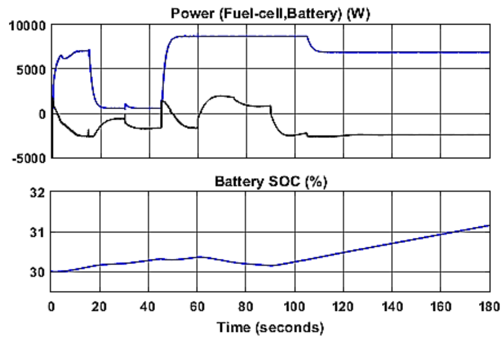
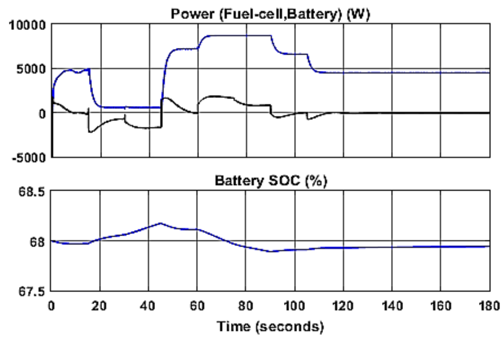


Fig. 6. Power (PV plant, Load) (W)

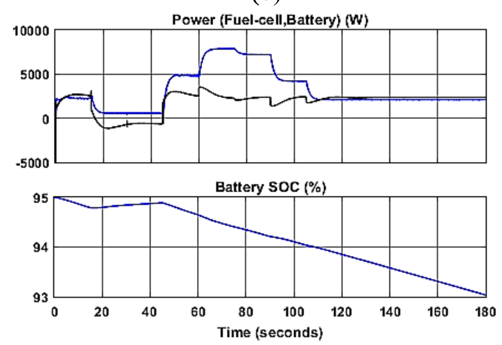
keep the battery SOC within the normal range, with charging the battery bank when its SOC is lower than the SOC_{min} and discharging it when its SOC is higher than the SOC_{max}. Fig. 9 shows the ANFIS-based energy management strategy implementation that is similar to the performance of the state machine control strategy, because the training, checking, and testing data is collected from the state machine control strategy. Similar to the state machine control strategy, the ANFIS-based control goal is to keep the battery bank operation inside the boundary conditions (SOC_{min} and SOC_{max}). As observed in Figs. 7-9, during the second 15s, the PV generation equals the demanded power. As a result, the fuel-cell power reduces to its minimum amount and the battery power is almost zero when the initial battery SOC is normal or high. In this stage, the fuel-cell provides only the battery bank charging power if the storage bank starts with a low SOC and the PV power is lower or equal to the load power. In the case in which the PV power is higher than the demanded energy, the PV system is responsible of chagrining the battery bank when the battery SOC is low. Subsequently, the PV power is higher than the load power. Then, the surplus PV power is used to recharge the battery bank, during the third 15s. In this case, the switch S_1 turns on if the extra power is higher than the battery bank optimal charging power. The electrolyzer absorbs the difference between the PV generation and the sum of the demanded and the battery charging power, to store it in the form of the hydrogen. In other words, charging the battery bank has priority to producing the hydrogen when the battery SOC is low or normal, in order to keep the battery at higher SOCs, which extends its lifetime. The PV additional power will be absorbed by the electrolyzer if the battery SOC is higher than the SOC_{max}, to use the free solar energy as much as possible and increase the battery useful lifespan by protecting it against overcharge. The hydrogen production when the battery starts with a high SOC is shown in Fig. 10. Then, the PV production decreases during the fourth 15s. Then, the fuel-cell power increases to supply the energy demand shortage. The fuel-cell delivers its maximum power during the fifth 15s, to meet the peak load power. Additionally, the battery bank is discharged, to share the load power with the fuel-cell when the PV production is approximately zero In other words, keeping the balance between total power generation and consumption has priority to recharging the battery bank, when initial battery SOC is low (see Figs. 7 (a), 8 (a) and 9 (a) for the fifth 15s). Of course, this is not a significant problem, because it lasts only for the peak load time interval and the battery bank is recharged normally during the whole load profile. As observed in Figs. 7 (b), 8 (b) and 9 (b), the fuel-cell aims to provide the energy demand shortage and keep the battery bank SOC within the normal range when the battery bank starts with a normal SOC. Therefore, the fuel-cell almost meets the load power, except during the states in which the storage bank works with its optimal discharge power or forced to discharge with a high discharge rate under high load demand intervals. Moreover, if the PV production exceeds the load demand, there is no way for the battery bank except charging. The battery bank is discharged with a slow rate to reach a nominal SOC when starts with a high SOC (see



(a)



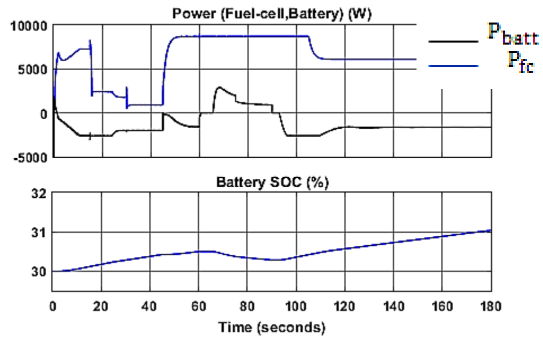
(b)



(c)

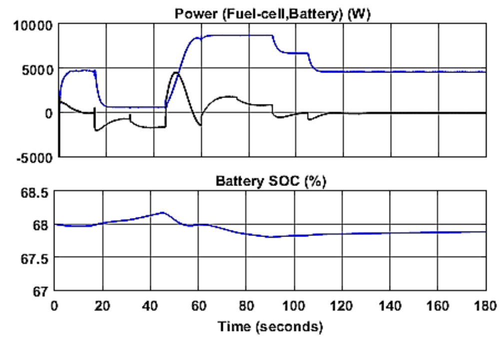
Fig. 7. Validation of the state machine control approach. (a) Initial SOC=30%. (b) Initial SOC = 68%. (c) Initial SOC =95%.

Figs. 7 (c), 8 (c) and 9 (c)). This means that the storage bank has higher priority than the fuel-cell for meeting the energy demand when it starts with a high SOC. In the following, the load power decreases and the PV production is zero and then both of them is assumed to be fixed to observe settling of the battery SOC at the reference value in the case of the PI-type fuzzy logic control strategy. The PI-type fuzzy logic control strategy performance for different battery SOC references is depicted in Fig. 11. In the first case, the SOC_{ref}

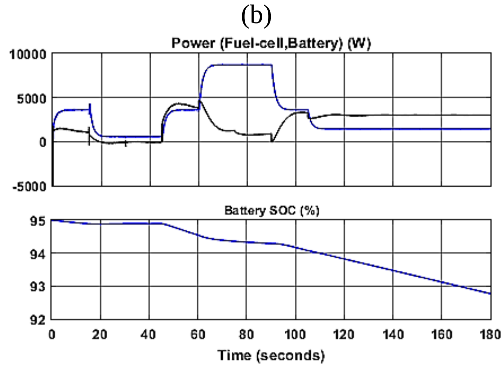


equals to 65% (see Fig.11 (a)). Then, the battery is discharged faster to reach the preferred reference (except in the second and third 15s, where the battery is recharged, imposed by the PV plant). In the second case, the SOC_{ref} is set to 67%. As observed, settling time is reduced, as expected. (see Fig.11 (b)). In the third case, 68.5% is selected for theSOC_{ref}, to observe the controller performance when the initial SOC is smaller than theSOC_{ref}.

(a)



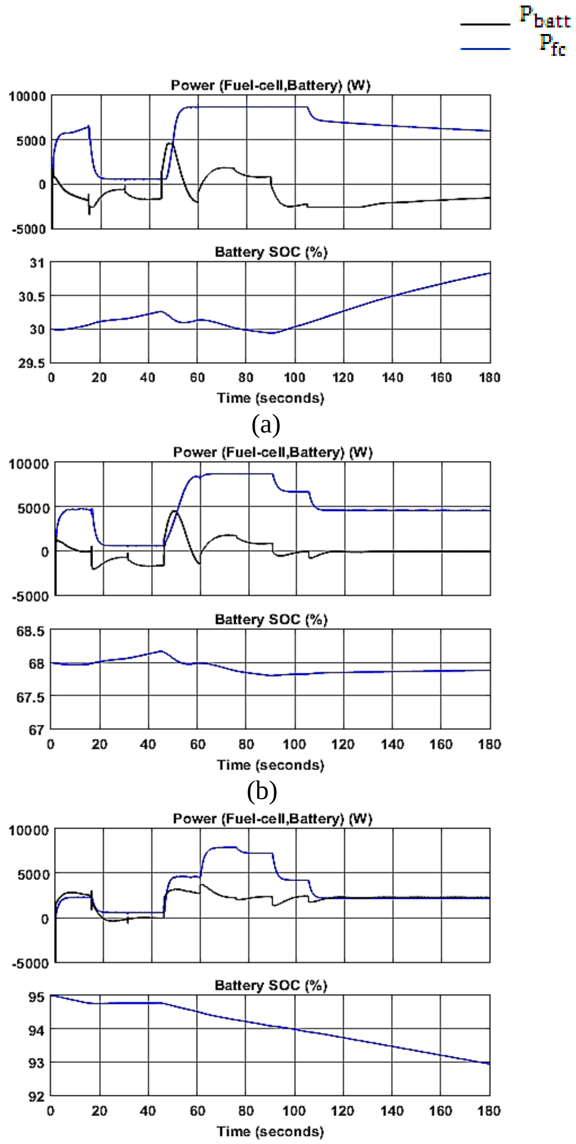
(b)



(c)

Fig. 8. Validation of the rule-based fuzzy logic strategy approach. (a) Initial SOC = 30%. (b) Initial SOC = 68%. SOC =95%.

As seen in Fig. 11 (c), the battery bank is recharged to reach 68.5%. (except in the fifth and sixth 15s). Fig.11 shows that the PI type fuzzy logic control strategy charges or discharges the battery bank such that its SOC approaches the desired reference unless the PV power or the load demand impose other conditions that postpones the settling time. The ECMS performance in different initial battery SOCs is shown in Fig. 12. Investigating the equivalent factor (EQ_1), expressed in section 2.4, shows that the ECMS tends to maintain the battery SOC around the "0.5 (SOC_{max} + SOC_{min})" (It is equal to 67.5% in this paper), which provides a potential reference for the battery SOC. The simulation results in Fig.12 confirm this conclusion, in which the battery charges when starts with a low SOC and discharges with the maximum rate when starts with a high SOC (see Fig.12 (a) and (c)). Moreover, the battery attempts to work around 67.5% if starts to operate with a normal SOC. The EEMS implementation is shown in Fig. 13. The battery discharges faster to reach the minimum limit if it's initial SOC is higher than the SOC_{min}, and charges with the optimum rate to reach the minimum limit when it starts with a lower SOC (see Fig. 13 (a), (c) and (d)). Starting the battery bank with the SOC_{min} (It is equal to 50% in this paper), leads to keep the battery SOC at the SOC_{min} (see Fig. 13 (b)). Therefore, the fuel-cell meets the load demand shortage. Consequently, setting higher values for the SOC_{min}, leads to employing the battery bank at higher SOCs. In other words, the SOC_{min} is a potential reference for the battery SOC, in this strategy. It can be concluded that there is a direct or indirect control on the battery SOC in the PI type fuzzy logic control strategy, the ECMS, and the EEMS. Then, it is essential to determine an approach that controls the battery SOC, the rate of charge and discharge of the battery bank at the design stage of the state machine control, the ANFIS-based energy management strategy, and the rule based fuzzy logic control, as considered in this paper.



(c)

Fig. 9. Validation of the ANFIS-based training. (a) Initial SOC =30%. (b) Initial SOC = 68%. (c) Initial SOC = 95%.

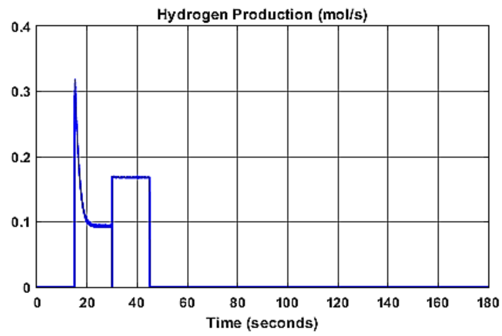
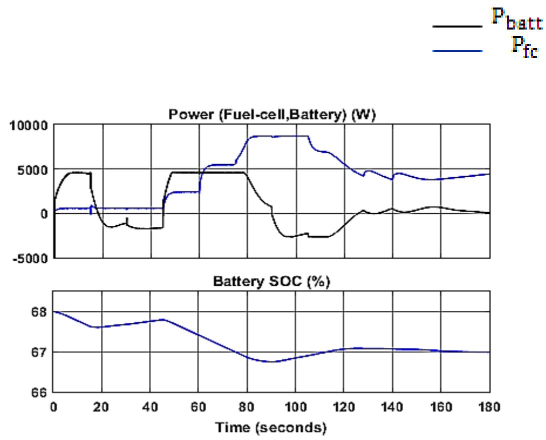
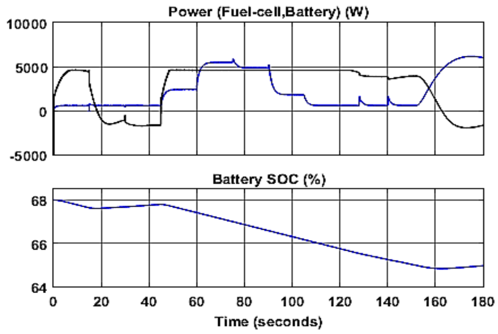


Fig. 10. Hydrogen production (mol/s) for SOC > 90% in the case of the rule based fuzzy logic control strategy



(a)



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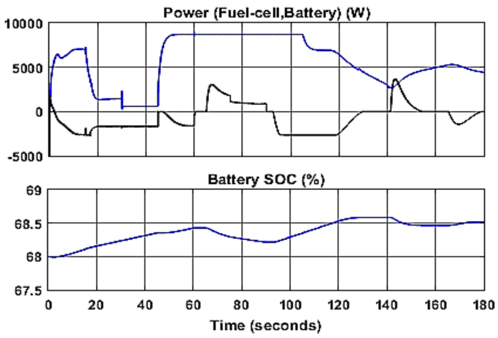
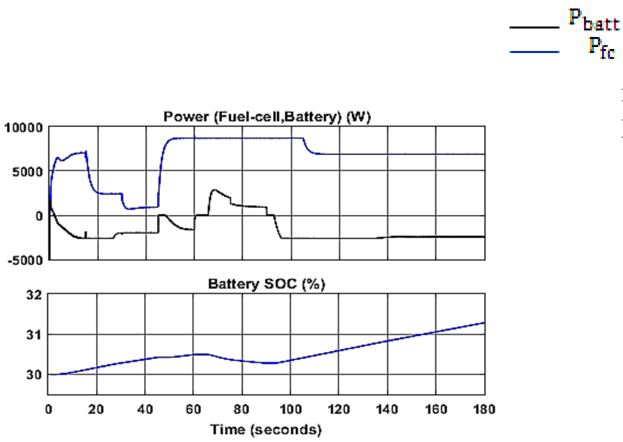
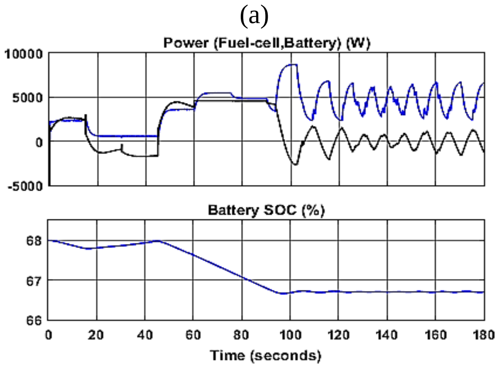


(c)

Fig. 11. PI-type Fuzzy logic control strategy performance for (a) SOC_{ref} =65% (b) SOC_{ref} =67%. (c) SOC_{ref} =68.5%



(a)



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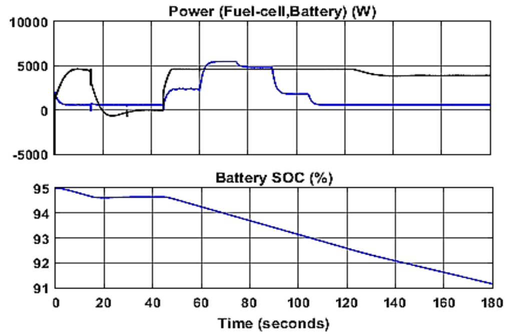


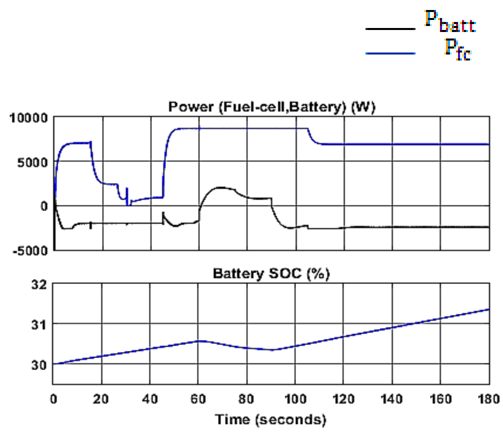
(c)

Fig. 12. Validation of the ECMS. (a) Initial SOC = 30%. (b) Initial SOC = 45%. (c) Initial SOC = 95%.

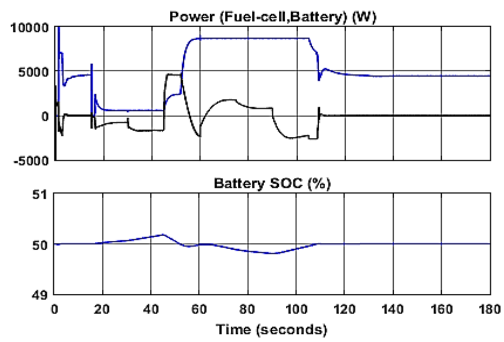
Therefore, the data required for the design of the ANFIS-based energy management strategy is gathered from the state machine control in order to integrate the state machine control approach, which is discussed in section 2.2, into the ANFIS-based energy management strategy. The Summary of the results, obtained by each energy management strategy, is shown in Table 6. Note that the most hydrogen consuming energy management strategy is the state machine control (174.95lit) and the least one is the EEMS (50.49 lit). It is obvious that the EEMS use more battery energy to meet the load demand shortage. (Compare the final SOCs, in the case of the EEMS and the state machine control strategy in Table6).

3.2. Random load and PV power

In this case, the energy management unit performance under a variable load for a residential home with the peak



(a)



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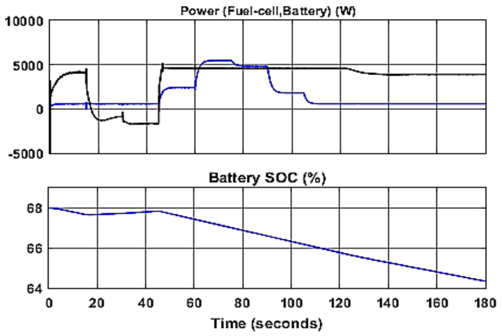

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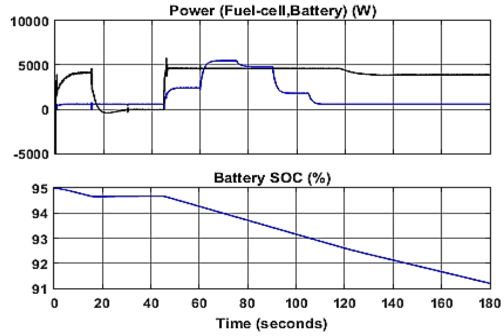

(d)

Fig. 13. Validation of the EEMS. (a) Initial SOC = 30%. (b) Initial SOC = 50%. (c) Initial SOC = 68%. (d) Initial SOC = 95%.

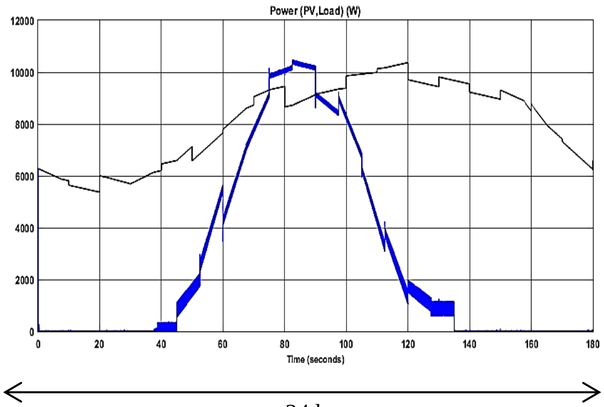

Fig. 14. Real Power (PV plant, Load) (W)

of 9500 W and a PV profile with the peak of 9500 W, which are ruled during 180 seconds of simulation as shown in Fig.14, is evaluated. Additionally, a random power of 1000 W is added to both of the load and PV power profiles The initial battery SOC is considered 68%. The overall behavior of the control strategies are similar to which is obtained in the case of pulsed loads. The state machine control, the rule based fuzzy logic control and the ANFIS based control strategy aim to maintain the battery SOC around the initial SOC. While the EEMS discharges the battery faster to reach the SOC_{min} , the ECMS works around the 0.5 $(SOC_{max}+SOC_{min})$” . Finally, the PI type fuzzy logic control strategy keeps the battery SOC at the reference command. Then, a summary of the results obtained from the random load and PV power is gathered in Table 7. In the case of random PV/load profiles, while the EEMS is still the least hydrogen consumption strategy, the rule-based fuzzy logic control strategy hydrogen consumption is higher than the state machine control. Furthermore, tables 6 and 7 shows that the most fuel (and fuel-cell) efficient strategy is the EEMS under pulsed and random loads. As seen in tables 6 and 7, the performance of the ANFIS-based control strategy is similar to the state machine control in both cases. Different energy management strategies fulfill different objectives. For instance, if the hydrogen minimization has higher priority to the battery life loss minimization, the EEMS can be employed to use the battery energy in the first place. If the battery life loss minimization has higher priority to the fuel consumption, the state machine control and the rule based fuzzy logic control strategy can be employed in the case of pulsed loads and random loads, respectively, to keep the battery energy reserved for subsequent use or charge the battery to

Table 6. Summary of the results obtained by Each Energy Management Strategy for Pulsed load and PV power

Initial SOC	68%				
Indicator / EMS	$P_{fc\ avreage}$	Fuel consumption (gr-lit)	Fuel-cell Efficiency (%)	Fuel Efficiency (joule/litre)	Final SOC (%)
Rule-based fuzzy logic	**4551.3**	**14.22-159.94**	**55.18**	**5122**	**67.54**
State Machine Control	**4936.6**	**15.55-174.95**	**54.7**	**5079.1**	**67.94**
PI-type Fuzzy Logic Control	**4149.3**	**12.97-145.92**	**54.7**	**4269.1**	**66.99**
ECMS	**3849.7**	**11.57-130.11**	**56.01**	**5325.9**	**66.7**
EEMS	**1585.1**	**4.49-50.49**	**59.4**	**5651.2**	**64.33**
ANFIS-based Control	**4891.1**	**15.44-173.66**	**54.77**	**5069.7**	**67.88**

Table 7. Summary of the results obtained by Each Energy Management Strategy for random load and PV power

Initial SOC	68%				
Indicator / EMS	$P_{fc\ avreage}$	Fuel consumption (gr-lit)	Fuel-cell Efficiency (%)	Fuel Efficiency (joule/litre)	Final SOC (%)
Rule-based fuzzy logic	**5531.4**	**17.99-202.33**	**54.03**	**4920.8**	**68.16**
State Machine Control	**5363**	**17.34-195.08**	**54.22**	**4948.5**	**68.02**
PI-type Fuzzy Logic Control	**4434**	**14.66-164.84**	**55.48**	**4841.8**	**66.88**
ECMS	**4149.3**	**13.4-150.71**	**55.72**	**4955.6**	**66.72**
EEMS	**1836**	**5.13-57.72**	**58.84**	**5726.4**	**64.33**
ANFIS-based Control	**5371.9**	**17.4-195.67**	**54.20**	**4941.6**	**68.02**

4. Summary

Remote (or rural) area electrification is one of the main concerns, especially in developing countries. This paper presents a detailed investigation of six energy control strategies (the state machine control strategy, the rule- based fuzzy logic control strategy, the ANFIS-based control strategy, the ECMS, the EEMS and the PI-type fuzzy logic control strategy) for a small-scale standalone microgrid, in a remote area. The proposed microgrid includes the solar (PV) panels, the fuel-cell stack, the batteries, the supercapasitors, the electrolyzer unit, the DC/DC, and DC/AC converters. An effective approach is used to design the state machine control strategy and the rule-based fuzzy logic control strategy. In this approach, the battery state of charge is divided into three regions: low, normal and high. If the battery starts with a low (initial) SOC, the fuel-cell will try to recharge it and provide the (load) power shortage, which is not met by the PV power generation. If the battery starts with a normal SOC, the fuel-cell cell will keep the battery SOC within the normal range and meet the energy demand shortage, and finally, if the battery starts with a high SOC, the storage bank will be discharged with a slow rate and the fuel-cell will supply the energy demand shortage, which is not satisfied by the PV system and the battery. The additional power, generated by the PV system, is used to recharge the battery bank and produce hydrogen. Aiming to design an efficient ANFIS-based control scheme, almost 9500 training, checking and testing data have been collected through the state machine control strategy implementation in different (initial) battery SOC cases with random PV and load power profiles. Two cost function based strategies are discussed. One of them is common in hybrid vehicles energy management systems (ECMS). The other one (EEMS) is proposed in [11] for a hybrid emergency power system.The results show that both of them have acceptable performance in microgrid application. Also, a different PI energy management strategy is used, to overcome some of the drawbacks of conventional PI controllers. All the strategies have been investigated considering different features, such as the battery SOC, design aspects, simplicity, economy, accuracy and so on. Additionally, the performances of all the strategies have been compared through simulation studies. Factors such as the stack efficiency, the hydrogen consumption, the fuel efficiency and the battery state of charge have been used for comparison. The simulation results showed that all the strategies are successful in keeping the DC bus voltage variations below 2%. Two scenarios (pulsed and random loads) have been considered to evaluate the performance of the energy management strategies for random PV and load profiles. Taking into account the fuel consumption, the EEMS is the least hydrogen consuming and the most fuel (and fuel-cell) efficient energy management strategy in both scenarios.

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NOMENCLATURE

PV	Photovoltaic
ECMS	Equivalent Consumption Minimization Strategy
EEMS	External Energy Maximization Strategy
SOC	(Battery) State of charge
SOC_{max}	Maximum State of charge (%)
SOC_{ref}	State of charge Reference (%)
SOC_{min}	Minimum State of charge (%)
V_{dc}	DC bus voltage (v)
$V_{dc\ ref}$	DC bus reference voltage (V)
V_{dcmin}	Minimum DC bus voltage (V)
V_{dcmax}	Maximum DC bus voltage (V)
$V_{dc,L}$	voltage at the low side of the battery converter (V)
ANFIS	Adaptive-Neuro Fuzzy Inference System
P_{load}	Load power (W)
PI	Proportional–Integral controller
$P_{fc_{ref}}$	Fuel-cell reference power(W)
P_{fc}	Fuel-cell power(W)
P_{fcmin}	Minimum fuel-cell power (W)
P_{fcmax}	Maximum fuel-cell power (W)
P_{fcopt}	Fuel-cell optimum power (W)
$V_{battnominal}$	Nominal battery voltage (V)
$P_{discharg\ max}$	Maximum battery discharge power (W)
$P_{optcharg}$	Battery charge power (W)
$P_{charg\ max}$	Maximum battery charge power (W)
$P_{battopt}$	Battery optimum power (W)
$P_{battref}$	Battery reference power (W)
$P_{optdischarg}$	Battery discharge power (W)
P_{batt}	Battery power (W)
P_{PV}	PV plant power (W)
$P_{fcavrege}$	Fuel-cell average power (W)

Appendix

Table8. Hybrid renewable system specification

PV System		Supercapacitors Pack	
PV cell open-circuit voltage (V)	21.3	Number of series supercapacitors	128
PV cell Short-circuit current (A)	3.11	Number of parallel supercapacitors	1
Number of solar cells in series	20	Total capacitance (F)	23.5
Number of solar cells in parallel	3	Nominal Voltage (V)	225
Fuel-cell Stack		**Battery system**	
Number of cells	65	Nominal Voltage (V	60
Nominal stack efficiency (%)	55	Rated Capacity (Ah)	40
Nominal Air flow rate (lpm)	300	Initial State-Of-Charge	65
Nominal supply pressure [Fuel (bar), Air (bar)]	[1.5, 1]	Battery buck converter [Inductance (H), Capacitance (mF), Efficiency (%), output voltage (v)]	[0.01, 800, 88, 67]
Fuel-cell boost converter [Inductance (H), Capacitance (mF), Efficiency (%), output voltage (V)]	[0.01, 800, 93, 220]	Battery boost converter [Inductance (H), Capacitance (mF), Efficiency (%), output voltage (v)]	[0.01, 800, 88, 220]
Nominal composition (%) [H2 O2 H2O (Air)]	[99.95, 21, 1]	Nominal Voltage (V)	60