Optimization of a Fuzzy Based Energy Management Strategy for a PV/WT/FC Hybrid Renewable System

Yousef Allahvirdizadeh *, Mustafa Mohamadian **‡, Mahmoud-Reza HaghiFam***, Amir Hamidi****

*Department of Electrical Engineering, Tarbiat Modares University, Jalal Ale Ahmad Highway, Tehran, Iran

**Department of Electrical Engineering, Tarbiat Modares University, Jalal Ale Ahmad Highway, Tehran, Iran

*** Department of Electrical Engineering, Tarbiat Modares University, Jalal Ale Ahmad Highway, Tehran, Iran

**** Electrical Engineering Department, Urmia University, P.O. Box: 5756151818, Urmia, Iran

(y.allahverdyzadeh@modares.ac.ir, mohamadian@modares.ac.ir, haghifam@modares.ac.ir, amir.hamidi.m@gmail.com)

‡ Corresponding Author; Mustafa Mohamadian, mohamadian@modares.ac.ir,
Tel.: 00982182884344.

Received: 25.03.2017 Accepted:26.04.2017

Abstract: Solar and wind energy as free and eco-friendly sources of energy have been considered a promising choice for remote (or rural) area electrification. While a fuel-cell system makes a clean backup available, incorporating both energy type and power type storage technologies, such as batteries, hydrogen-based storage systems, and supercapacitors, extends the energy sources/storage units useful lifespan and decreases the operation cost of the system. An energy control system is required to provide the load with reliable, continuous, high quality and economical energy. Considering PV/WT production uncertainty, load power variations and measurement imprecision, energy management system based on fuzzy logic technique serves an effective method to meet the design objectives, such as energy efficiency maximization, reliable and continuous energy supply, DC bus voltage stabilization etc. Aiming to optimize preferred aspects of the fuzzy controller, it should be combined with evolutionary algorithms, such as genetic. Therefore, this paper deals with the rule-based fuzzy logic energy control of an off-grid PV/WT/FC/UC hybrid renewable system. Applying the genetic algorithm, the ECMS and the EEMS) are utilized to tune off-line the fuzzy logic control, in order to the fuel consumption optimization. To reduce computation time during the optimization process, the fuzzy rule set remains fixed. Employing a simulation model of the hybrid renewable system, multiple criteria such as the fuel efficiency, the fuel-cell stack efficiency, and the fuel consumption are taken into account to evaluate the energy management strategy's performance. Simulation results show that The fuzzy-ECMS and the fuzzy-EEMS keeps the battery SOC around the “0.5 ($\mathrm{SOC_{max}}$+ $\mathrm{SOC_{min}}$)” and the $\mathrm{SOC_{min}}$, respectively. As a result, better fuel economy and higher battery lifetime can be achieved via the fuzzy-EEMS and the fuzzy-ECMS, respectively.

Keywords: ECMS, Genetic algorithm, Optimization, EEMS, Fuel-cells, PV/WT system, energy management

1. Introduction

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 [1, 2]. To tackle the aforementioned challenge, one practical and cost effective solution to rural electrification is distributed generation [3, 4]. Renewable generation provides more efficient and cost effective energy than their centralized fossil-fuel based counterparts, since they can be installed near the load centers and do not require new transmission lines, which causes losses in the power system. [1, 3, 5]. Thus, to overcome energy production drawbacks using fossil fuels, which are expensive, environmentally hazardous and exhaustible, hybrid renewable energy systems have drawn increasing attention, as they are free, environmentally friendly, and available [6,7, 8]. Taking into account random and intermittent behavior of PV/WT systems, coordination of them with support sources, such as fuel- cells and storage units are necessary to satisfy the load requirements [3, 9, 10]. Fuel-cells play a backup role to meet the demanded energy when it is not supplied by the PV/WT system [11]. Moreover, batteries, supercapacitors and electrolyzers (along with hydrogen tanks) are hybridized to store the PV/WT surplus generation and provide the load demand when there is not enough power or the load is at its peak level [1,10-12]. Electrolyzers are used for long term storage due to limited capacity of batteries [13]. Frequency and charge/discharge rates, depth of discharge (DOD), and varying operating temperature affect the batteries lifespan and performance [14, 15]. Therefore, it is a common practice to include supercapacitors as high power storage units in off-grid hybrid systems [14]. Supercapasitors usually are applied to shave the demanded power peaks, protect the support system/storage units from overloading and avoid oversizing the battery bank or the backup system to meet the energy demand [16, 17,18]. Employing a smart energy control unit with the motivations of the fuel consumption minimization, the hybrid system efficiency maximization, control and protection, reducing the operation and maintenance costs, and extending useful energy sources/storage banks lifespan is necessary in hybrid power systems [1,18, 19]. Various algorithms are available for energy management strategies, such as centralized and decentralized classes. Energy control strategies can also be divided into two groups:

a) Online Energy Management Strategies: This group is based on real-time information of the hybrid renewable system, such as the renewable energy sources power, the battery power, the battery/supercapacitors state of charge, and etc.

b) Off-line Energy Management Strategies: This group is practical if the future information of the hybrid renewable system, such as the load profile, is available in advance. Then optimization techniques such as the genetic algorithm or particle swarm optimization can be employed to optimize the operation of the hybrid renewable system [20]. Batteries usually require high initial investment and short lifetime [21]. As a result, the battery lifespan in renewable energy systems studies has attracted researchers' attention [21]. Reviewing the literature, in long term analysis, with a time scale of hour, the fuel consumption minimization of a hybrid renewable system, consisting PV panels, wind turbines, gas engine and combined heat and power (CHP) is discussed in [22]. Energy management of a PV/diesel hybrid system, considering the battery life time, was studied in [15], in which a combination of a diesel generator and a battery bank is considered as a support system. Two objectives, including minimization of the fuel consumption of the diesel generator and increasing the battery bank lifespan were taken into account. The operation optimization of a PV/WT/Diesel stand-alone microgrid, employing NSGA-II algorithm, was proposed in [21]. Giving the same weight to the objectives of minimizing the electricity cost and battery lifespan, the performance of the proposed method was studied in two cases of shortage and abundance of the PV/WT power production. Nowadays hydrogen based support system replaces the diesel backup system [23, 24], because of low maintenance requirements, long lifespan, fuel availability and flexibility, and low-pollutant energy production [25]. As it is known, when it comes to the optimization of the Diesel generator based hybrid systems, factors such as the pollutant emissions/maintenance costs minimizations and fuel consumption optimizations are used to optimize the control strategy. In the case of the fuel-cell, fuel consumption optimization has higher significance. As a result, the fuel-consumption is selected as the main factor for optimization. In short term analysis, the adaptive control of a fuel-cell/ battery was presented in [26]. The control strategy was employed to regulate the fuel-cell reference current, considering the battery SOC. Among intelligent control strategies, the rule-based fuzzy logic control strategy has been presented by the authors in [27, 28]. The authors usually define the fuzzy rules such that the battery SOC is kept at a reasonable level, to increase battery useful lifespan. Increasing nonlinearity, uncertainty and complexity of smart power systems, necessitate designing a fuzzy logic based controller. This scheme requires only an approximate modeling of the hybrid system and is not sensitive to the inaccuracies of (the hybrid system parameters) measurement [29]. Additionally, it provides more efficiency and robustness and moreover a faster response than conventional state machine based controllers [30, 31]. But appreciating the merits of this scheme, it is dependent on the expert prior experience and knowledge about the system [31]. Therefore, it is not an optimal strategy and has weaker performance in comparison to local and global optimization algorithms [32]. To tackle this drawback, off-line optimization using evolutionary algorithms such as genetic leads to a more economical energy dispatch. Focusing on energy efficiency maximization, DC bus voltage stabilization, reliable and continuous energy supply and fuel consumption minimization, this paper presents the rule based fuzzy logic energy control strategy for a standalone microgrid comprising solar panels, wind turbines, PEMFCs, supercapasitors, batteries, an electrolyzer package and power electronic converters. The structure of the above discussed standalone microgrid is shown in Fig. 1. The main contribution of this paper is dealing with the optimization of the fuzzy logic energy control strategy with two different cost function, in order to minimize total fuel consumption of the microgrid. The ECMS is a well-known optimization concept that is popular in hybrid vehicle studies. PV/WT renewable resources are cost free. Then, this scheme aims to assign a reference power to the fuel-cell in a way that total fuel consumption of the support system and the energy storage units are minimized [31]. In other words, this strategy provides an economical demand shortage dispatch between the fuel-cell stack and the battery/supercapacitor bank. Due to the dependency of the ECMS on the load profile, the authors in [33] introduced the external energy maximization strategy for energy management of a more electric aircraft. In this scheme maximizing the energy of the storage banks, results in the total fuel consumption minimization. Investigating [15, 21], it can be concluded that higher battery SOCs results in longer battery lifespan. Thus, the fuzzy rule set is determined such that it avoids employing the battery bank at low SOCs. In addition, charging the battery bank over the SOC_{max}, which causes charge loss increase is eluded. Then, considering the rule set is known, the ECMS and the EEMS are utilized to tune the membership functions of the rule-based fuzzy logic control strategy off-line. In the following, the rule-based fuzzy logic control along with the off-line optimized rule-based fuzzy logic control strategy is implemented for the proposed PV/WT/FC/UC hybrid power system for residential application. Subsequently, their performances are compared, considering indicators such as the hydrogen consumption, the fuel efficiency, and the fuel-cell efficiency. The performance assessment of the energy management strategies is presented for two scenarios. In the short term analysis, the PV/WT production and the load power have step changes, while in the long term case; the PV/WT and load demand have random behavior. The hybrid renewable system components specification is presented in appendix.

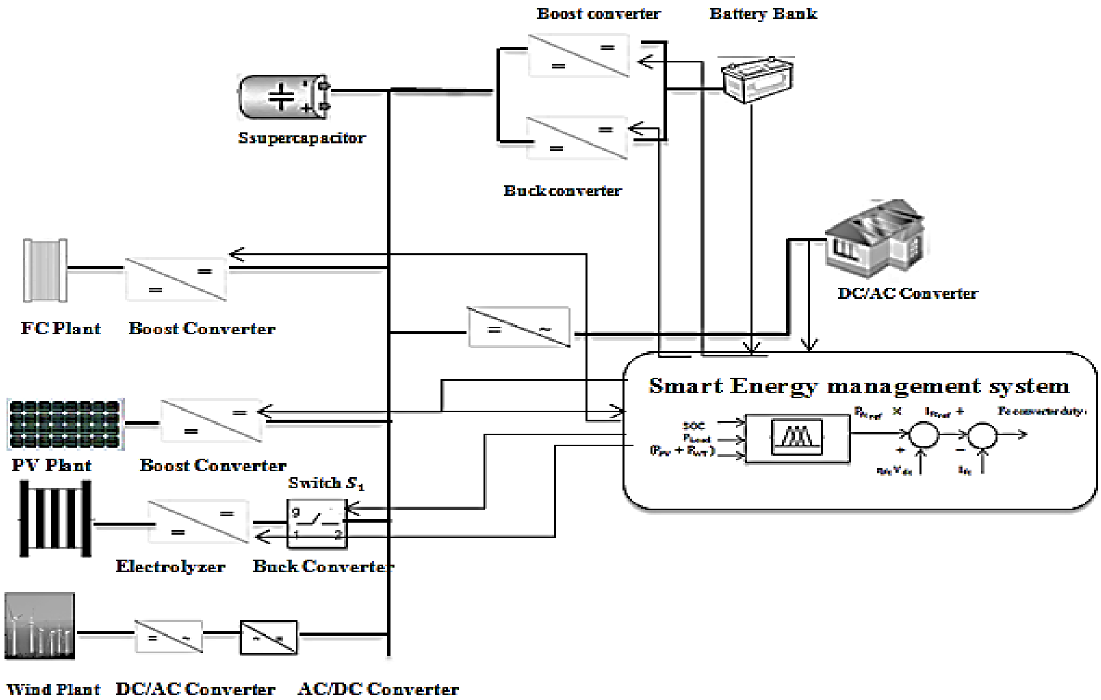


Fig. 1. Structure of the PV/FC/SC Standalone Microgrid.

2. Energy Management Strategies

2.1. Rule- Based Fuzzy Logic Energy Control System

When it comes to complexity, nonlinearity or uncertainty, intelligent energy management strategies, such as fuzzy logic control, attract more attention [34] Random and uncertain behaviors of the renewable energy sources leads toward the rule based fuzzy logic control strategy [35]. In this paper, the Mamdani type rule based energy control strategy with three inputs and one output is considered. Moreover, centroid method is employed for defuzzification. Fig. 2 shows the rule-based fuzzy logic control strategy. The energy controller aims to provide the energy shortage, which is not supplied by the renewable energy sources, from the battery bank and the fuel-cell in order to improve the fuel economy, which subsequently avoids the storage units/energy sources from oversizing. While the renewable energy sources contributions, the load power along with the battery SOC are the controller inputs, the fuzzy decision maker determines the fuel-cell power as the output. The supercapacitor pack supplies the load power in transient time intervals. In other words, the battery power equals the load power that is not supplied with the PV/WT and the fuel-cell, at the steady state. The distribution of the load power shortage between the support system and storage units based on the designated membership functions and the rule set affects the hybrid renewable system efficiency, the fuel consumption, the fuel efficiency, the stress on the hybrid renewable system components and other design requirements. The fuzzy rules and membership functions are derived based on the author's knowledge and the hybrid renewable system components limitations [31]. As mentioned before, the battery lifespan degrades when it operates at low SOCs. In addition, charge losses increases at high SOCs [15, 16]. Then, following the manufacturer recommended minimum and maximum battery SOCs, the battery bank SOC is divided into three SOC areas, namely: low (SOC<60%), medium (60% < SOC< 90%), and high (SOC>90%). Hence the rule sets are defined such that the battery bank is charged entering the low area and is discharged with almost 50 percent of its capacity at high SOCs. Aiming to maintain the battery bank at the medium SOC area, the battery either works with a discharge rate much lower than high SOCs area or it does not provide load power, in the medium SOC area. Therefore, the battery bank is recharged with the fuel-cell at low SOCs and with the renewable energy excess power at low and medium SOCs. The electrolyzer turns on at high SOCs to absorb the renewable energy surplus energy, in other words, hydrogen production is prior to charging the battery bank at high SOCs. For low and medium battery SOCs, any excess renewable energy power more than the battery charging power (50% of the battery capacity) is directed to the electrolyzer. Then, the command signal of the electrolyzer switch is controlled as shown in Fig. 3. Table 1 shows the fuzzy rule set. The membership functions of the PV/WT/FC/Load power, the battery SOC are depicted in Fig.4.

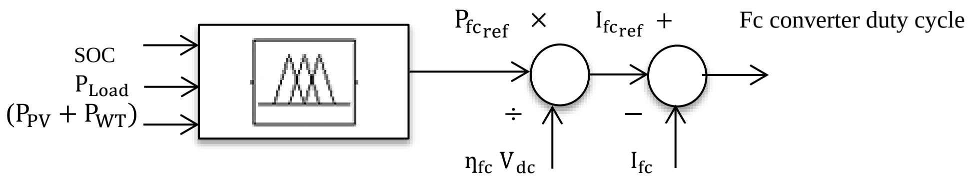


Fig. 2. Rule-based fuzzy logic control strategy.

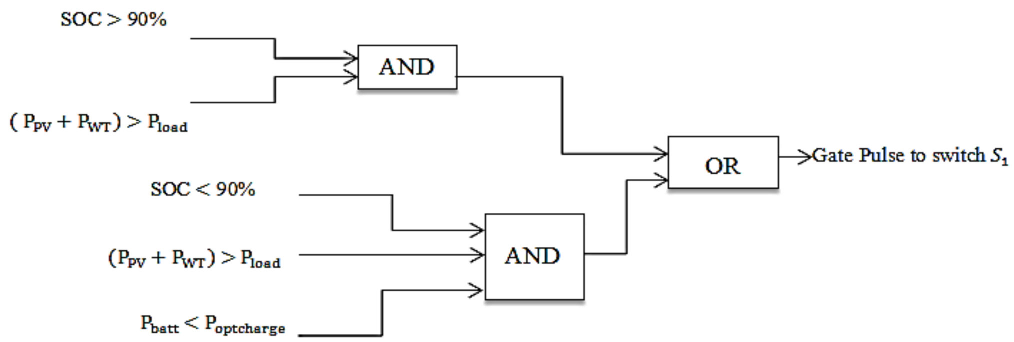


Fig. 3. Electrolyzer switch controller.

2.2. Optimization of the Rule Based Fuzzy Logic Energy Management Strategy

As discussed before, the empirical nature of the fuzzy logic energy control strategy has an important role in the performance of the rule based fuzzy logic energy management unit [36, 37]. In other words, design objectives such as the fuel consumption/pollutant emissions minimization, the battery lifetime/ the hybrid system efficiency maximization are affected by the membership functions parameters and the rule set description. Then, designing a system that combines the rule-based fuzzy scheme with one of the evolutionary algorithms, such as genetic algorithm, to tune the performance of the fuzzy system, seems reasonable [34, 38]. Fig. 5(a) shows the flowchart of such an approach that is called genetic fuzzy system [38]. The genetic fuzzy system provides the user with global search capability of the genetic algorithm along with the robust and flexible modeling of the fuzzy logic that is beneficiary for uncertainty or measurement imperfections [39]. The first step in designing a genetic fuzzy system is to choose the part of the system that is going to be tuned with the genetic algorithm [40]. Three different conditions are possible [38, 40] as follows:

- **Definition of the Data Base based on the Genetic Algorithm:** Optimization of the membership functions while the fuzzy rules are designed based on the prior knowledge and experience of the expert.
- **Derivation of the Rule Base based on the Genetic Algorithm:** Optimization of the fuzzy rule base while the membership functions are designed based on the prior knowledge and past experience of the expert.
- **Derivation of the Rule Base and definition of the Data Base based on the Genetic Algorithm**: optimization of the membership functions and the fuzzy rule base simultaneously.

The fuzzy rule set is determined based on the approach which is discussed in the previous section to provide the battery bank with a reasonable SOC. The second step is to prepare this part in the form of a chromosome, to be optimized by the genetic algorithm [41]. As mentioned earlier, this paper deals with the genetic definition of the database**,** hence the membership function parameters must be coded into a chromosome, as shown in Fig. 6. To make the length of the chromosome shorter, some of the parameters, such as the boundary parameters are assumed fixed, which are determined based on the prior knowledge of the designer and the hybrid system components limitations. As observed in Fig. 7, three trapezoidal Membership Functions (MFs) are assigned to the battery SOC, four trapezoidal MFs are designated to the PV/WT and the Load power, and finally five trapezoidal MFs fuzzify the fuel-cell power. Hence the first two parameters of all the VL functions in the case of the PV/WT and the Load power MFs, the last parameter of all the H functions, the first two parameters of L function in the case of the battery SOC MFs, and the first two parameters of all the VVL functions in the case of the

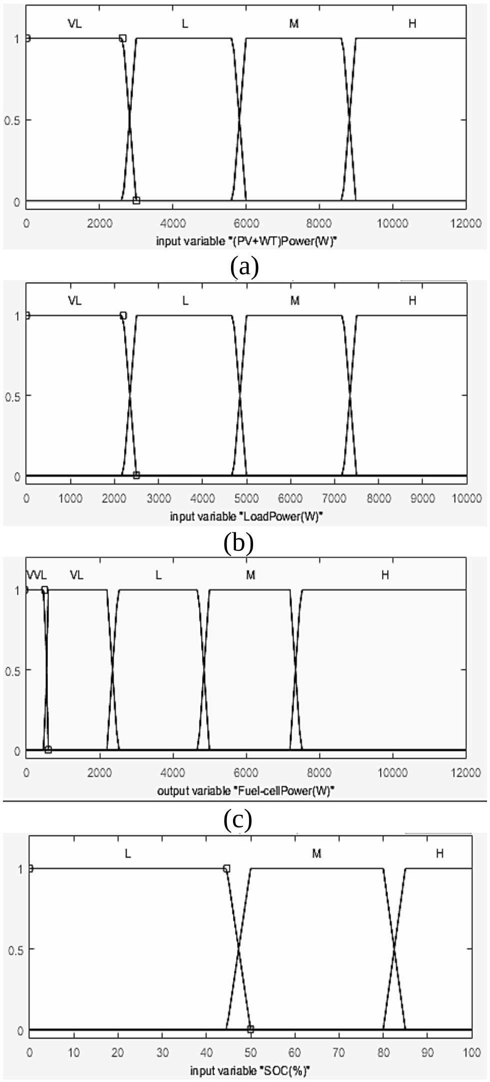


Fig. 4. Membership functions of Sugeno type fuzzy logic control. (a) PV/WT power. (b) Load power. (c) Fuel-cell power. Battery SOC

fuel-cell power MFs are considered constant, so that are not coded into the chromosome. Consequently, considering 9 variables for the battery SOC, 13 variables for the PV/Load power, and 17 variables for the fuel-cell power, a chromosome with 52 genes represents the genetic fuzzy system. Besides, the battery SOC and the fuel-cell variables are limited to the ranges of [0,100] and [0, 12544], respectively. Additionally, in order to achieve a trapezoidal geometric shape and to cover all operating states that the system may go through, some constraints are taken into consideration. The aforesaid constraints for the MFs parameters of the SOC, the PV/WT power, the demanded power, and the fuel-cell power are as follows:

1) x (i) < x (i+1) ; i=1:9

2) y (i) < y (i+1) ; i=1:13

3) z (i) < z (i+1) ; i=1:13

4) o (i) < o (i+1) ; i=1:17

Table 1. The fuzzy rule set

SOC	P_{pv} \ P_{load}	$P_{fc_{ref}}$			
L	VL	L	M	H	H
	L	VL	L	M	H
	M	VVL	VL	L	M
	H	VVL	VVL	VL	L
M	VL	VL	L	M	H
	L	VVL	VL	L	M
	M	VVL	VVL	VL	M
	H	VVL	VVL	VVL	VL
H	VL	VVL	VL	L	M
	L	VVL	VVL	VL	L
	M	VVL	VVL	VVL	VL
	H	VVL	VVL	VVL	VVL

Where x (i) ; i=1:9, y (i) ; i=1:13, z (i) ; i=1:13, and o (i) ; i=1:17 represent the battery SOC variables, the load power variables, the PV/WT power variables, and the fuel-cell power variables, respectively. Fig. 8 presents the variables. Fig. 5(b) shows the genetic fuzzy algorithm. It is seen that an initial group of individuals is selected and crossover and mutation operators are applied to adapt them to the specified indicator, which is called the fitness function [38, 40]. Moreover, two point crossover approach is selected, in this study. Receiving the PV/WT and the load power as the inputs and considering the tuned MFs parameters in each round, the fuzzy logic controller calculates the fitness function and then the optimization creations are checked. If the optimization creations are met, then the optimization process is completed. In this study, the stop criterion is the minimum number of 30 iterations. Fig. 8 shows the optimal rule based fuzzy logic energy management strategy. It is seen that the fuel-cell reference current is calculated considering fuzzy controller output, the fuel-cell voltage and efficiency.

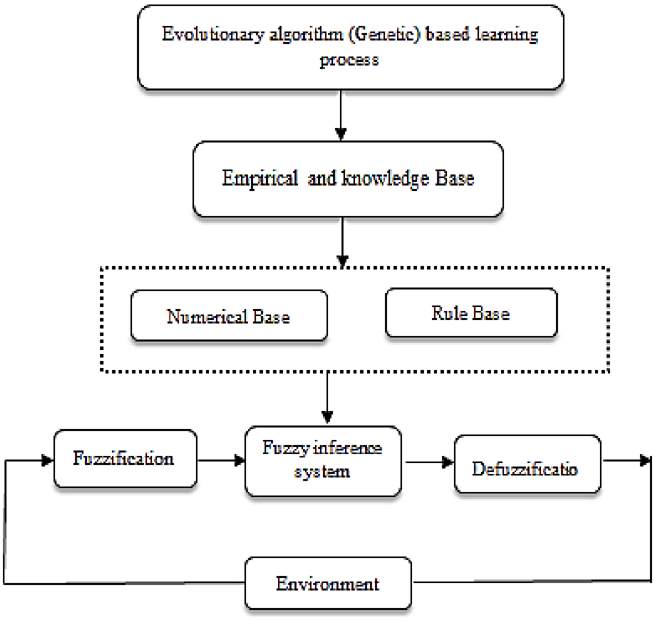
2.3. Fitness Function

Two cost function optimization strategies that are used to optimize the membership functions are as below:

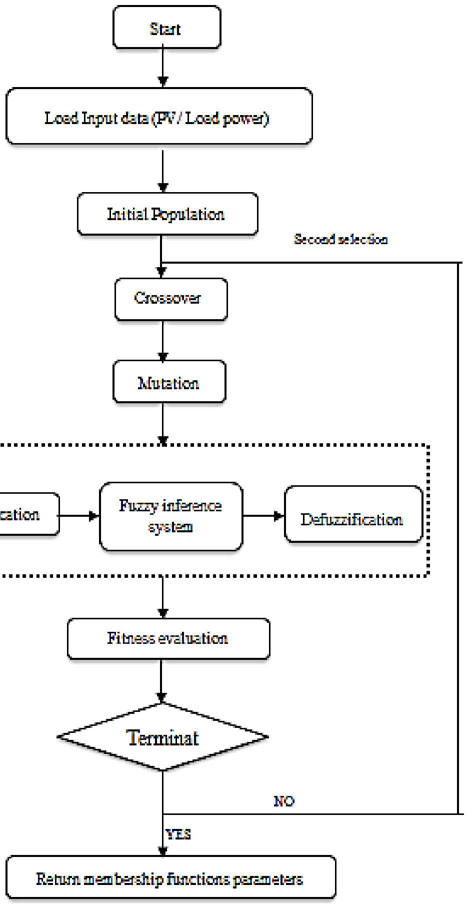
2.3.1. ECMS

PV/WT plant production is free of cost. The extra energy demand above the PV/WT production must be assigned to the backup system and the storage banks such that the total fuel consumption is minimized. The supercapacitors provide sudden increase or decrease in the load power. Thus, their contribution can be neglected [41]. Additionally, the battery equivalent fuel-consumption can be calculated using an equivalent factor (α) that is dependent on the battery SOC [31]. Since the fuel-cell hydrogen consumption and the battery equivalent fuel consumption are related to the fuel-cell power and the battery power, respectively, so that the fuel consumption related cost function (C_1) can be written as [42]:

$$C_1 = (P_{fc} + \alpha . P_{BAT}) . \Delta T \quad (1)$$



(a)



(b)

Fig. 5. (a) Genetic fuzzy system [33]. (b) Genetic fuzzy algorithm.

2.3.1.1 Constraints

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

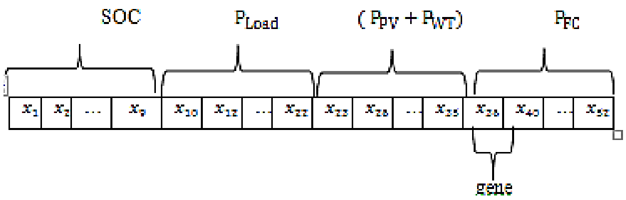
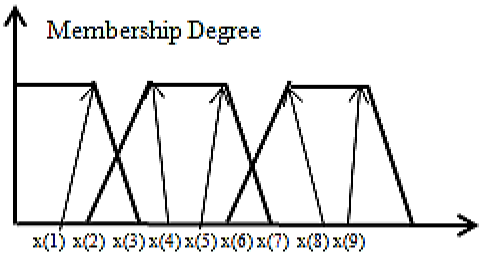
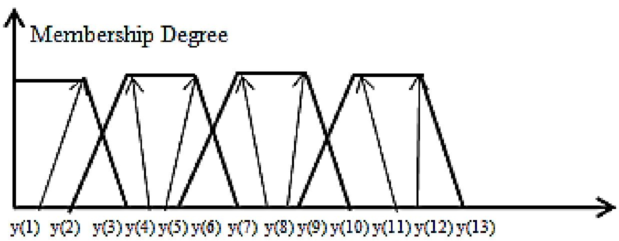


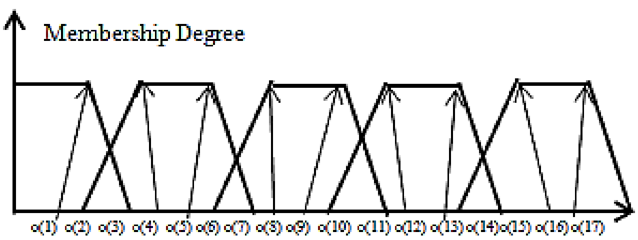
Fig. 6. Chromosome Identification.



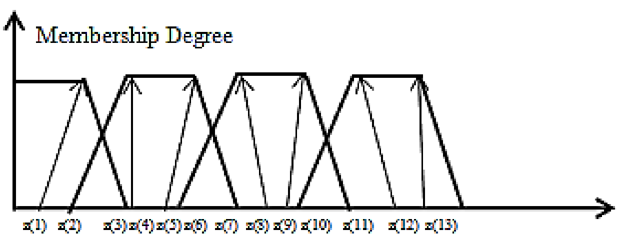
(a)



(b)



(c)



(d)

Fig. 7. MFs parameters. (a) Battery SOC. (b) PV/WT power. (c) Fuel-cell power. (d) Load power

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

The equivalent factor α can be defined as [21, 28]:

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

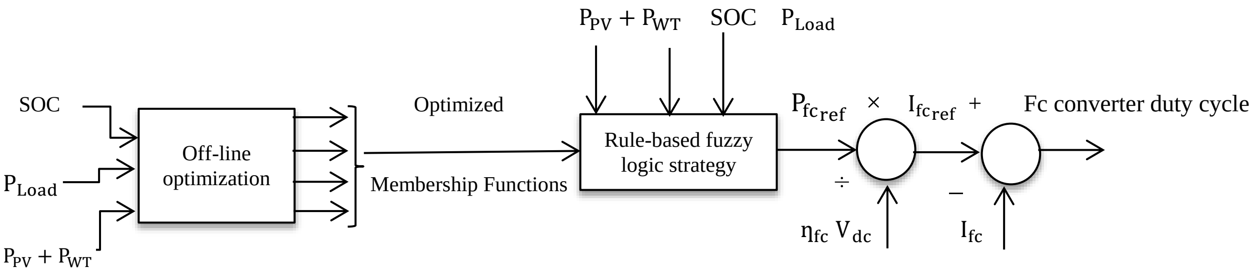


Fig. 8. Optimized Rule-based fuzzy logic Control Strategy.

Where μ is a constant that is called battery SOC coefficient, and assigned 0.6 to control the battery SOC, ΔT is the sampling time in which the optimization process is renewed. The boundary limits to the ECMS are as follows:

$$P_{fcmin} < P_{fc} < P_{fcmax} \tag{4}$$
$$P_{charg\,max} < P_{batt} < P_{discharg\,max} \tag{5}$$
$$SOC_{min} < SOC < SOC_{max} \tag{6}$$
$$0 < \alpha < 2 \tag{7}$$

2.3.2. EEMS

By definition, the equivalent fuel consumption of the storage banks is the fuel amount that is utilized to keep the storage banks SOC within the desired limits, over the load profile. Thus, the ECMS is sensitive to the load profile. To improve the robustness, authors either found new ways to express the equivalent factors [43] or introduced new cost function optimization strategies [33]. The external energy maximization strategy has been presented by the authors in [33] to maximize the energy of the storage banks which subsequently reduces the fuel consumption. The EEMS can be formulated as:

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

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

The boundary conditions to the EEMS are as follows:

$$P_{charg\,max} < P_{batt} < P_{discharg\,max} \tag{9}$$

$$V_{dcmin} < V_{dc} < V_{dcmax} \tag{10}$$

The inequality constraint is:

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

Where Q is the battery bank nominal capacity. The supercapacitor charge/discharge voltage (ΔV) will be added to the DC bus voltage reference to force the supercapasitors to charge or discharge [33]. Table 2 shows a summary of the design requirements.

4. Simulation Results

4.1. Load

A generic model is used to model the equivalent load as applied in [31], in which a controlled current source is employed. The demanded power is divided by the DC bus voltage to feed the current source. Moreover, in order to consider the random dynamic of the residential load, a random power is added to the load power, as shown in Fig. 9 (a). Subsequently, the dynamic response of the hybrid renewable system toward pulsed loads is considered as shown in Fig.9 (b).

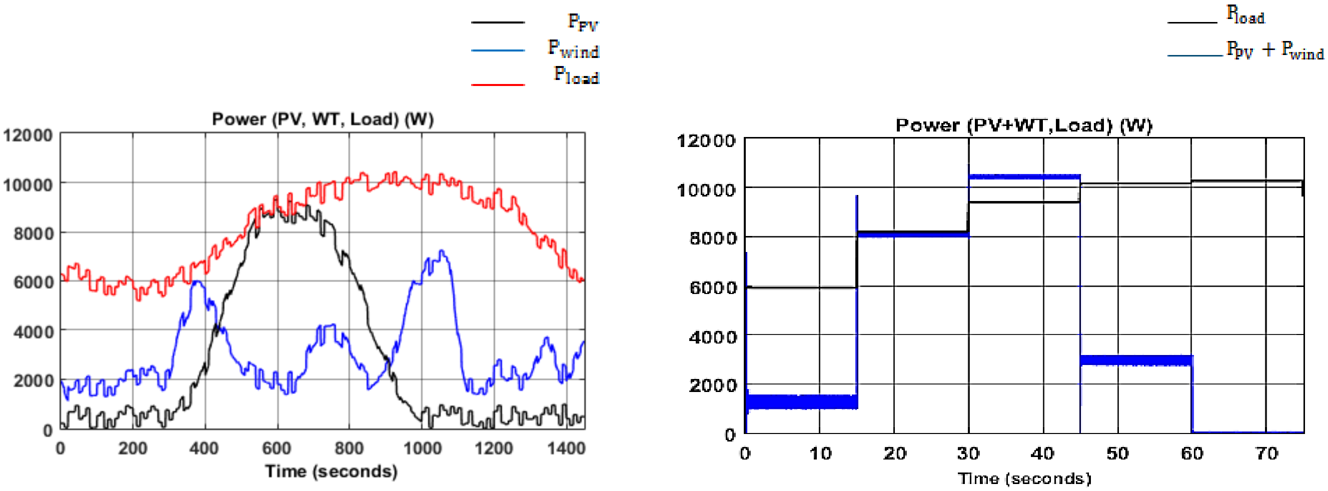
4.1.1. Long term Analysis

Figs. 10 and 11 show the membership functions of the battery SOC, the load power and the PV/WT system contribution, in the case of the fuzzy-ECMS[1] and fuzzy-EEMS[2], respectively. Two scenarios are taken into account to evaluate the energy management unit performance under different operating conditions. In the first scenario, a variable load for a residential home with the peak of 10 KW and a PV/WT profile with the peak of 11 KW is taken into account, as shown in Fig. 9 (a). Additionally, a random power of 1000 W and 2000 W is added to the load demand and PV/WT power profiles, respectively. The implementation of the fuzzy logic energy control strategy and the optimized fuzzy logic energy control strategy (fuzzy-ECMS, fuzzy-EEMS) for the initial battery SOCs of 30% and 100% is shown in Figs. 12-14. The PV/WT system power generation has priority in meeting the energy demand, so that only the extra energy demand ($P_{load} - (P_{PV} + P_{WT})$ is supplied with the fuel-cell/battery system. The rule based fuzzy logic control strategy keeps the battery SOC in the medium range. Therefore, the fuel-cell takes the responsibility of supplying the load demand, since the battery SOC is within the normal range and the fuzzy rules necessitate keeping the battery SOC around the initial value. Considering the equation (2), it can be concluded that the ECMS aims to employ the battery bank around "0.5 ($SOC_{max}+$

[1] The rule based fuzzy logic control that is optimized with the ECMS.

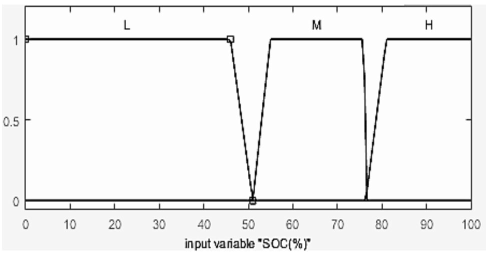
[2] The rule based fuzzy logic control that is optimized with the EEMS.

SOC_{min})”. Moreover, the equation (8) demonstrates that the EEMS tend to keep the battery SOC around the SOC_{min}. Hence the fuzzy- ECMS and the fuzzy-EEMS show a similar performance, as seen in Figs. 12(a)- 14(a), maintaining the battery bank SOC around “0.5 (SOC_{max}+ SOC_{min})” and the SOC_{min}, respectively. Thus, it is obvious that the fuzzy-ECMS uses more fuel than the fuzzy-EEMS. Therefore, the fuzzy logic control strategy, the fuzzy–ECMS, and the fuzzy-EEMS aim to charge/discharge the battery bank, to protect the battery bank against deep discharge/ overcharge, when the battery starts to work with a low and high initial SOC, respectively, as seen in Figs. 12(b) and 14(b). As the load power /Renewable sources production decreases/ increases, the fuel-cell output power is decreased, as expected.

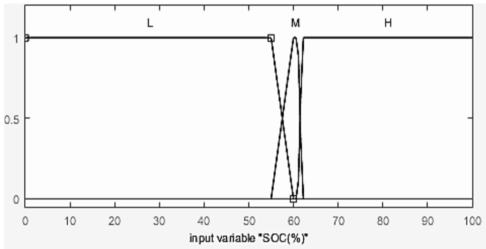


(a) (b)

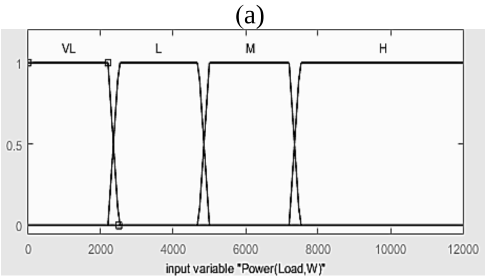
Fig. 9. Power (PV/WT, Load) (W). (a) Random Load. (b) Pulsed Load.



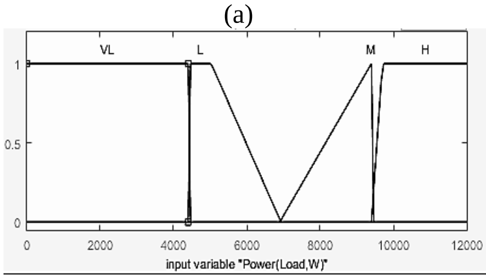
(a)



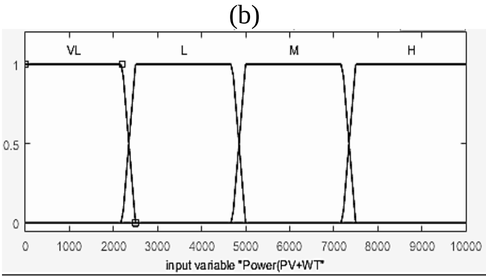
(a)



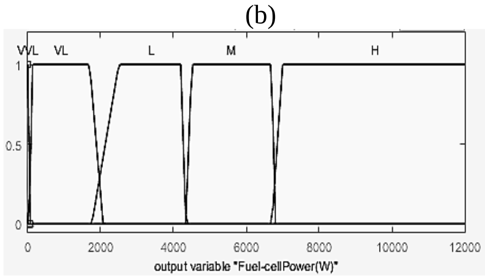
(b)



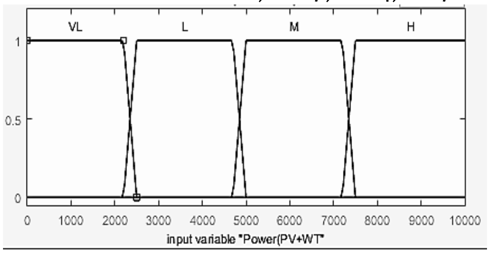
(b)



(c)

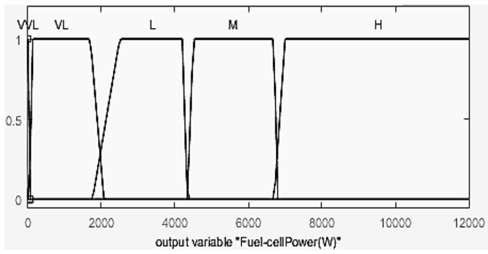


(c)



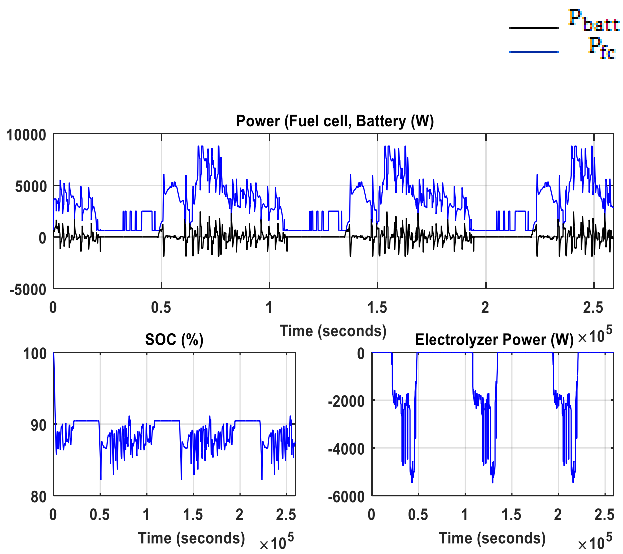
(d)

Fig.10 Membership functions of fuzzy-ECMS. (a) Battery state of charge. (b) Load power. (c) PV/WT power (W). (d) Fuel-cell Power.

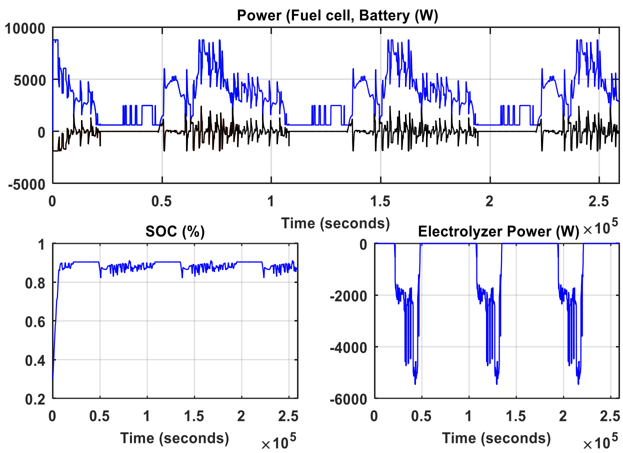


(d)

Fig.11. Membership functions of fuzzy-EEMS. (a) Battery state of charge. (b) Load power. (c) PV/WT power (W). (d) Fuel-cell Power.

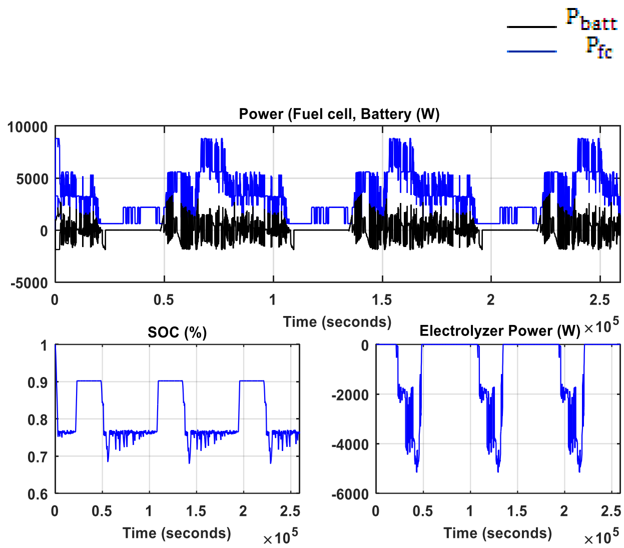


(a)

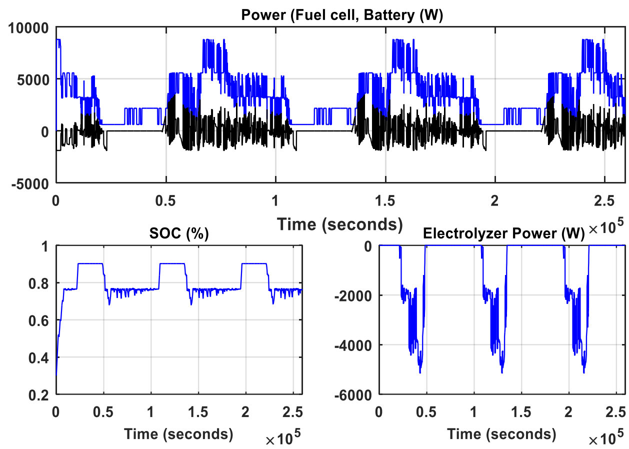


(b)

Fig. 12. Long term analysis of the rule based fuzzy logic control strategy (Fuel-cell / battery power, battery SOC). (a) SOC_{ini}=100%. (b) SOC_{ini}=30%.



(a)



(b)

Fig. 13. Long term analysis of fuzzy-ECMS (Fuel-cell / battery power, battery SOC). (a) SOC_{ini}=100%. (b) SOC_{ini}=30%.

Additionally, the excess PV/WT power is used to recharge the battery bank up to the SOC_{max}, as seen in Fig. 12(a)-14(a), for the time interval between 5:30h to7h. In the following any remaining renewable energy is absorbed by the electrolyzer to produce hydrogen, when the battery bank reaches the SOC_{max} (90%). Hydrogen production using PV/WT surplus power guarantees the fuel-cell desired operation during 24 hours. Reduction of PV/WT contribution during the night, leads to increase in the fuel-cell power or the battery bank SOC decrease as seen in Fig. 12(a)-13(a). Additionally, the battery power, the fuel-cell power, and the electrolyzer power are depicted in Figs. 12-14. Table 3 shows a summary of the results that are achieved by each strategy for one day operation. Indicators for comparison are as follows: Hydrogen consumption, Fuel efficiency, and Fuel-cell efficiency that can be formulated as: [31, 44].

$$\text{Hydrogen consumption} = \left(\frac{N_{fc}}{F}\right) . \int_0^{t_{cycle}} i_{fc} dt \quad (12)$$

$$\text{Fuel efficiency} = \frac{\int_0^{t_{cycle}} P_{fc} dt}{\text{Hydrogen Consumption}} \quad (13)$$

$$\text{Fuel-cell efficiency} = \frac{V_{fc}}{1.48.\ N_{fc}} . (\text{HHV.} (\%)) \quad (14)$$

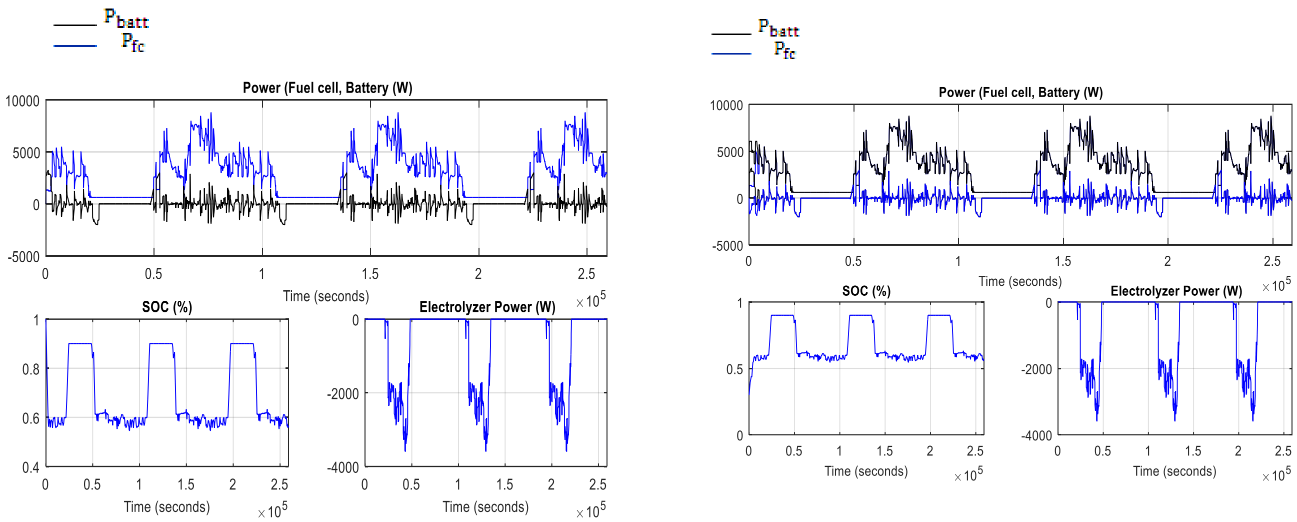
Where t_{cycle} is the simulation time, and HHV (%) is the hydrogen higher heating value. The fuel efficiency is de fined as the ratio between the fuel-cell output power and the fuel consumption. Table 3 demonstrates that the fuzzy-EEMS offers higher fuel (and fuel-cell) efficiency than the fuzzy-ECMS, of course at the expense of employing the battery bank at a wider range. In other words, the fuzzy-ECMS offers a higher battery lifetime than the fuzzy-EEMS since it utilizes the battery bank at higher SOCs.

4.1.2. Short term Analysis

In the second case, the renewable system is simulated with pulsed PV/WT /load profiles, as observed in Fig. 17 (b). Therefore, the dynamic response of the hybrid system to step changes is investigated in this section. Fig. 15 presents the simulation results for the fuzzy logic control strategy, the fuzzy-ECMS, and the fuzzy-EEMS with the initial battery SOC of the 75%. For the first 15s, the PV/WT generation is insufficient to provide the load power, and therefore the fuel-cell and the battery bank share the power shortage demand. Next, the renewable energy sources contribution increases such that it is sufficient to supply the load. Then, the fuel-cell output power decreases to almost the minimum amount. In the following, the surplus power charges the battery bank.

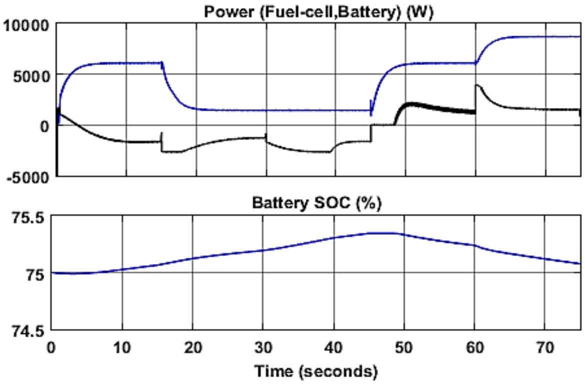
Table 3. Summary of results for long term analysis with initial SOC of 100%

Initial SOC	100%				
Indicator / EMS	$P_{fc\ avreage}$	Fuel (litre-gram)	Fuel-cell Efficiency (%)	Fuel-cell Efficiency (joule/litre)	Final SOC (%)
Rule-based fuzzy logic	3001.8	43286-3848.4	51.43	5991.7	87.54
Fuzzy-ECMS	2955.1	42907-3814.8	51.46	5950.6	76.06
Fuzzy-EEMS	2869.2	41043-3649.1	51.6	6039.8	56.63

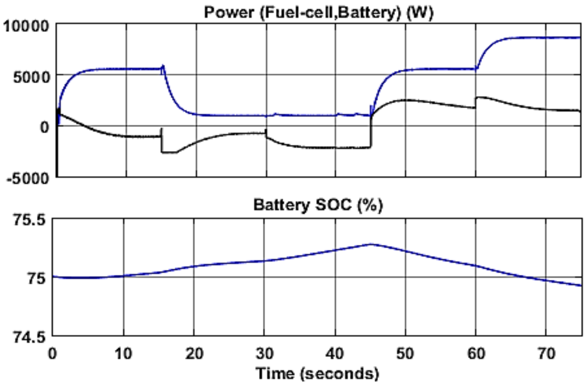


(a) (b

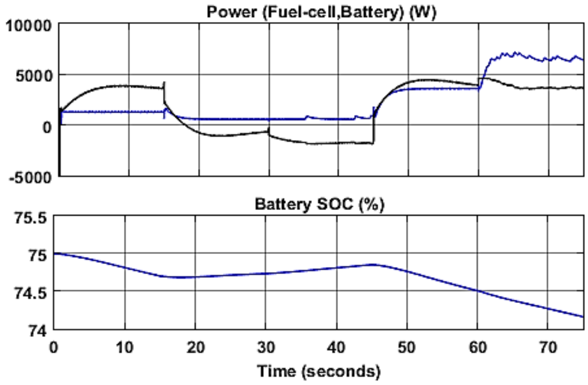
Fig. 14. Long term analysis of fuzzy-EEMS (Fuel-cell / battery power, battery SOC). (a) SOC_{ini}=100%. (b) SOC_{ini}=30%.



(a)



(b)



(c)

Fig. 15. Simulation results for initial battery SOC of 75%. (Fuel-cell / battery power, battery SOC). (a) Rule-based fuzzy logic control strategy. (b) Fuzzy-ECMS (c) Fuzzy-EEMS

Next, the PV/WT power reduction forces the fuel-cell and the battery bank to share the energy demand shortage. It is seen that to reach the $\mathrm{SOC_{min}}$, the fuzzy-EEMS, as expected, discharges the bank faster for the last 30s. Also, the fuzzy- ECMS has a slower rate of the battery discharge since the initial battery SOC is equal to the 0.5 (SOC_{max}+ $\mathrm{SOC_{min}}$) and the fuzzy-ECMS aims to keep the battery bank SOC around the 0.5 (SOC_{max}+ $\mathrm{SOC_{min}}$) (75% in this paper).

5. Conclusion

In this paper, the optimization of the fuzzy logic control strategy of a PV/WT//FC/SC hybrid power system has been discussed. Considering a trade-off between the computation time of the genetic algorithm and the expert prior knowledge, the membership functions were optimized while the rules were known in advance. The ECMS and the EEMS are utilized to optimize the fuel consumption of the hybrid renewable system. Finally, the energy management strategies assessment has been presented, employing a simulation model of the system. The simulation study covered short term and long term implementation of all the energy management strategies. Additionally, the fuel efficiency, the fuel-cell average power, the fuel-cell efficiency, the battery SOC, and the fuel consumption are compared in the case of all the energy management strategies. The simulation results demonstrated the following results:

- The fuzzy-ECMS and the fuzzy-EEMS keeps the battery SOC around the “0.5 (SOC_{max}+ $\mathrm{SOC_{min}}$)” and the $\mathrm{SOC_{min}}$, respectively.
- In this paper, the $\mathrm{SOC_{min}}$ and the $\mathrm{SOC_{max}}$ have been selected as 60, and 90%, respectively. Then, The fuzzy-ECMS and the fuzzy-EEMS kept the battery SOC around 75% and 60%, respectively
- It can be concluded that better fuel economy and higher battery lifetime can be achieved via the fuzzy-EEMS and the fuzzy-ECMS, respectively.

Appendix

Paramitrization of the renewable system is available in Table 4.

Table 4. Hybrid System Parameters.

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

	Operating temperature (Celsius) 25 Total resistance (Ω) 0.02
Fuel-cell Stack	**Battery system**
Number of cells 65 Nominal stack efficiency (%) 55 Operating temperature (Celsius) 65 Nominal Air flow rate (lpm) 300 Nominal supply pressure [Fuel (bar), Air (bar)] [1.5, 1] Fuel-cell boost converter [Inductance (H), Capacitance (mF), Efficiency (%), output voltage (V)] [0.01, 800, 93, 220] Nominal composition (%) [H2 O2 H2O (Air)] [99.95, 21, 1]	Nominal Voltage (V 60 Rated Capacity (Ah) 40 Initial State-Of-Charge 65 Maximum Capacity (Ah) 40 Battery buck converter [Inductance (H), Capacitance (mF), Efficiency (%), output voltage (v)] [0.01, 800, 88, 67] Battery boost converter [Inductance (H), Capacitance (mF), Efficiency (%), output voltage (v)] [0.01, 800, 88, 220] Nominal Voltage (V) 60
Electrolyzer	**WT System**
Number of cells 10 Faraday's constant 96,484,600 ckmol^{-1}	**PMSG generator** Nominal Voltage (V) 560 Nominal speed 1700 RPM Nominal torque 67.27 N.M Stator phase resistance Rs (ohm): 0.0485 Armature inductance (H) 0.000395 pole pairs 4

References

[1] Daogui Tang ; Xinping Yan; Yupeng Yuan; Kai Wang, Liqiang Qiu, "Multi-agent Based Power and Energy Management System for Hybrid Ships", 4th International Conference on Renewable Energy Research and Applications (ICRERA), PP.383-387, Palermo, Italy, 22-25 Nov 2015.

[2] M S Hossain Lipu, Md. Golam Hafiz, Md. Safi Ullah, , Ahad Hossain, Farzana Yasmin Munia, "Design Optimization and Sensitivity Analysis of Hybrid Renewable Energy Systems: A case of Saint Martin Island in Bangladesh", International journal of renewable energy research , Vol.7, PP. 988-998, 2017.

[3] Bouthaina Madaci , Rachid Chenni, Erol Kurt, Kamel Eddine Hemsas, "Design and control of a stand-alone hybrid power system", International journal of hydrogen energy, pp. 1-12, 2016.

[4] Yosoon Choi, Chaeyoung Lee, Jinyoung Song, "Review of Renewable Energy Technologies Utilized in the Oil and Gas Industry", International journal of renewable energy research , Vol. 7, PP. 592-598, 2017.

[5] Gokay Bayrak, Mehmet Cebeci, "Grid connected fuel cell and PV hybrid power generating system design with Matlab Simulink", International journal of hydrogen energy, vol. 39, pp. 8803-8812, 2014.

[6] Logeswaran T, Senthilkumar A, Karuppusamy P, "Adaptive neuro-fuzzy model for grid-connected photovoltaic system", International Journal of Fuzzy Systems, vol. 17(4), pp. 585-94, 2015.

[7] Altın N, "Interval type-2 fuzzy logic controller based maximum power point tracking in photovoltaic systems", Advances in Electrical and Computer Engineering, vol. 13(3), pp. 65-70, 2013.

[8] Victor O. Okinda, Nicodemus A. Odero, "Modelling, Simulation and Optimal Sizing of a Hybrid Wind, Solar PV Power System in Northern Kenya, International journal of renewable energy research , Vol. 6, PP. 1199-1211, 2016.

[9] Tugrul Atasoy, Hülya Erdener Akinç, Özden Erçin, "An Analysis on Smart Grid Applications and Grid Integration of Renewable Energy Systems in Smart Cities", 4th International Conference on Renewable Energy Research and Applications (ICRERA), PP.547-550, Palermo, Italy, 22-25 Nov 2015.

[10] Ram Shankar Yallamilli, Mahesh K. Mishra, "Power Management of Grid Connected Hybrid Microgrid with Dual Voltage Source Inverter", 5th International Conference on Renewable Energy Research and Applications (ICRERA), pp. 407-412, Birmingham, UK, 20-23 Nov 2016.

[11] Erkan Dursun, Osman Kilic, "Comparative evaluation of different power management strategies of a stand-alone PV/Wind/PEMFC hybrid power system", Electrical Power and Energy Systems, vol. 34, pp. 81-89, 2012.

[12] Ekin Ozgirgin, Yılser Devrim, Ayhan Albostan, "Modeling and simulation of a hybrid photovoltaic (PV) module-electrolyzer-PEM fuel cell system for micro-cogeneration applications", International journal of hydrogen energy, pp. 1-7, 2015.

[13] Bahram Panahandeh, Jochen Bard, Abdelkader Outzourhit, Driss Zejli, "Simulation of PV/Wind-hybrid systems combined with hydrogen storage for rural electrification", International journal of hydrogen energy, vol. 36, pp. 4185-4197, 2011.

[14] Fengbing Li, Kaigui Xie , and Jiangping Yang, "Optimization and Analysis of a Hybrid Energy Storage System in a Small-Scale Standalone Microgrid for Remote Area Power Supply (RAPS)", Energies, vol. 8, pp. 4802-4826, 2015.

[15] Henerica Tazvinga , Xiaohua Xia, Bing Zhu,"Optimal energy management strategy for distributed energy Resources, Energy Procedia, vol. 61, pp. 1331 – 1334, 2014.

[16] O.C. Onar, M. Uzunoglu, M.S. Alam, "Modeling, control and simulation of an autonomous wind tur-

bine/photovoltaic/fuel cell/ultra-capacitor hybrid power system", Journal of Power Sources, vol. 185, pp. 1273–1283, 2008.

[17] Rudi Kaiser, "Optimized battery-management system to improve storage lifetime in renewable energy systems", Journal of Power Sources, vol. 168, pp. 58–65, 2007.

[18] T.Bogaraj, J.Kanakaraj, "A Novel Energy Management Scheme using ANFIS for Independent Microgrid", International journal of renewable energy research , Vol.6, PP. 735-746, 2016.

[19] Huiqing Wen, Huan Yu, Yihua Hu, "Modeling and Analysis of Coordinated Control Strategies in AC Microgrid", 5th International Conference on Renewable Energy Research and Applications (ICRERA), pp. 702-707, Birmingham, UK, 20-23 Nov 2016.

[20] Javier Solano Martinez, Robert I. John, Daniel Hissel, Marie-Cécile Péra, "A survey-based type-2 fuzzy logic system for energy management in hybrid electrical vehicles", vol.190, pp. 192-207, 2012.

[21] Bo Zhao, Xuesong Zhang, Jian Chen, Caisheng Wang, and Li Guo, "Operation Optimization of Standalone Microgrids Considering Lifetime Characteristics of Battery Energy Storage System", IEEE transactions on sustainable energy, vol. 4, pp. 934-942, 2013.

[22] Hernandez-Aramburo C A, Green TC, Mugniot N, "Fuel consumption minimization of a microgrid", IEEE Trans. Ind. Appl, vol. 41(3), pp. 673–68, 2005.

[23] Eroglu M, Dursun E, Sevencan S, Song J, Yazici S, Kilic O, "A mobile renewable house using PV/wind/fuel cell hybrid power system", International journal of hydrogen energy, vol. 36(13), pp. 7985–92, 2011.

[24] Erdinc O, Uzunoglu M, "A new perspective in optimum sizing of hybrid renewable energy systems: consideration of component performance degradation issue", International journal of hydrogen energy, vol. 37(14), pp. 10479–88, 2012.

[25] Onur E, Ugur SS, "A comparative sizing analysis of a renewable energy supplied stand-alone house considering both demand side and source side dynamics", Applied Energy, vol. 96, pp. 400-8, 2012.

[26] Jiang Zhenhua, Gao Lijun, Dougal Roger A, "Adaptive control strategy for active power sharing in hybrid fuel cell/battery power sources", IEEE Trans Energy Conver , vol. 22, 2007.

[27] Emad M. Natsheh, Alhussein Albarbar, "Hybrid Power Systems Energy Controller Based on Neural Network and Fuzzy Logic", Smart Grid and Renewable Energy , vol. 4, pp. 187-197, 2013.

[28] Zhao, Haoran; Wu, Qiuwei; Wang, Chengshan; Cheng, Ling; Rasmussen, Claus Nygaard, "Fuzzy Logic based Coordinated Control of Battery Energy Storage System and Dispatchable Distributed Generation for Microgrid", Journal of Modern Power Systems and Clean Energy, vol. 3, pp. 422-428, 2015.

[29] Pablo García, Carlos Andrés García, Luis M. Fernández, Francisco Llorens, and Francisco Jurado, "ANFIS-Based Control of a Grid-Connected Hybrid System Integrating Renewable Energies, Hydrogen and Batteries", IEEE Transactions on industrial informatics, vol. 10, pp. 1107-1117, 2014.

[30] Suganya B S, Arivalahan R, "Power Management of Hybrid Renewable System Integrated with Energy Storage System", International journal of innovative research in electrical, electronics, instrumentation and control engineering, vol. 3, pp. 123-128, .2015.

[31] Souleman Njoya Motapon, Louis-A, "Dessaint and Kamal Al-Haddad. A Comparative Study of Energy Management Schemes for a Fuel-Cell Hybrid Emergency Power System of More-Electric Aircraft", IEEE transactions on industrial electronics, vol. 61, pp. 1320-1334, 2014.

[32] Mohammad Ali Karbaschian, Dirk Soffkerm, "Review and Comparison of Power Management Approaches for Hybrid Vehicles with Focus on Hydraulic Drives", Energies, vol. 7, pp. 3512-3536, 2014.

[33] Souleman Njoya Motapon, Louis-A. Dessaint and Kamal Al-Haddad, "A Robust H2-Consumption-Minimization-Based Energy Management Strategy for a Fuel Cell Hybrid Emergency Power System of More Electric Aircraft.", IEEE transaction on industrial electronics, vol.61, pp. 6148-6156, 2014.

[34] A. T. Azar, Fuzzy Systems, Vienna, Austria: In Tech, 2010.

[35] S. Caux, W. Hankache, M. Fadel , D. Hissel, "On-line fuzzy energy management for hybrid fuel cell systems", International journal of hydrogen energy, vol.35, pp. 2134-2143, 2010..

[36] Ahmed Mohamed, M. Elshaer, Osama Mohammed, "Control enhancement of power conditioning units for high quality PV systems", Electric Power Systems Research, vol. 90, pp. 30– 41, 2012.

[37] Rudi Kaiser, "Optimized battery-management system to improve storage lifetime in renewable energy systems", Journal of Power Sources, vol. 168, pp. 58–65, 2007.

[38] M. Bostanian1, S. M. Barakati, B. Najjari, D.Mohebi Kalhori, "A Genetic-Fuzzy Control Strategy for Parallel Hybrid Electric Vehicle", International Journal of Automotive Engineering, vol. 3, pp.482-495, 2013.

[39] Pawar, Prashant M., Ganguli, Ranjan, "Structural Health Monitoring Using Genetic Fuzzy Systems". 2011.

[40] Azar Zafari, Developing a fuzzy interface system by using genetic algorithm and expert knowledge, Master thesis, University of Twente, February, 2014.

[41] Basavaraj Shalavadi, Ravindranadh V ,Udaykumar R.Y, "Modelling and Analysis of a Standalone PV/Micro Turbine/ Ultra Capacitor Hybrid System", International journal of renewable energy research , Vol.6, PP. 847-855, 2016.

[42] P. García, J.P. Torreglosa, L.M. Fernández, F. Jurado, "Viability study of a FC-battery-SC tramway controlled by equivalent consumption minimization strategy", International journal of hydrogen energy, vol. 37, pp. 9368 – 9382, 2010.

[43] heng, C. H., N. W. Kim, and S. W. Cha, "Optimal control in the power management of fuel cell hybrid vehicles", International Journal of Hydrogen Energy, vol. 37, pp. 655-663, 2012.

[44] Phatiphat Thounthonga, Viboon Chunkagb , Panarit Sethakula , Suwat Sikkabutc , Serge Pierfederici, Bernard Davatd, "Energy management of fuel cell/solar cell/supercapacitor hybrid power source", Journal of Power Sources, vol. 196, pp. 313–324.

NOMENCLATURE

PV	Photovoltaic
ECMS	Equivalent Consumption Minimization Strategy
EEMS	External energy maximization strategy
Ref	Reference
SOC	(Battery) State of charge
SOC_{max}	Maximum State of charge (%)
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)
P_{load}	Load power (W)
$P_{fc_{ref}}$	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)
I_{fc}	Fuel-cell current (A)
η_{fc}	Fuel-cell converter efficiency (%)
$I_{fc_{ref}}$	Fuel-cell reference current (A)
$P_{discharg\ max}$	Maximum battery discharge power (W)
$P_{optcharg}$	Battery charge power (W)
$P_{charg\ max}$	Maximum battery charge power (W)
$P_{optdischarg}$	Battery discharge power (W)
P_{batt}	Battery power (W)
P_{PV}	PV plant power (W)
L	Low
VL	Very low
M	Medium
H	High
WT	Wind turbine
P_{load}	Load power (W)
P_{WT}	Wind turbine power (w)