A Comparative Study of Energy Control Strategies for a Standalone PV/WT/FC Hybrid Renewable System

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Abstract- This paper aims to design and control a standalone hybrid renewable system, comprising PV panels and wind turbines as the main energy sources along with a fuel-cell stack as a support system. In this paper several energy management strategies are designed, simulated and their performance is compared. The energy management strategies taken into account for comparative investigation in the addressed hybrid renewable system are the most commonly used ones, as follows: the state machine control, the rule-based fuzzy logic control, the ANFIS-based control strategy, the equivalent consumption minimization strategy (ECMS) and the external energy maximization strategy (EEMS). The ANFIS-based control strategy data requirements (training, checking and testing data set) are prepared via the state machine control, which determines the operation of the backup system and the storage units based on the battery state of charge and the energy demand shortage. The main contribution of the state machine control and the rule based fuzzy logic design approach, in addition to the demanded energy provision, is protecting the battery bank against deep discharge and overcharge. two scenarios are taken into account: Constant loads, for short term analysis, and Random loads, for long term analysis. The simulation study demonstrates successful operation of the energy management strategies for different initial battery SOCs, which are selected in a way to cover the operation of the controller in three battery SOC ranges. Also, design requirements such as the hydrogen consumption, the fuel efficiency, and the fuel-cell stack efficiency are evaluated in the case of all the energy control strategies.

Keywords- ANFIS-based energy management; state machine control; Renewable energy; fuel efficiency; fuel consumption,

1. Introduction

Tendency toward renewable power systems, especially PV and Wind plants, have been increased both in rural and urban areas in recent years [1]. This tendency is mainly due to the limited natural resources, green gas emissions, increased energy consumption, and economic aspects [2]. In addition to mitigating environmental crisis, standalone hybrid renewable systems can be an alternative to electrification of remote regions which large power grids cannot meet their energy needs. Due to unpredictable and random sun insolation and wind speed which leads to fluctuant renewable energy generation, any mismatch between the energy demand and the energy production can lead to instability, power quality degradation, failure, etc. [3]. Thus, interconnecting a support system and storage units is a necessary step to regulate the electricity generation and provide a reliable path for power generation and consumption [4]. The batteries and hydrogen based storage technologies provide a reasonable solution for this problem [5]. Additionally, supercapacitors, with peak demand shaving, reduce the energy production cost, overcome high renewable energy/load power fluctuations, and prolong the energy sources and the battery banks life span [6]. The support system can be conventional diesel generators or fuel-cells. Of course, due to lower maintenance cost and near zero pollutant emissions, fuel-cells are more preferable than diesel generators [7]. The proper operation of hybrid renewable systems depends on an elaborate design of an energy management unit [8-10] which meets the load power requirements, controls the batteries/supercapacitors SOC, optimizes the fuel consumption, minimizes the pollutant emissions, and etc. An isolated hybrid renewable power system, which is also known as microgrid, comprising PV and wind renewable energy sources along with various energy storage technologies, is chosen for study, as shown in Fig.1. Analysis of microgrids via the centralized energy management strategies, such as dynamic programming [9], model predictive control [10], sequential quadratic programming [11] and mixed integer programming [12] normally require high computations and have been discussed in the literature. A comparative study of different state machine power management strategies for a renewable energy system has been discussed in [13], in which in addition to comparison of the approaches, the effect of the minimum battery state of charge and the fuel-cell output power on the hydrogen inventory has been discussed for a four month time interval. The state machine is an energy control strategy with short response time, but is sensitive to the measurement accuracy and moreover requires an exact mathematical model of the system. Hence uncertainties in hybrid renewable systems such as unpredictable and fluctuated PV/Wind power generation, the variations in the load power, mathematical model inaccuracies, and complexity of the hybrid system led the authors toward the fuzzy logic based energy management systems [14]. Focusing on the optimization of the battery lifetime and the utilization cost, the authors in [14] presented a fuzzy logic based supervisory control for a PV/WT hybrid system. Given the challenges such as the fuzzy logic control dependency on prior knowledge and past experience of the designer and time consuming tuning process of the membership function's parameters by trial and error and difficulty of selecting the most appropriate rule set, the ANFIS based energy management strategy is attracting growing attention. It is well known that the ANFIS-based energy management strategy in addition to serving the capabilities of the fuzzy logic (control strategy) along with learning abilities of artificial neural networks, improves the reliability of the hybrid renewable system, because of employing the Sugeno type fuzzy interface system [15-19]. Thus, the authors in [15-19] employed the ANFIS-based energy management system for a grid connected hybrid renewable system. Moreover, short term analysis of hybrid renewable systems based on the state machine control [16] and the fuzzy logic control [17] has been presented by the authors in the past. The authors in [18] designed the fuzzy rules based on the battery SOC, to increase the battery lifetime. This paper presents a comparative investigation of the conventional state machine control, the rule based fuzzy logic control, the ANFIS based control strategy, and the equivalent consumption minimization strategy (ECMS) for the standalone hybrid renewable system shown in Fig.1. In this paper, the state machine control is designed based on the battery bank SOC and the load power shortage that is not supplied with the PV and wind energy sources. Besides the demanded energy supply, the state machine control aims to protect the battery bank from deep discharge and overcharge. The ANFIS based energy control is based on the input/output data process of the hybrid renewable system. The data requirements of the ANFIS-based control can be satisfied via the state machine control strategy [15]. On the other hand, the input/ output data generated through the state machine control, gives the opportunity of mixing the ANFIS-based control strategy capabilities with the design approach of the state machine control. Hence, in addition to extending the battery lifetime, more efficiency and robustness is achieved with the ANFIS-based control capabilities. The ECMS minimizes the fuel consumption of the fuel-cell and equivalent hydrogen consumption of the battery bank via a cost function which employs an equivalent factor to calculate the battery bank equivalent hydrogen consumption. It uses a local optimization algorithm to allocate the load power (or a part of the load power) to the fuel-cell and the energy storage banks in a way that total fuel consumption is minimized [19]. Similar to ECMS, the EEMS employs a local optimization algorithm. In this strategy, maximizing the instantaneous energy of the battery bank and the supercapacitors, leads to economized fuel consumption [2]. The hybrid renewable system components specification is presented in Table1.

2. Overall Power Management

As discussed before, to maximize the free energy, generated by the photovoltaic panels and wind turbines, only the load power that is not met by the renewable energy sources are provided by the backup system and the storage banks. Additionally, the excess power of the free energy sources, if available, is utilized to recharge the battery or is consumed by the electrolyzer to produce the hydrogen, according to the approach that is discussed in section 2.2. Thus, the overall power balance constraint can be described as:

$$P_{net} = P_{load} - (P_{PV} + P_{wind}) = P_{fc} + P_{batt} \quad \text{if} \quad P_{load} > (P_{PV} + P_{wind}) \tag{1-1}$$

$$(P_{PV} + P_{wind}) + P_{BAT} = P_{load} \quad \text{if} \quad P_{load} < (P_{PV} + P_{wind}) \ \& \ \text{(Battery) SOC} < SOC_{max} \tag{1-2}$$

$$(P_{PV} + P_{wind}) + P_{elec} = P_{load} \quad \text{if} \quad P_{load} < (P_{PV} + P_{wind}) \ \& \ \text{(Battery) SOC} > SOC_{max} \tag{1-3}$$

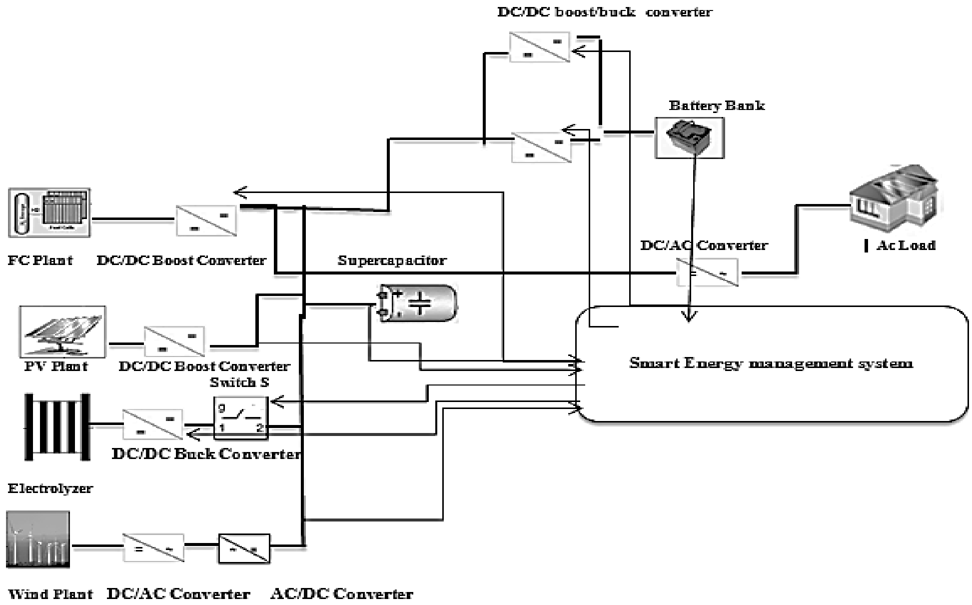


Fig. 1. A typical PV/WT/FC/UC hybrid Power System for residential application.

Table1. 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
Electrolyzer		**WT System (PMSG generator)**	
		Nominal Voltage (V)	560
Number of cells	10 Faraday's	Nominal speed	1700 RPM
constant	96,484,600 ckmol^{-1}	Nominal torque	67.27 N.M
		Stator phase resistance Rs (ohm)	0.0485
		pole pairs	4
		Armature inductance (H):	0.000395

2.1. State machine Control

The state machine control is designed based on the battery SOC and its lifetime characteristics, considering the energy demand requirements, as follows:
a) For high battery SOCs: The battery discharges with the optimal rate and the fuel-cell meets the remaining load requirements.
b) For normal battery SOCs: the battery provides its optimal power and the fuel-cell helps with meeting the load demand.
c) For low battery SOCs: The fuel-cell charges the battery bank with the optimum charge rate, while meeting the load power requirement. Considering the discussed approach, fifteen states are designed, as shown in Table 2.

Table 2. State machine Control States

2.2. Rule- Based Fuzzy Logic Energy Control System

In this paper, the designated inputs of the rule-based fuzzy controller are the battery SOC, the PV/WT production, and the demanded power and the output is the fuel-cell power. Three fuzzy subsets for the battery SOC, four fuzzy subsets for the PV/WT generation and the load power and five fuzzy subsets for the fuel-cell power is allocated. For fuzzification, the Mamdani type fuzzy controller and for defuzzification of the rule-based fuzzy logic controller output, centroid defuzzification method is used. The main problem arises here is how to express the rules and to tune the membership functions

SOC	State	P_{load}	P_{fc}
SOC >85	1	$P_{load} \leq P_{PV} + P_{wind}$	0
	2	$P_{net} \leq P_{fcmin}$	P_{fcmin}
	3	$P_{fcmin} < P_{net} \leq P_{fcmin} + P_{optdischarg}$	P_{fcmin}
	4	$P_{fcmin} + P_{optdischarg} < P_{net} \leq P_{fcmax} + P_{optdischarg}$	$P_{net} - P_{optdischarg}$
	5	$P_{net} > P_{fcmax} + P_{optdischarg}$	P_{fcmax}
50<SOC<85	6	$P_{load} \leq P_{PV} + P_{wind}$	0
	7	$P_{net} \leq P_{fcmin}$	P_{fcmin}
	8	$P_{fcmin} < P_{net} \leq P_{fcopt} - P_{battopt}$	P_{net}
	9	$P_{fcopt} - P_{battopt} < P_{net} \leq P_{fcopt} + P_{battopt}$	$P_{fcopt} - P_{battopt}$
	10	$P_{fcopt} + P_{batt\,opt} < P_{net} \leq P_{fcmax}$	P_{net}
	11	$P_{net} > P_{fcmax}$	P_{fcmax}
SOC<50	12	$P_{load} \leq P_{PV} + P_{wind}$	0
	13	$P_{net} \leq P_{fcmin}$	P_{fcmin}
	14	$P_{fcmin} < P_{net} \leq P_{fcmax} + P_{optcharge}$	$P_{net} - P_{optcharge}$
	15	$P_{net} > P_{fcmax} + P_{optcharge}$	P_{fcmax}

$P_{net} = P_{load} - (P_{PV} + P_{wind})$

The performance of the fuzzy logic controller is affected by the type and the parameters of the membership functions and the rule set definition. The algorithm of the rule-based fuzzy logic energy management strategy for the proposed microgrid is shown in Fig. 2, which is similar to the one that is used for the state machine control. To avoid overcharging the battery bank which leads to charge losses, the surplus power of the PV/WT will be stored in the form of the chemical energy (hydrogen) in hydrogen tanks when the battery SOC is higher than 90%, by switching the electrolyzer on. If the battery SOC is low or medium and extra PV/WT power is available, the surplus power after recharging the battery bank will be directed to the electrolyzer. If the battery state of charge is above 90%, the batteries are discharged approximately with the optimal discharge rate to meet the energy demand shortage in the first place and the fuel-cell provides only the portion of the energy that is not met by the PV/WT system and the batteries. As mentioned before, batteries have short lifetime, which adversely affects the economy of the hybrid power system. The lifetime degrades when operating at SOCs lower than the minimum limit [20]. Therefore, the fuel-cell will recharge the battery bank when its SOC is lower than SOC_{min} (60%), to have a reasonable amount of energy reserved and protect the battery bank against deep discharge. The supercapacitors compensate the transient peaks. Thus, the batteries will provide them with the same amount of energy they have delivered, subsequently [21]. Hence only the battery bank state of charge is taken into account in the energy management system design process. The membership functions of the Mamdani type fuzzy control are shown in Fig. 3. Table 3 shows the fuzzy rules that are designed according to the energy sources' limitations [22].

2.3. ANFIS- Based Energy Management Strategy

The fuzzy rule set and the type and the parameters of the membership functions are determined based on the design er's past knowledge and experience. Besides being time consuming to designate the membership functions and assigning the fuzzy rule set based on the trial and error, optimal response is not guaranteed in fuzzy logic control. The ANFIS serves the user the capabilities of both the fuzzy logic and neural networks simultaneously [23]. Originated from ANN+FIS, the ANFIS employs learning capability of the neural networks to train the fuzzy logic controller parameters such that the most proper fuzzy logic control is obtained to map the input/output data set [24]. In this study, the hybrid algorithm is utilized to tune the membership functions and the fuzzy rule set. Moreover, Gaussian membership function is chosen to reduce the training error, which is approximately 2%. The state machine control strategy is employed to provide the ANFIS- based energy control strategy with the training, checking and testing date. 30% of the total 2260 data is allocated to the testing and checking data, to avoid over-fitting [14]. The tuned membership functions are shown in Fig. 4.

2.4. ECMS

The PV/WT plant provides the load with free energy. Moreover, the hydrogen energy is required to feed the fuel-cell and keep the battery charge at the desired range. Hence, when then load demand cannot be met by renewable sources, the fuel-cell and the battery bank provide the load with the electrical energy. In addition, the transient peaks are guaranteed with the supercapacitor pack, but the steady state load demand is supplied with the PV/WT/FC and the battery bank. Then, it is not necessary to take into account the supercapacitors contribution on the cost function based energy management strategy [25].

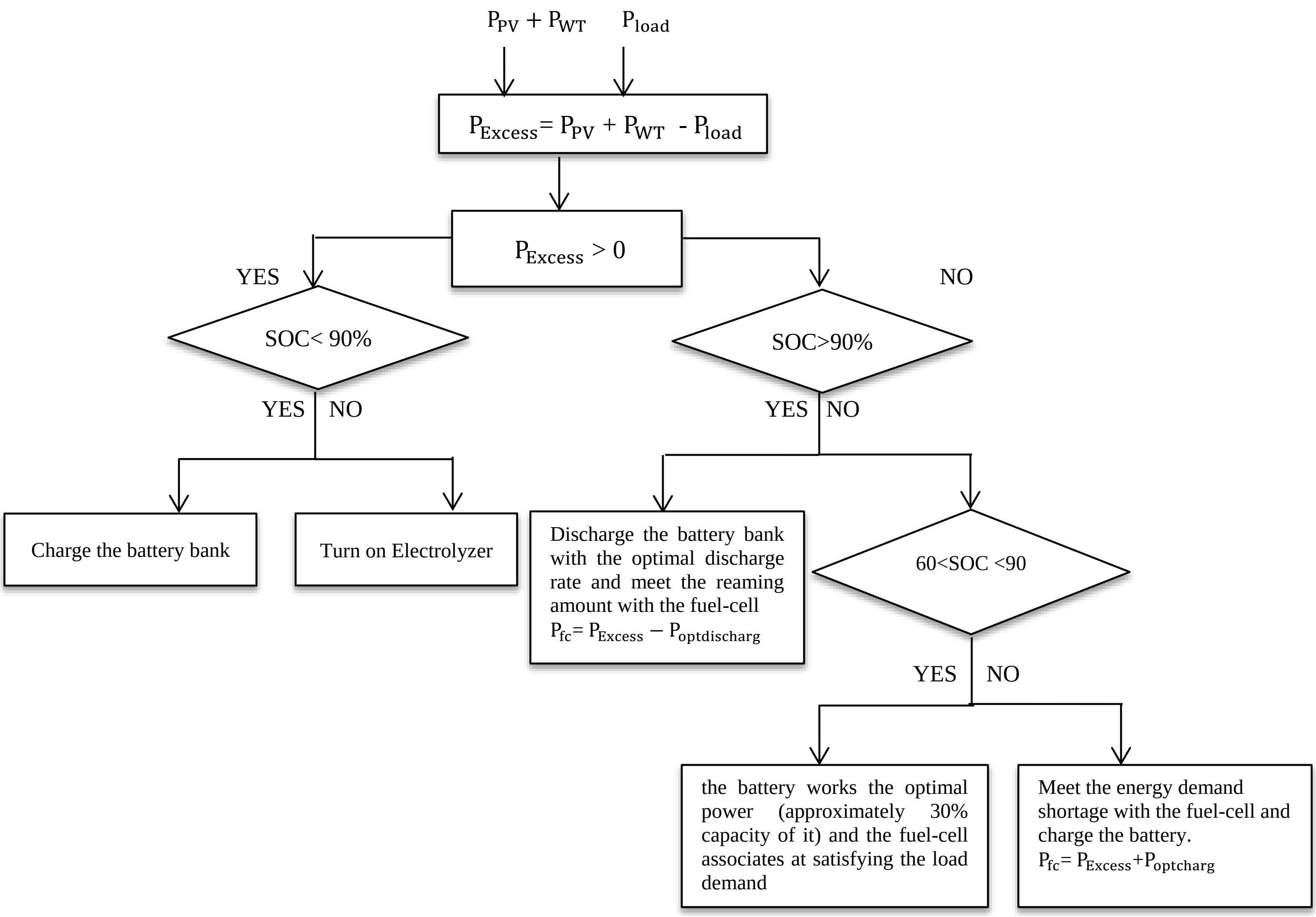


Fig. 2. Rule based fuzzy logic energy Management system overall Algorithm

Table 3. Fuzzy Rules

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

Moreover, the hydrogen that is consumed by the fuel-cell or is employed to keep the battery SOC at the desired range has a direct relation with the fuel-cell/battery power. The cost function based energy management strategy can be written as [25]:

$$C_1 = (P_{fc} + \alpha . P_{BAT}). \Delta T \quad (2)$$

Where μ is a constant called battery SOC coefficient, and is set to 0.6 in this paper to control battery SOC. ΔT is the sampling time, and α is the equivalent factor that can be defined as [26, 25]:

$$\alpha = 1 - 2 * \mu * \frac{(SOC - 0.5(SOC_{Max} + SOC_{Min})}{SOC_{Max} + SOC_{Min}} \quad (3)$$

The boundary limits to the ECMS are as follows:

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

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

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

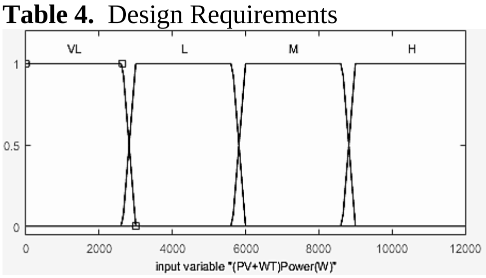
$$0 < EQ_1 < 2 \quad (7)$$

2.5. The External Energy Maximization Strategy (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.

Table 4. 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



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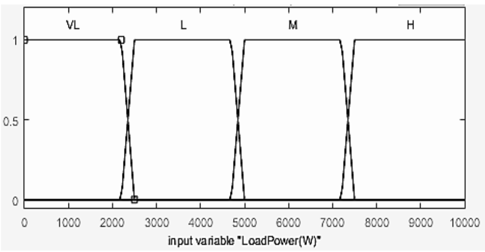

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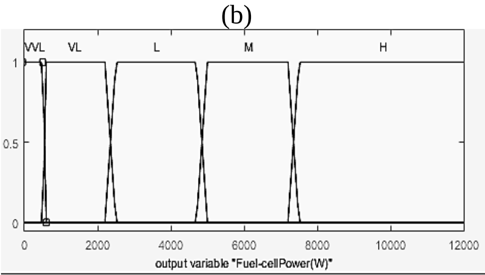

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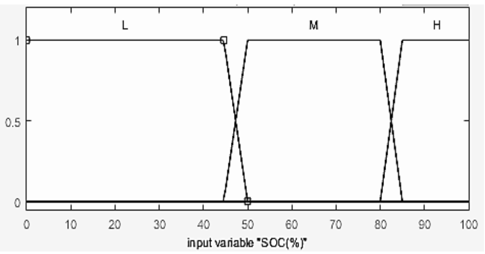
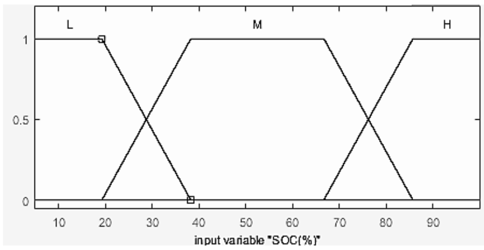


(d)

Fig. 3. Membership functions of Sugeno type fuzzy logic control. (a) (P_{PV} +P_{WT}) power. (b) Load power. (c) Fuel-cell power. (d) Battery state of charge



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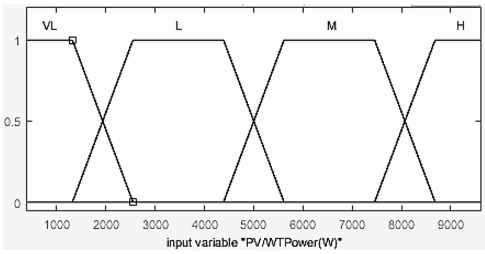

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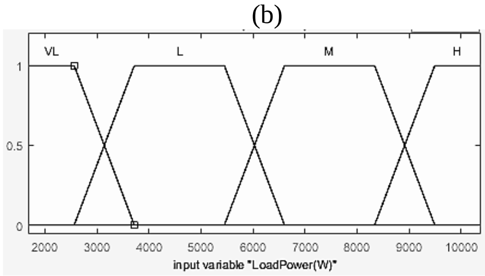


(c)

Fig. 4. Membership functions. (a) Battery SOC. (b) Load Power. (c) (PV +Wind) Power

. Thus, the ECMS is sensitive to the load profile. To improve the robustness, authors either found new ways to express the equivalent factors [27] or introduced new cost function optimization strategies [27]. The external energy maximization strategy has been presented by the authors in [27] to maximize the energy of the storage banks which subsequently reduces the fuel consumption. The EEMS can be formulated as:

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

Where C, Δ T 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:

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

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

The inequality constraint is

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

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 [27]. The energy management unit design requirements are shown in Table4.

3. Simulation Results and Discussion

3.1. Long term Analysis

In long term analysis, the evaluation of the hybrid system performance under a typical PV/WT power profile with the peak of 11 KW and a residential load power with a peak of 10 KW, while a 2KW and 1KW random power is added to

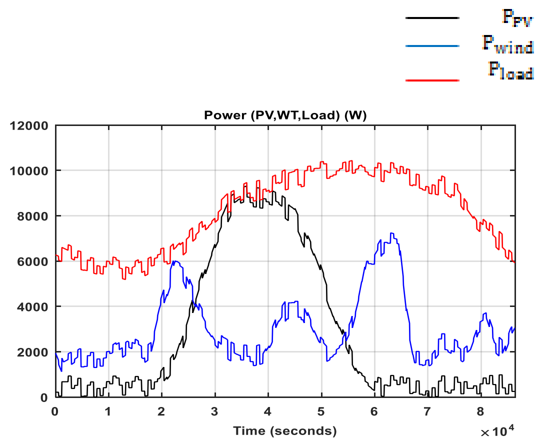
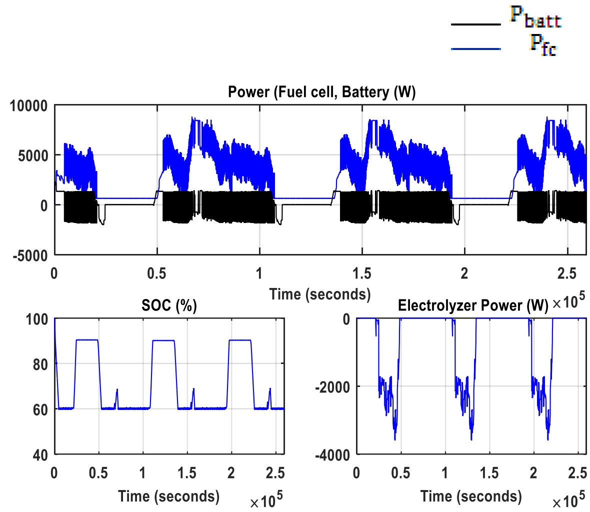


Fig. 5. Power (PV/WT, Load) (W).

the PV/WT power profile and the load power, respectively, is presented in Fig. 5. The simulation study results for 72 hours for the state machine control and the rule based fuzzy logic control strategy is as follows (Figs. 6 and 7): If the renewable energy sources (PV, and wind power) contribution is insufficient to meet the load demand requirements, the fuel-cell and the battery operate based on the approach described in section 2.1. The ANFIS based control has a similar performance to the state machine control, because of providing the training, testing and checking data through the state machine control. In the case of all the energy management strategies, as mentioned before, the battery discharge rate is higher in the case of high SOCs (see Figs. 6(a)-10(a) for the time interval between 0-1440s). When the renewable energy sources are enough to supply the energy demand, the fuel-cell power is at the minimum level and the battery power is almost zero (see Fig. 6(a)-10(a) for time interval between 5:30h-14h). As discussed, if the load power is lower than the sum of the PV and WT power , then the battery bank will be charged when its current SOC is below the maximum limit and any remaining portion will be absorbed by the electrolyzer ($P_{load} - (P_{PV} + P_{wind})$-$P_{charge}$). Additionally, in the case where the battery SOC is higher the SOC_{max}, the excess free energy (($P_{load} - (P_{PV} + P_{wind}$)) is directed to the electrolyzer (see Fig. 6(a)-10(a) for time interval between 7h-14h). The electrolyzer power is depicted in Fig 6-10. Investigating equation (3), it can be derived that the ECMS tends to keep the battery SOC around the $0.5(SOC_{Max} + SOC_{Min})$. Then, for the battery SOCs above the $0.5(SOC_{Max} + SOC_{Min})$, the battery has higher priority than the fuel-cell in the load demand provision.



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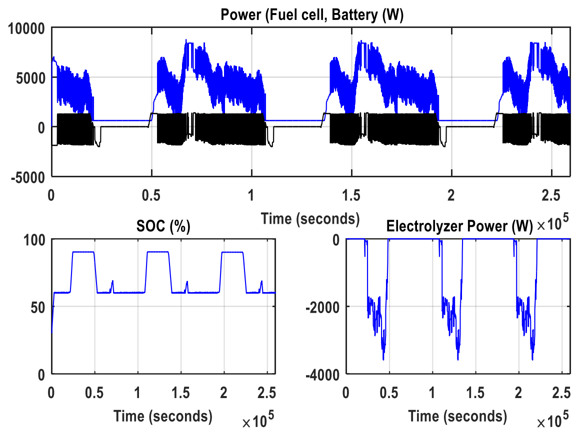


(b)

Fig. 6. Long term analysis of the state machine control strategy (Fuel-cell / battery power, battery SOC). (a) SOC_{ini}=100%. (b) SOC_{ini}=30%

Moreover, the fuel-cell charges the battery bank for the SOCs below the $0.5(SOC_{Max} + SOC_{Min})$, as seen in Fig. 9. Additionally, equation (24) demonstrates that the EEMS aims to maintain the battery SOC around the SOC_{min}, as seen in Fig. 10. Figs. 6(a)-10(a) depict the battery recharging via the fuel-cell for the SOCs lower than minimum value in the case of the state machine control, the rule based fuzzy logic control, the ANFIS based control, the ECMS and the EEMS. The state machine control, the rule based fuzzy logic strategy, the ECMS and the EEMS employ an approach that controls the battery SOC, and the rate of charge and discharge of the battery bank .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 2.1, into the ANFIS-based energy management strategy. The fuel efficiency is defined as the ratio between the fuel-cell output power and the fuel consumption . Moreover, the hydrogen consumption and the fuel-cell efficiency can be calculated as [26, 45]:

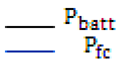
$$\text{Hydrogen Consumption} = \frac{N_{fc}}{F} \cdot \int_0^{t_{cycle}} i_{fc} dt \qquad (31)$$

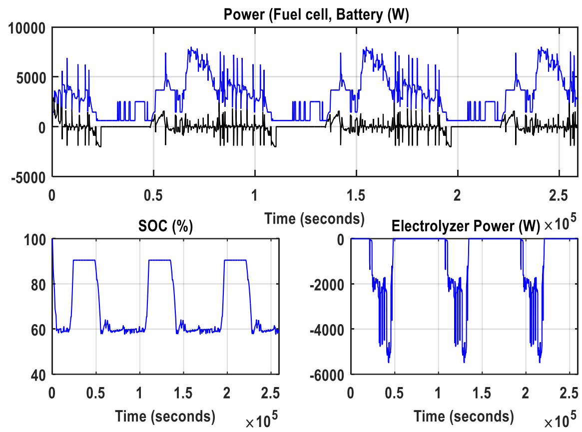
$$\eta_{fc}=\frac{V_{fc}}{1.48.\ N_{fc}}.\,(HHV.\,(\%)) \tag{10}$$

Where F is the Faraday's constant, t_{cycle} is the simulation time, and HHV (%) is the hydrogen higher heating value. Table 5 depicts the fuel efficiency, the fuel-cell average power, the fuel-cell efficiency, the battery SOC, and the fuel consumption for the PV/WT contribution and the load demand that is shown in Fig. 5.

3.2. Constant Loads

Tables 6, 7 and 8 describes the fuel efficiency, the fuel-cell average power, the fuel-cell efficiency, the battery SOC, and the fuel consumption for different battery SOCs for constant loads. For all the strategies, the numerical study is presented for different load demands and zero PV/WT power, because they are sensitive only to the energy demand shortage, except the rule based fuzzy logic control strategy and the ANFIS-based energy management strategy, for which the numerical study is done for constant PV/WT and load demands.





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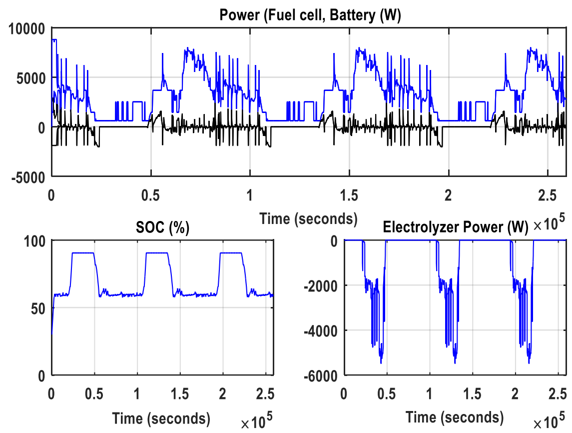

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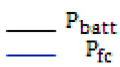
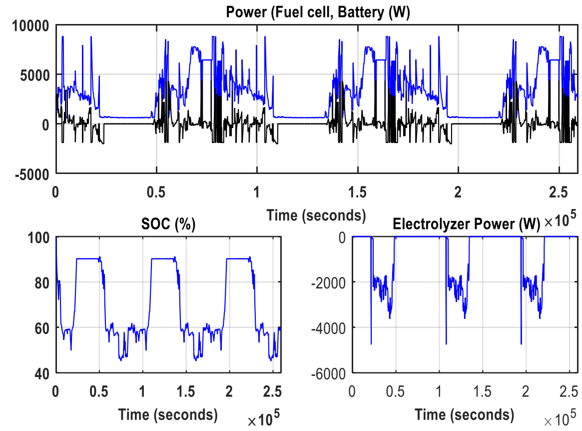
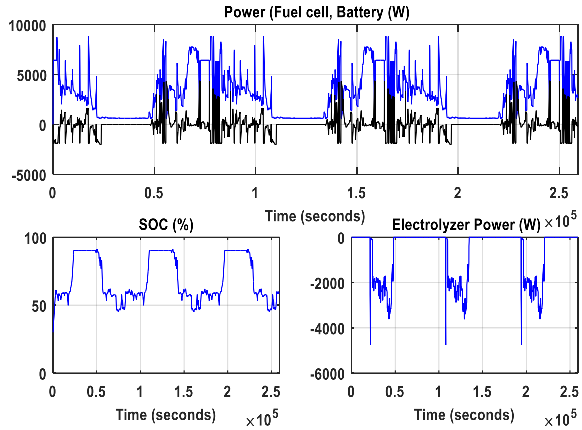


Fig. 7. Long term analysis of the rule based fuzzy logic control strategy (Fuel-cell / battery power, battery SOC). (a) SOC_{ini}=100%. (b) SOC_{ini}=30%.



(a)



(b)

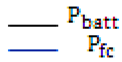
Fig. 8. Long term analysis of the ANFIS-based control strategy (Fuel-cell / battery power, battery SOC). (a) SOC_{ini}=100%. (b) SOC_{ini}=30%

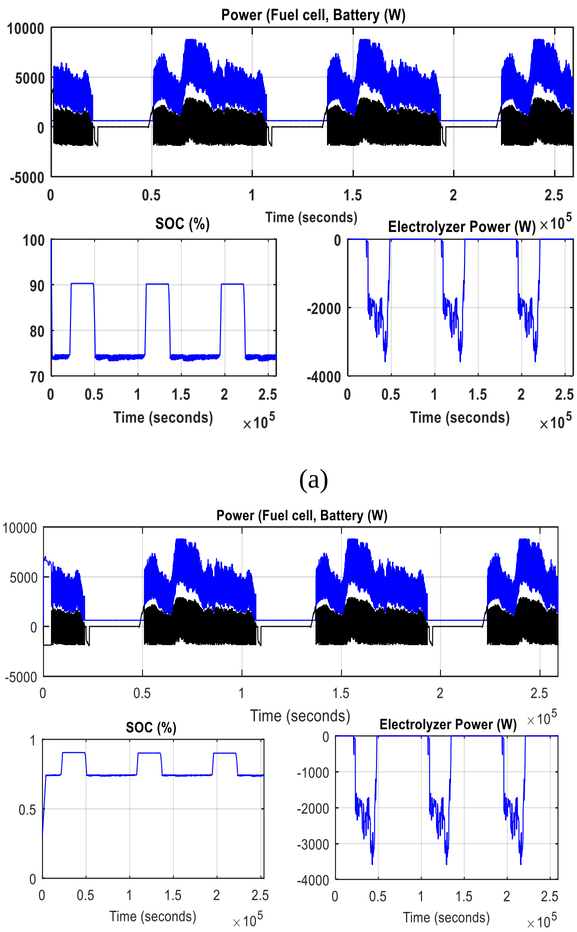
Thus, $P_{loadnet}$ is the net load power that must be provided with the fuel-cell and the battery bank. In all energy management strategies, as the demanded energy increases, the fuel-cell normally provides more energy and consumes more hydrogen. Additionally, the fuel-cell power increases in response to the battery SOC decrement, to charge the battery bank. If the PV and wind power are low and the load power is high, the support system and the energy storages must satisfy the load demand requirements. Employing the fuel-cell at the maximum power prevents the battery bank from charging, with its optimal charging power (50% capacity of the battery) when it's initial SOC is low (Table 5 and 6 for the load power of 10 kW when the battery SOC is low). Investigating tables 6 and 7, it can be derived that higher fuel (and fuel-cell) efficiency is achieved in the case of low load power and high battery SOCs. In other words, as the fuel-cell power increases, in response to the load power increment or the battery SOC decrement, the fuel (and fuel-cell) efficiency decreases. Consequently, operating the system at low battery SOCs is not economical, considering both the reduced battery life and lower fuel efficiency. Sensivity of the ECMS to $0.5(SOC_{Max}+SOC_{Min})$, is demonstrated in Table 6. The control strategy discharges the battery bank for higher SOCs (above 90%) and chrges it for low SOCs (below 50%), to keep it around $0.5(SOC_{Max} + SOC_{Min})$.

Table 8 shows the sensitivity study of the EEMS to the SOC_{min}. It is shown that for the SOCs above the SOC_{min}, the battery bank has higher priority than the fuel-cell for the load demand shortage provision. Hence, the fuel-cell supplies only the fraction of the load that is not provided by the PV/WT/battery bank. For the SOCs below the SOC_{min}, the fuel-cell, in addition to supplying the load demand shortage, is responsible of the battery bank charging. Finally, if the battery SOC equals the SOC_{min}, the fuel-cell only provides the load demand shortage. The PV.WT excess power, along the day, will recharge the battery bank to higher SOCs.

Table 5. Summary of the results obtained by Each Energy Management Strategy for long term analysis with initial SOC of 100%

Initial SOC	100%				
Indicator / EMS	$P_{fc\ avreage}$	Fuel (litre-gram)	Fuel-cell Efficiency (%)	Fuel Efficiency (joule/litre)	Final SOC (%)
Rule-based fuzzy logic	**2896.6**	**41280-3670.1**	**51.58**	**6062.7**	**59.07**
ECMS	**2966.9**	**44012-3913**	**51.38**	**5824.3**	**73.88**
State Machine Control	**2905.5**	**42307-3761.4**	**51.51**	**5935.8**	**59.63**
ANFIS-based Control	**2993.2**	**43850-3898.6**	**51.39**	**5897.6**	**59.23**

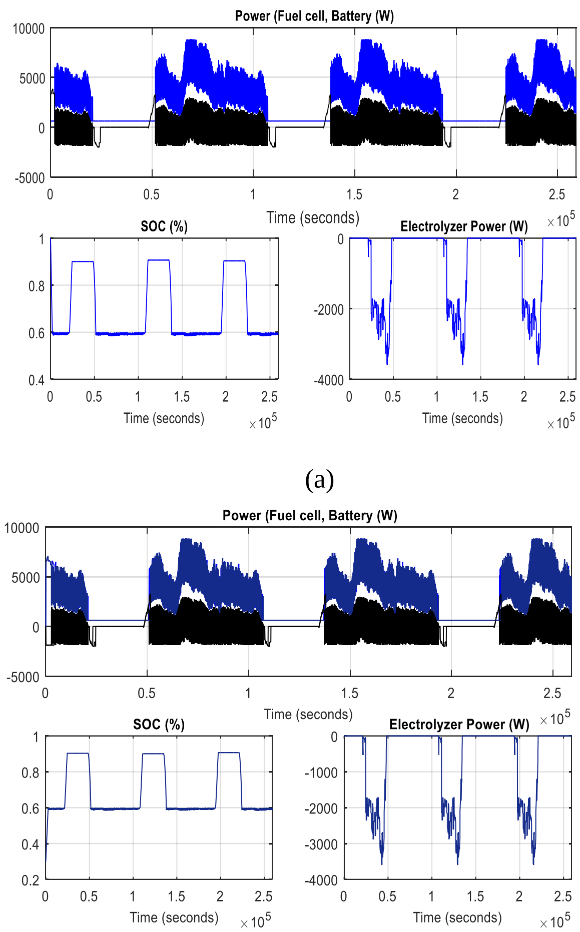




(a)

(b)

Fig. 9. Long term analysis of the ECMS (Fuel-cell / battery power, battery SOC). (a) SOC_{ini}=100%. (b) SOC_{ini}=30%.



(a)

(b)

Fig. 10. Long term analysis of the EEMS (Fuel-cell / battery power, battery SOC). (a) SOC_{ini}=100%. (b) SOC_{ini}=30%.

Table 6. Summary of the results obtained by State Machine Control and Rule-based fuzzy logic Strategy for Constant Loads.

	EMS	State Machine Control				Rule-based fuzzy logic Strategy			
SOC	$P_{loadnet}$ (KW) Indicator	1	4	7	10	1	4	7	10
95%	P_{fcave} (W)	549.34	1575.3	4440.4	7280.3	549.34	1395.6	3486.8	5861
	H_2cons (lit)	2.63	7.9	24.52	44.89	2.63	6.94	18.62	34.07
	η_{fc} (%)	61	58.5	54.76	51.27	61	59.02	55.97	53.07
	η_{fuel} (joule/litre)	6261.5	5985.3	5432.8	4865.1	6261.5	6030.4	5618.4	5161.1
	Final SOC (%)	94.93	94.58	94.56	94.53	94.93	94.55	94.38	94.26
75%	P_{fcave} (W)	549.34	2498.4	5351.8	8329.7	1395.6	3487.2	3486.9	5861.4
	H_2cons (lit)	2.63	12.92	30.52	54.11	6.94	18.62	18.62	34.07
	η_{fc} (%)	61	57.18	53.67	49.81	59.02	55.96	55.96	53.06
	η_{fuel} (joule/litre)	6261.5	5801.2	5260.3	4618.4	6030.4	5618.12	5618.4	5161
	Final SOC (%)	74.93	74.75	74.72	74.71	75.06	74.92	74.38	74.26
30%	P_{fcave} (W)	3087.8	6031.2	8329.6	8329.7	3091.5	5810.8	8326.9	8327.3
	H_2cons (lit)	16.32	35.32	54.11	54.11	16.34	33.72	54.08	54.08
	η_{fc} (%)	56.45	52.84	49.81	49.82	56.44	53.12	49.83	49.83
	η_{fuel} (joule/litre)	5679.3	5123.3	4618.4	4618.4	5670	5169.7	4619.2	4619.2
	Final SOC (%)	30.29	30.28	30.19	29.71	30.29	30.26	30.19	29.71

Table 7. Summary of the results obtained by ECMS and ANFIS-based Control for Constant Loads.

	EMS	ECMS				ANFIS-based Control			
SOC	$P_{loadnet}$ (kw) Indicator	1	4	7	10	1	4	7	10
95%	P_{fcave} (W)	549.34	549.34	2153.5	5010	549.34	549.34	4055.4	7481.5
	H_2cons (lit)	2.63	2.63	11.01	28.22	2.63	2.63	22.1	46.56
	η_{fc} (%)	61	61	57.64	54.08	61	61	55.22	51.02
	η_{fuel} (joule/litre)	6261.5	6261.5	5867.4	5325.9	6261.5	6261.5	5505.4	4828
	Final SOC (%)	94.39	94.39	94.19	94.18	94.93	94.39	94.49	94.06
75%	P_{fcave} (W)	549.34	1961.6	3394.3	5010	549.34	4650.2	5711.6	8327.2
	H_2cons (lit)	2.63	9.9658	18.07	28.22	2.63	25.86	33.01	54.08
	η_{fc} (%)	61	57.89	56.08	54.08	61	54.51	53.25	49.83
	η_{fuel} (joule/litre)	6261.5	5905.1	5635.3	5325.9	6261.5	5393.7	5190.4	4619.2
	Final SOC (%)	74.93	74.65	74.36	74.18	64.93	65.1	64.78	64.71
30%	P_{fcave} (W)	3087.8	6031.2	8329.6	8329.7	3071.6	6059.9	6059.1	8327.2
	H_2cons (lit)	16.31	35.32	54.11	54.11	16.23	35.54	35.53	54.08
	η_{fc} (%)	56.45	52.83	49.81	49.81	56.46	52.74	52.76	49.83
	η_{fuel} (joule/litre)	5697.2	5123.3	4618.4	4618.4	5676.3	5108.8	5115.7	4619.2
	Final SOC (%)	30.28	30.28	30.17	29.71	30.28	30.28	30.28	29.71

Table 8. Summary of the results obtained by EEMS for Constant Loads.

	EMS	EEMS			
SOC	$P_{loadnet}$ (W) Indicator	1	4	7	10
95%	P_{fcave} (kw)	549.35	549.35	2152.8	5008.7
	H_2cons (lit)	2.63	2.63	11	28.21
	η_{fc} (%)	61	61	57.64	54.09
	η_{fuel} (joule/litre)	6261.5	6261.6	5867.7	5326.3
	Final SOC (%)	94.96	94.44	94.16	94.17
%60	P_{fcave} (W)	796.36	3790.1	6798	8327
	H_2cons (lit)	3.88	20.68	41.4	54.08
	η_{fc} (%)	60.36	55.42	51.7	49.83
	η_{fuel} (joule/litre)	6157.8	5499	4924.6	4619.2
	Final SOC (%)	60	60	60	59.79
30%	P_{fcave} (W)	3088	6145	8326.8	8327
	H_2cons (lit)	16.29	36.12	54.08	54.08
	η_{fc} (%)	54.44	52.72	49.83	49.83
	η_{fuel} (joule/litre)	5686.9	5104.2	4619.2	4619.2
	Final SOC (%)	30.28	30.28	30.25	29.79

Summary

Current environmental and energy crisis push the electric utilities to satisfy the customers' energy needs using green power technologies. Hence renewable energy source penetration into the power system tends to increase rapidly. On the other hand, hybrid renewable energy systems, which consist more than one renewable energy source, become a practical alternative to rural electrification. Energy control system has an important role in the proper, cost effective, and efficient operation of hybrid renewable energy systems. This paper dealt with the energy control of a hybrid renewable system comprising two main green energy sources, one backup system, two storage banks, one electrolyzer pack, and the associated DC/DC converters. The energy management strategies investigated are the most commonly used ones, as follows: the state machine control, the rule-based fuzzy logic control, the ANFIS-based control strategy, the equivalent consumption minimization strategy (ECMS) and the external energy maximization strategy (EEMS). The state machine control strategy was used to generate the required data of the ANFIS-based control strategy. The state machine control and the rule-based fuzzy logic control design approach was based on the energy demand shortage and the battery bank protection from deep discharge and overcharge. Using the input/output data set, generated by state machine control, the ANFIS-based control strategy has a similar performance to the state machine control strategy. The simulation study showed the successful operation of all energy management strategies for different battery SOCs, while the PV / WT power and the load power were changing. Additionally, it was shown that the ECMS and the EEMS keeps the battery SOC around the "0.5 (SOC_{max}+ SOC_{min})" and the SOC_{min}, respectively. Finally, the design requirements such as the hydrogen consumption, the fuel efficiency, and the fuel-cell stack efficiency were compared in both strategies. The results showed that the EEMS provides lower fuel consumption, in comparison to the other energy control strategies.

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NOMENCLATURE

PV	Photovoltaic
P&O	Perturbation & Observation
Mppt	Maximum power point tracking
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)
I_{fc}	Fuel-cell current (A)
η_{fc}	Fuel-cell converter efficiency (%)
$I_{fc_{ref}}$	Fuel-cell reference current (A)
$V_{battnominal}$	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)
$P_{batt_{ref}}$	Battery reference power (W)
$P_{optdischarg}$	Battery discharge power (W)
I_{batt}	Battery current (A)
$I_{batt_{ref}}$	Battery reference current (A)
P_{batt}	Battery power (W)
P_{PV}	PV plant power (W)
T	Temperature
fc	Fuel-cell
L	Low
VL	Very low
M	Medium
H	High
R	Ideal gas constant
d	Molecular radius (m)
V_{fc}	Fuel-cell voltage (V)
$P_{fc\ avreage}$	Fuel-cell average power (W)
Ref	Reference