Electrical Energy Storage on the Hybrid Grid of Renewable Energy System Using Fuzzy Controller Optimization Algorithm

Parviz Ghoflghari*, Hossein Nasiraghdam
Department of Electrical Engineering, Ahar Branch, Islamic Azad University, Ahar, Iran,

Abstract

The main risks of arising from the using fossil fuels can be referred to environmental pollution, the effects of greenhouse gases, climate change and acid rain. For this reason, efficient use of energy in economic development has always been considered as an important goal of sustainable development. In this study, the effects of time-varying electricity prices in the energy storage components performance is examined for a HRES in network by settings FLC based on optimization. The modeling results indicate that the performance of energy storage devices on the network HRES strongly affected by the price of the electricity grid as well as applying the capacity of the FLC is essential for this kind of data. Optimized FLC results have shown better performance compared to non-optimized counterpart have with applied settings for both daily and weekly operating period. The findings of this study indicate that the FLC optimize is better when is used on the HRES network according to the forecast periods shorter, in other words, prediction short-term results will conducive to the best performance on more accurate prediction of the data and settings of FLC for more than one day.

Keywords: electric energy storage, hybrid networks, renewable energy, fuzzy controller optimization algorithm

1. Introduction

Consumption of fossil fuels such as oil and gas as energy sources prevailing in the country will be caused to provide irreparable damage to humanity. To the extent that excessive use of these resources will increases the amount of water vapor, carbon dioxide and toxic gases such as co and so2 [1]. With increasing amount of carbon dioxide into the atmosphere, the Earth's temperature increases.

A large amount of solar energy on shorter wavelengths, which can pass of the Earth's atmosphere and absorbed these pollutants, the earth appears thermal radiation when the earth takes the heat from sun, but the energy of the earth is in long wavelengths and is absorbed to carbon dioxide, this phenomenon will lead to the increasing temperature in the Earth's surface. The main risks of ascending from the applying fossil fuels can be referred to environmental pollution, the effects of greenhouse gases, climate change and acid rain. For this reason, efficient applying of energy

In economic development has always been considered as an important goal in sustainable development. The solar energy, wind energy and geothermal energy, etc. is recommended to avoid the impact of these disadvantages of renewable energy or the energies compatible with environment such as.

2. Materials and Methods

2.1 Shuffled Frog Leaping Algorithm

SFL algorithm is based on super innovative population has been designed to follow a global optimal solution by intelligent heuristic Search using a heuristic function. This is implemented in evolution of done behavioral patterns by global interaction and exchange of information among the population [2]. Although population-based evolutionary and genetic adhere to the same basic principles, they look to the degree that the variation mechanisms have been used for disseminating one member’s information of population to other different members. Population-based evolution is very flexible mechanism is. Ideas between all people in the population are transition while interactions are allowed only in genetic algorithm (GA) as a parenthesis.

Table 1 FLC rules to manage energy storage components performance for on-grid HRES

dp	SOC	Price	P_h	$P_{bi-conv}$
N	L	L	P	N
N	M	L	Z	N
N	H	L	Z	Z
N	L	H	P	Z
N	M	H	P	Z
N	H	H	Z	Z
Z	L	L	P	N
Z	M	L	Z	Z
Z	H	L	N	Z
Z	L	H	P	Z
Z	M	H	Z	Z
Z	H	H	P	P
P	L	L	Z	Z
P	M	L	N	Z
P	H	L	N	P
P	L	H	Z	Z
P	M	H	P	P
P	H	H	P	P

Pay attention to a group of leap-frog in a swamp. Swamp has a number of stones that frogs can move on it. The goal of these frogs is to find the stone with a maximum amount of food available as quickly as possible by improving behavioral patterns. Frogs can communicate with each other and can transfer their behavioral patterns (data transfer) to the other.

Improved results of behavior patterns are implemented only by adjusting the size of the mutation step in changing the position of frog. Leap Frog in the PSO algorithm is used as a tool local search and competition of ideas and information to move towards to global solution of leads Shuffled Complex Evolution algorithm as a parallel-local [3].

In these algorithms, unique frogs are very important and they are not considered as a host for memes and defined as an amemetic vector. Leap Frog's behavior improves and increases its performance towards the. Leap Frog is an extension of the process used in PSO. After a certain number of population-based evolutionary stages, the datum between meme complexes in a process caused to enhance the quality of memes, and then frogs transmitted from infected meme complex.

After the collision, the search is resumed for optimal solutions by using the information in independent meme complex. The local search process continues until a satisfactory convergence criterion happen [4, 5]. Convergence curve for PSO algorithm and leap-frog with 100 repeats has been shown in Fig 2.

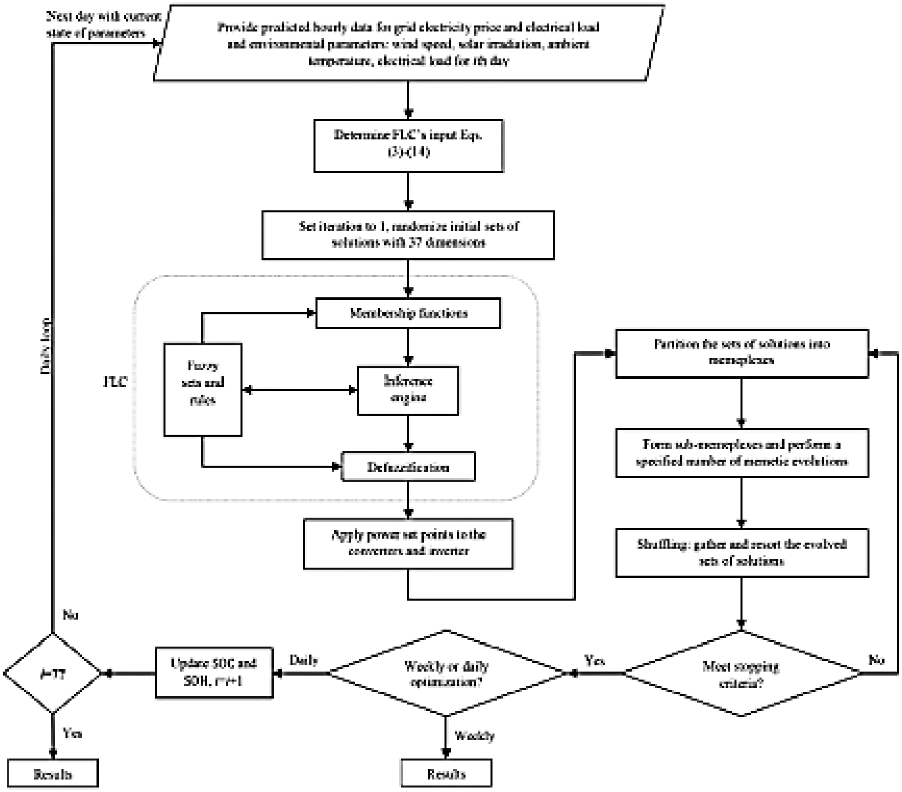

Fig. 1. Flowchart optimization method is designed in this study for FLC to manage performance energy storage components for on-grid HRES.

Table 2 characteristic parameters of SFL algorithm [3, 5]

Parameters	Specifications	amount
m	The number of meme complex	30
n	The number of frogs in the meme complex	17
q	The number of frogs in the submemplexes	9
N	The amount of memetic assessment before shuffling	17
d_{max}	The allowed- size amount	100

2.2 Statistical data for simulation

For the simulation, a set of data has been recorded for three weeks is divided into two parts. The first two weeks as historical data has been used for forecasting data for the third week. The second part is the actual data in the third week what has later been used to investigate the effects of FLC-optimize operational on-grid HRES forecast data. A set of data recorded as hours for grid electricity price and electricity and environmental parameters has been used to simulate on-grid HRES in Ontario, Canada [6, 7], as shown in fig 3, the winter wind speed is variation. Note that for better representation of performance of the FLC about the price of electricity network is shown in fig 3, defines three levels of pricing are used including high range (above $ 0.06), medium range (0.06 to $ 0.04) and low range (below $ 0.04) for later analysis FLC performance for various prices conditions (Fig 4).

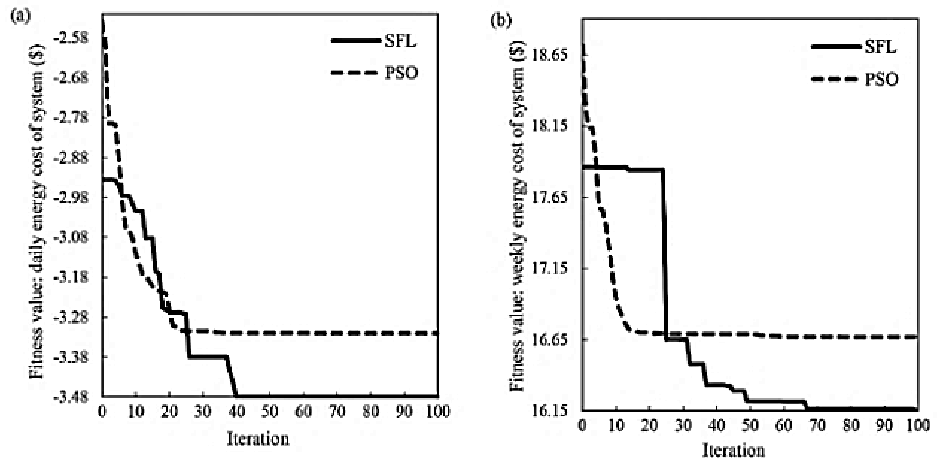

Fig. 2. Curve for the convergence of PSO and SFL algorithm: (a) day (forth-day) and (b) weekly downloads energy costs for on-grid HRES.

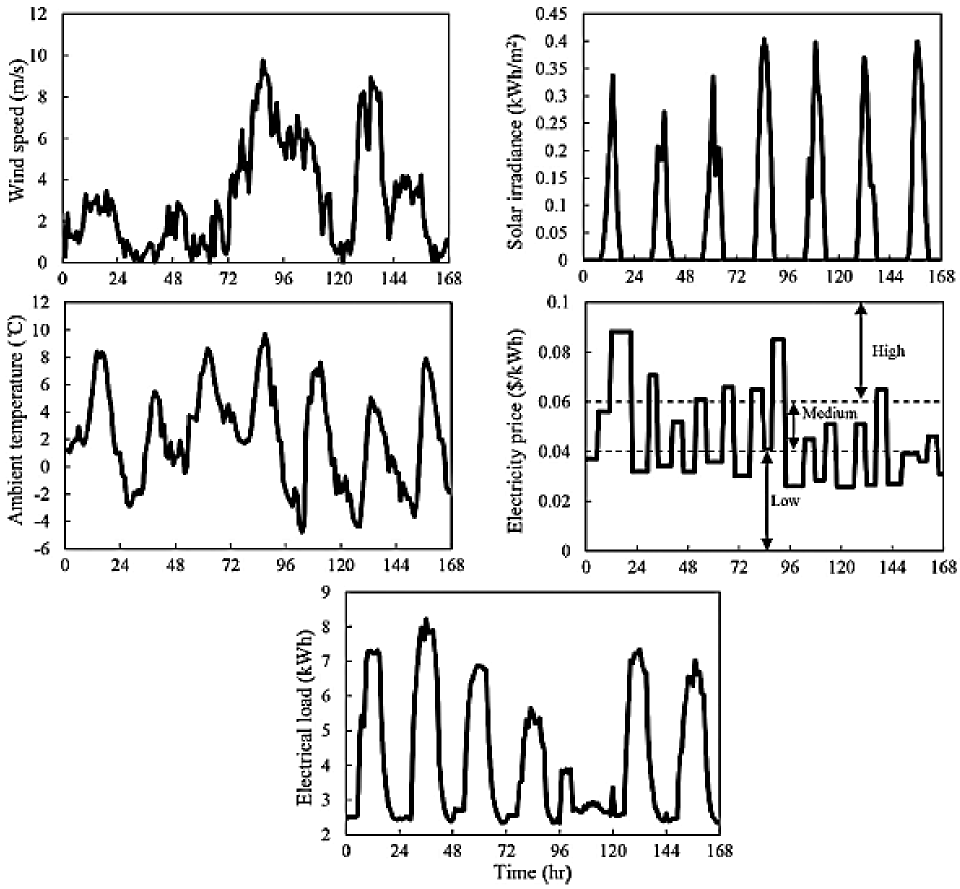

Fig 3. Hourly Data [8] will be logged for a week for environmental parameters such as wind speed, solar radiation and ambient temperature and the price of electricity grid [9] and electricity.

3. Results and Discussion

The simulation results for energy storage devices has been presented in Table 3 based on the network performance management HRES using the PSO algorithm and SFL algorithm in different states including non-optimized modes, weekly optimized and the daily optimized, HRES network is based on SFL algorithm.

Table 3. Comparing results of the simulation algorithm PSO; and SFL algorithm for FLC in conditions of non-optimized, weekly optimized and the daily optimized

State	Method	SOC Average (%)	$J_{EL}(kWh)$	$J_{Fc}(kWh)$	Weekly operational costs ($)
Non-optimized-FLC		53.38	82.04	25.39	18.64
Weekly optimized-FLC	PSO	57.05	42.87	23.15	16.67
	Leap Frog	58.33	40.65	22.73	16.16
daily optimized-FLC	PSO	62.40	38.23	22.11	15.51
	Leap Frog	62.88	20.83	20.83	14.34

It should be noted that 4th-day results have been selected and represents MF for use in daily FLC energy expenditure optimization. In all three non-optimized modes, weekly optimized and the daily optimized, HRES network is based on SFL algorithm presented in Table 4.

The total operational energy costs during the last 7 days for FLC in conditions of non-optimized, weekly optimized and the daily optimized was 18.64, 16.16, 14.34 dollars respectively.

As it stands, FLC in conditions of weekly optimized and the daily optimized has low costs, which are respectively 13.3% and 23% compared to non-optimized counterpart.

Table 4. Comparing energy costs for FLC daily HRES network FLC in conditions of non-optimized, weekly optimized and the daily optimized based on leap-frog.

Optimization mode	Day							
	1	2	3	4	5	6	7	Total
non-optimized	7.68	4.75	4.87	-2.67	0.55	-0.05	3.51	18.64
weekly optimized	7.22	4.21	4.57	-3.33	0.37	-0.12	3.22	16.16
daily optimized	6.84	4.19	4.54	-3.48	-0.30	-0.62	3.16	14.34

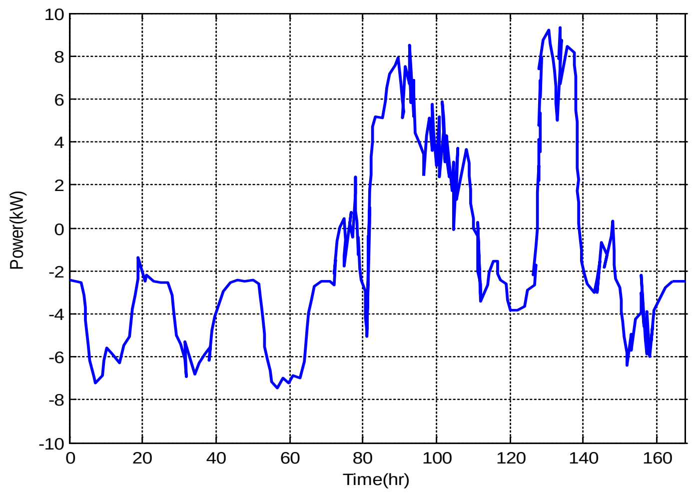

Fig 4. Net power inflow of grid-connected HRES for times: (+) for more power and (-) for lack of power.

Net power flow has been presented in fig. 4 for the operation grid and satisfying the electricity. For the first three days, you need to buy energy from the grid (net inflow of negative power) because in this time period of wind speed has been considered low. Then, with increasing wind speed, production of wind power increases and net power flow in the grid utilization would be increased and selling energy has been done to the grid or storage.

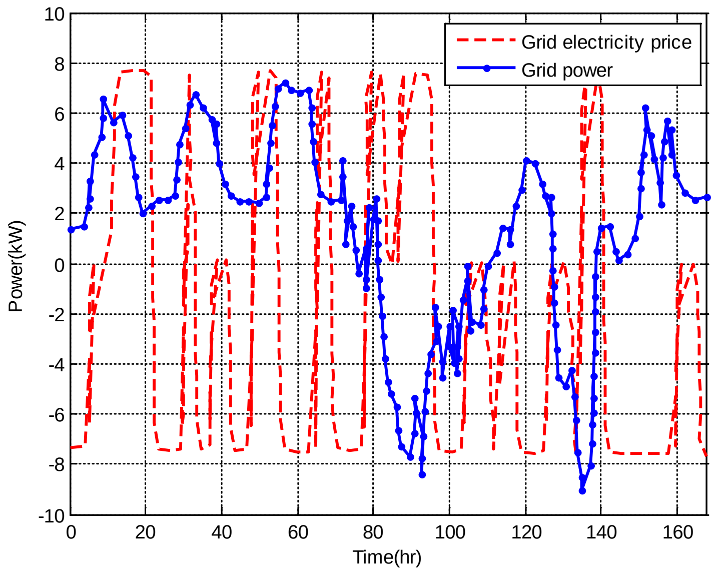

Fig. 5. The impact of network electricity prices in the exchange of FLC network daily optimized: (+) to purchase (-) to sale.

Fig. 5 shows price impact of the power grid in the exchange of FLC network daily optimized for 0-48 hours, To buy power from the grid in the range of medium and high price grid power is needed due to negative net power flow (Fig 4-3) and lack of energy stored in the hydrogen storage tank (Fig 9).

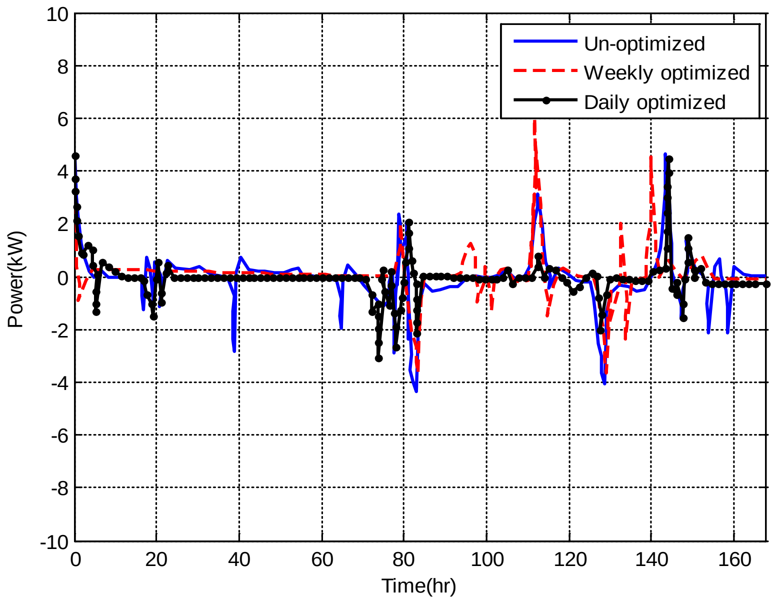

Fig. 6. Comparing operational performance of energy hourly storage management in connected-HRES network by FLC using stack battery power

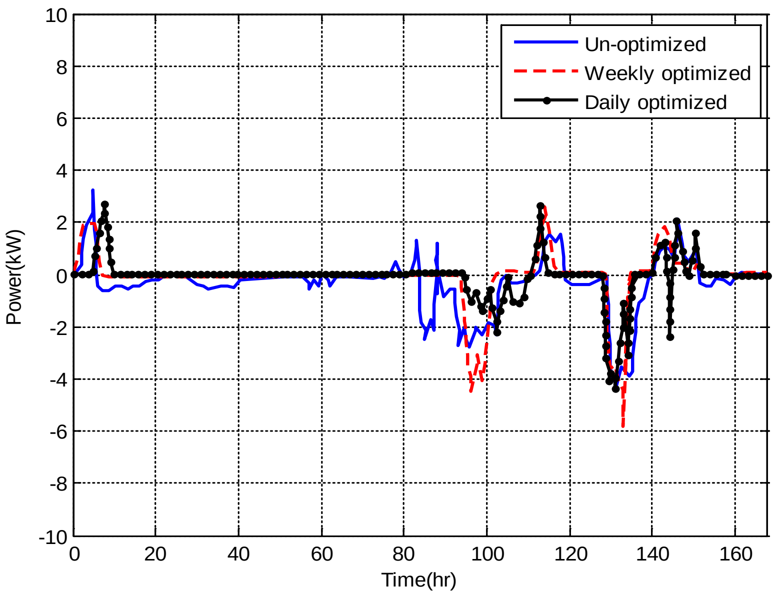

Fig. 7. Comparing operational performance of energy hourly storage management in connected-HRES network by FLC using fuel cell Power / electrolyzer

Implement hourly operational Profile on the HRES network for stack batteries and fuel cell / electrolyzer is shown in Fig. 6 to Fig. 10 in conditions of non-optimized, weekly optimized and the daily optimized.

As a result, compared with optimized FLC in conditions of non-optimized, weekly optimized and the daily optimized requires less operating time in battery stacks and fuel cell / electrolyzer, in other words, HRES network operating costs reduces (Table 2).

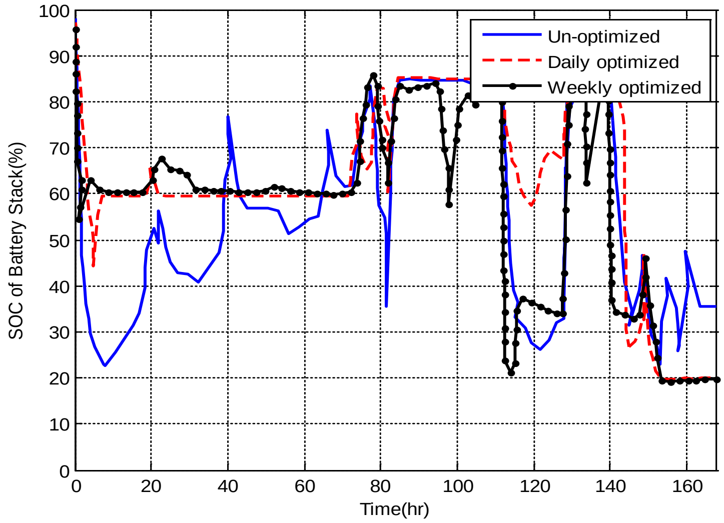

Fig. 8. Comparing operational performance of energy hourly storage management in connected-HRES network by FLC using SOC battery stack

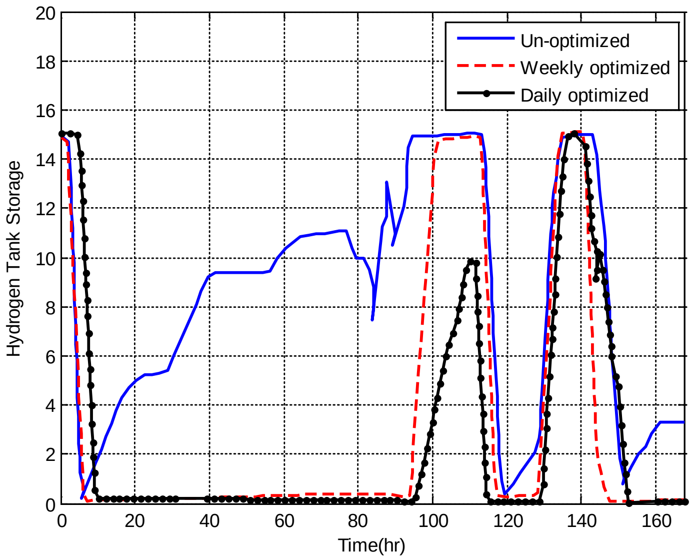

Fig. 9. comparing operational performance of energy hourly storage management by FLC in connected-HRES network in the level of hydrogen tank

To meet the needs of short-term storage, as shown in Fig. 9 is shown, the average value of SOC is higher than non-optimized control modes and weekly optimized in conditions FLC daily optimized; in other words, the average battery SOC stack for FLC, operational period of 7 days, respectively, is 53.38, 58.33, 62.88 percent in conditions of non-optimized, weekly optimized and the daily optimized. Fig. 9 represents a hydrogen reservoir storage level over 7 days has been optimized on HRES practical network FLC in conditions of non-optimized, weekly optimized and the daily optimized.

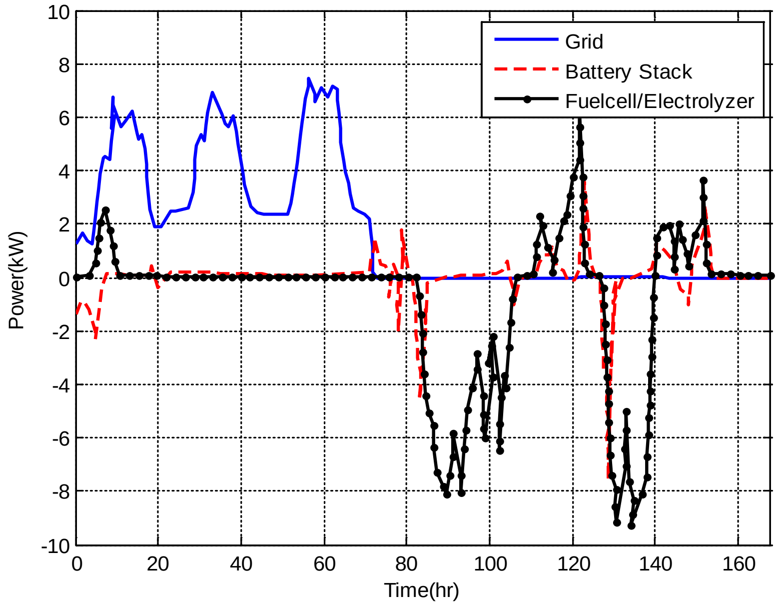

Fig. 10. the effect of network disconnect in the first 4 days for FLC in condition of daily optimized on power grid and power storage devices

When a network connection is created, it is usually due to weather conditions or other events occur, the operation of HRES network is converted to out of the network state (Independent of the network) and Fig. 10 shows hourly profiles of the operational performance on the HARES network with being independent in the beginning of the 4 day. While HARES network performance shown in Fig. 5 in the first three days is the same.

Disconnect network effects and be delivered in time by HRES is shown in Fig (4-10). It is observed that despite the fact that prior to disconnection of network storage would be done; there is no loss of power delivery and load fully provided by the HRES network, However, after the network disconnection, load demand has been unmet in the hour of 75, 80, 81, 124-127 where the system has been designed out of the network HRES and electricity shortages get severe during the last few hours on the seventh-day (152-168). Then, the SOC battery stack and the hydrogen storage levels are shown in fig. 12 and fig. 13, by disconnecting from the network.

After the network disconnection, the stored energy is the only source to meet the load and there is negative net power flow, fluctuations has become more severe in the performance of storage devices (72-168 hours) (Fig. 12 and Fig. 13) For Loss of Power Supply Probability (LPSP), In the event that it is possible that output is insufficient power supply, When HRES is not able to meet the demand in out of the network modes in [10], the optimal configuration is determined from HRES components. This configuration has been implemented based on the optimum size method presented in Reference [11]

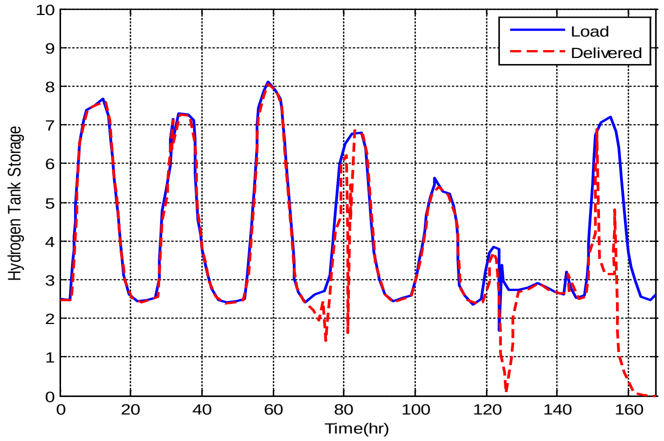

Fig. 11. on-grid and off-grid HRES performance at the start of 4 days with daily optimized by delivery power FLC (production, storage and purchasing) and load power

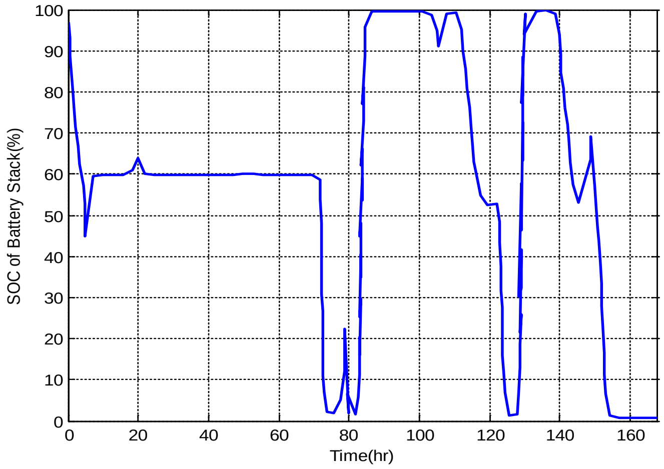

Fig. 12. The effect of network disconnect in the first 4 days for FLC in condition of daily optimized on the performance of HRES network storage devices in SOC battery stack

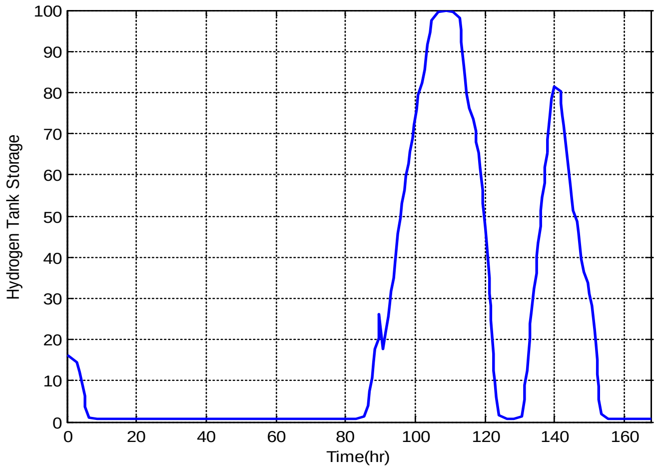

Fig. 13 the effect of network disconnect in the first 4 days for FLC in condition of daily optimized on the performance of HRES network storage devices on the network HRES hydrogen tank

Table 5 comparing the costs of HARES for on-grid and off-grid configuration with optimal size

Type	On-grid HRES	Off-grid HRES	Price / Unit
Wind Turbine	11kW	20kW	2500$/kW
PV array	6kW	10kW	6000$/kw
Fuel cell	8kW	10kw	3000$/kW
Electrolyzer	8kW	8kW	2000$/kW
Battery	10kWh	30kWh	200$/kWh
Hydrogen Tank	100kWh	130kWh	30$/kW
Converter	8kW	10kW	1000$/kW
HRES Price	116,500	175,900	

4. Conclusion

In this study, the implications of time-varying electricity prices based on the optimization are studied in the performance of energy storage components for HRES in a network by adjustments FLC. Leap Frog algorithm in order to optimize due to the better integration and lower operating costs, SFL algorithm compared to the algorithm PSO.

That is modeled for finding optimized-MF values in FLC based on the in data forecasting for the period of daily and weekly operations. FLC-optimized results have respectively shown better performance with applied settings for both daily and weekly operating period compared to non-optimized counterpart. Optimizing FLC is leading to less volatility than average of SOC battery, which directly affects the battery life. The findings of this study indicate that FLC Optimizing is better when is used on the HRES network based on the shorter forecasting periods, In other words, short-term results in more accurate prediction of expected data and regulation of FLC for more than one day will conducive to the best performance.

References:

[1] Hourly Electric Supply Charges, National Grid, http://www.nationalgridus.com/niagaramohawk/business/rates/5_hour_charge.asp, [accessed 08.06.13, 05.23.15].

[2] Environmental parameters data, Climate weather, http://climate.weather.gc.ca/index_e.html, [accessed 10.15.13, 05.23.15].

[3] R.C. Eberhart, Y. Shi, Particle swarm optimization: developments, applications and resources, in: Evolutionary Computation, 2001. Proceedings of the 2001 Congress on, IEEE, 2001.

[4] M.M. Eusuff, K.E. Lansey, Optimization of water distribution network design using the shuffled frog leaping algorithm, J. Water Resour. Plan. Manag. 129 (3) (2003) 210e225.

[5] Q. Duan, S. Sorooshian, V. Gupta, Effective and efficient global optimization for conceptual rainfall-runoff models, Water Resour. Res. 28 (4) (1992) 1015-1031.

[6] D.-H. Nguyen, T.-H. Huynh, A SFLA-based fuzzy controller for balancing a ball and beam system, in: Control, Automation, Robotics and Vision, 2008. ICARCV 2008. 10th International Conference on, IEEE, 2008.

[7] A.P. Engelbrecht, Computational Intelligence: An Introduction, John Wiley & Sons, 2007.

[8] H. Yang, W. Zhou, L. Lu, Z. Fang, Optimal sizing method for stand-alone hybrid solarewind system with LPSP technology by using genetic algorithm, Sol. Energy 82 (4) (2008) 354-367.

[9] D. Kothari, A. Ahmad, Fuzzy dynamic programming based optimal generator

maintenance scheduling incorporating load forecasting, in: Advances in Intelligent Systems, IOS Press, 1997.
[10] R.M. Hilloowala, A.M. Sharaf, A rule-based fuzzy logic controller for a PWM inverter in a stand alone wind energy conversion scheme, Industry Appl. IEEE Trans. 32 (1) (1996) 57-65.
[11] P. Bacher, H. Madsen, H.A. Nielsen, Online short-term solar power forecasting, Sol. Energy 83 (10) (2009) 1772-1783.