Management and Production Engineering Review
Volume 14 • Number 1 • March 2023 • pp. 127–136
DOI: 10.24425/mper.2023.145371

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A Robust Control Strategy for Microgrid Energy Using Fuzzy Logic

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Received: 01 June 2022
Accepted: 14 January 2023

Abstract
This paper highlights the storage charging and discharging issue. The study objective is to manage the energy inputs and outputs of the principal grid at the same time in order to maximize profit while decreasing costs, as well as to ensure the availability of energy according to demand and the decisions to either save or search for energy. A fuzzy logic control model is applied in MATLAB Simulink to deal with the system's uncertainties in scheduling the storage battery technology and the charging- discharging. The results proved that the fuzzy logic model has the potential to efficiently lower fluctuations and prolong the lifecycle.

Keywords
Energy control, Renewable energy sources, Fuzzy logic system, Microgrid, Storage system, Smart grid.

Introduction

With the increasing scarcity of fossil fuels (i.e. oil, gas, coal), the search for less energy dependence and the fight against greenhouse gas emissions, it is increasingly necessary to use renewable energy sources (RES), which, unlike fossil fuels, can regenerate at the same rate as which they are used. For this purpose, many countries intend to adapt the new MG (i.e. microgrid) concept. The MG system is a grid system powered by local RES, i.e. solar panels, to generate electricity for the building. The MG transmits not only energy, but also production and consumption status, along with storage data if required. Although each MG is connected directly to the network, in case of breakdown, some systems can operate in "island mode" standalone units (Meliani *et al.*, 2021). Figure 1 present the conceptual framework of an interconnected system. Along with power and heat generation, using mainly RES, these systems can store the energy in batteries for local distribution, the so-called energy storage systems (ESS). ESS systems are designed to save electricity during off peak periods and deliver it back during on peak periods.

The ESS's performance relies on its material, charge-to-discharge performance, sizing, power density, lifetime, power electronic interface, source type, and loads (Faisal *et al.*, 2018). Therefore, researchers are still attempting to select efficient ESSs and apply them to MGs. In comparison to other storage devices, Li-ion storage technology is becoming highly adopted. A series of research on Battery Energy Storage System (BESS) in MG applications have been conducted. Despite the fact that they exist a diver's storage devices, batteries have drawn interest of researchers for their maturity, control, and effectiveness. Their main benefit is their ability to operate as standalone storage or to be used as hybrid storage by including additional batteries or non-battery storage devices (Li *et al.*, 2016).

In general, the conventional charge-discharge controlling methods are related to complexities, charging cycle time, accuracy, high temperatures, and overcharge or self-discharge problems. As a way to overcome these problems, fuzzy logic systems to control the charge and discharge BESS devices were proposed from various researchers, among different other approaches. Table 1 summarizes the advantages and lim-

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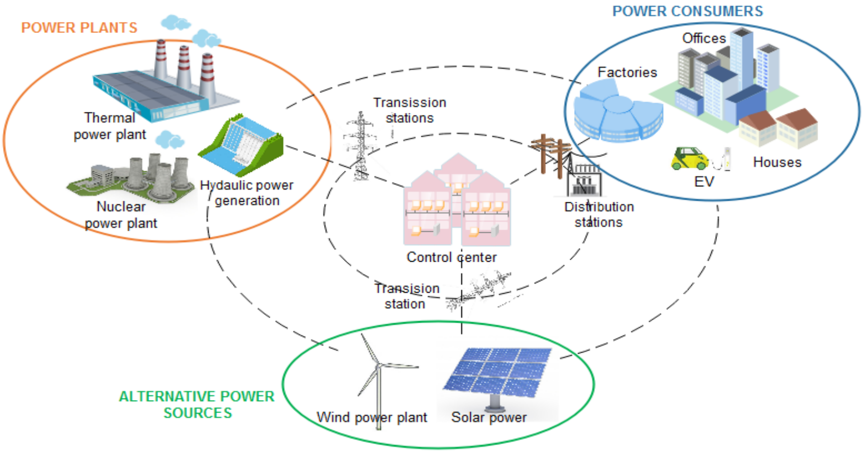

Fig. 1. Interconnected system concept

Table 1
Advantages and disadvantages of the most used approaches in the storage control field

	Avantages	Limitations
Rule based control – Fuzzy logic	Making decisions with uncertain information; Good robustness; Very effective in regulating both source and load variations for both voltage and frequency fluctuations.	Limited number of input usage variables; Long system run time; Lower accuracy.
Multi-agent system	Lower computational load on agents; Capacity to run multiple services in parallel; Independency of the programming language; Management and error control independent of the agents.	Need for robust communications; Restricted reliability for computational purposes.
Model predictive Control	Simple control policy for complex systems; Generic consideration of constraints; Generic consideration of complex control goals; Disturbance robustness.	Plant model is required; High computational load; High algorithmic complexity; High number of control parameters.
PSO (Particle Swarm Optimization)	Effective for non-linear optimization problem with multiple constraints on generator output power limits; Easy constraints; Good for multi-objective optimization.	Low quality solution; Needs memory to update velocity; Early convergence.
ARIMA (Autoregressive Integrated Moving Average)	Straight forward; Parametric and autoregressive model used for forecasting applications; General class of nonlinear model used for forecasting a regression model and developing a fit; High computational speed.	Need data linearization; Less accuracy with time series data; Presumed linear form of the related time-series; Includes complex data preprocessing; Hard to automate; Highly sensitive to outliers; Requires complex differentiation, and recording techniques for data linearization; Work only with stationary data.
ANN (Artificial Neural Network)	Can be easily automated; Able to identify non-linear relationships; Predictive power; Less restrictions and assumptions.	Low interpretability; Low scalability in handling large volumes of data; Requires large volumes of data.

itations of the most adapted approaches. The major benefit of the fuzzy logic controller (FLC) is that mathematical calculations are not needed, which allows easy implementation for battery charge-discharge control (Faisal *et al.*, 2019). It is inherently robust since it does not require precise, noise free inputs and can be programmed to fail safely if a feedback sensor quits or is destroyed. The fuzzy logic (FL) system is not limited to a few feedback inputs and one or two control outputs, and it does not require measurement or calculation of rate-of-change parameters for implementation. It also controls also the complex non-linear systems. This strategy permits the minimization of unnecessary consumption during storage before injection.

In Arcos-Aviles *et al.* (2018), a fuzzy-based BESS approach for controlling the SOC (state of charge) of battery is introduced, wherein its SOC limit was fixed between 50% and 100%. Another similar approach was followed by Martínez *et al.* (2018), in which twenty one fuzzy rules were employed in controlling the battery SOC over five membership functions (MFs). However, the limitation in this paper is considering the limit of the SOC from 0% to 100%, only the load control method was developed. Therefore, considering fuzzy inputs and outputs for battery charge and discharge control in MG applications remains a major challenge to bound the SOC from 20% to 80% of the operating range. Table 2 lists a brief overview of some research on battery charge and discharge control using the FLC. Based on the analysis above, an FL-based control system with Mandani type structure was considered, and inference, for MGs with batteries, which ensures the power balance according to the load demand, taking into account the improvement of the MG performance. Multiple constraints were considered, such as distributed generation optimization, priority, and real-time user consumption information. In order to address the challenge of controlling energy storage efficiently, and to optimise the energy consumption of an MG.

In this paper, the focus is only on Time To Decision (TTD) for injection shutdown and meanwhile storage activation. The model's objective is make the decision automatically whether to store the power generated by different RES waiting for injection by using fuzzy logic reasoning of fictitious load losses.

The aim of the proposed fuzzy inference system (FIS) is to lower the network fluctuations, and extend the battery life cycle through charge and dis-

Table 2
Researches on ESS charge and discharge controllers

Work	Objective	Features
	Controlling the charging and discharging with the FLC.	21 rules are performed from 5 MF of two inputs.
Martínez *et al.* (2018)	Controlling battery SOC in terms of secure limit.	SOC limits 50% to 100% using 72 kWh lead-acid battery bank. MF ZE is applied to maintain the battery SOC.
Cheng *et al.* (2018)	ESS charging control based on Fuzzy model.	The input of SOC is 0 to 100%. Only charging condition is fulfilled.
Moradi *et al.* (2015)	Minimize the MG optimal cost sizing while choosing the FLC operational strategy.	The optimization is based on PSO program. An integration of the RES to maximize the profit.
Viegas & da Costa (2021)	Fuzzy logic controllers for electric vehicle battery charging-discharging. A comparison of two fuzzy logic controllers and a meta-heuristic optimizing method.	The optimizing method adopted is annealing simulation. Off peak pricing, smart pricing, and peak pricing are the pricing approaches considered. Along with demand side management techniques.
Natsheh *et al.* (2013)	Managing energy flow with standalone hybrid power system	The authors used 3 MFs. For the inputs they consider PV power and load demand, and as output SOC. While for battery storage an S-R is used.
Faisal *et al.* (2020)	FLC for charging and discharging and scheduling the ESSs in an MG	FLC is optimized using PSO accounting the available power, load demand, battery temperature and SOC. 25 rules where performed.
Leonori *et al.* (2020)	Controlling the battery charging-discharging. life cycle and charging efficiency.	An MG energy management system based on genetic algorithms is defined for improving the ESS-grid power balance.

charge decision-making, depending on the RES and current state-of-charge (SOC) of the energy storage system. Section II presents the adopted MG, the characteristics and parameters of the RES considered (e.g. PV, wind turbine, battery). Section III describes the model proposed, the fuzzy logic system, its structure, and the rules adopted for the controller. Results and discussion of the simulation are outlined in Section IV. And section V, conclusion.

The adopted MG system

In this study, an MG was considered that includes distributed generators (e.g. diesel generators, fuel cells), RES (wind turbines, PV panels), local demand and storage batteries. The adopted MG, based in Fez, Morocco, is illustrated in Figure 2. Note that the MG is operating in main network connected mode. The system is made of 8 PV solar panels, 36 cells each, and the load varies between 4 kW. The PV panels are powered by a wind turbine due to weather conditions and to guarantee energy accessibility. Batteries are also integrated to store excess or provide energy during low RES production.

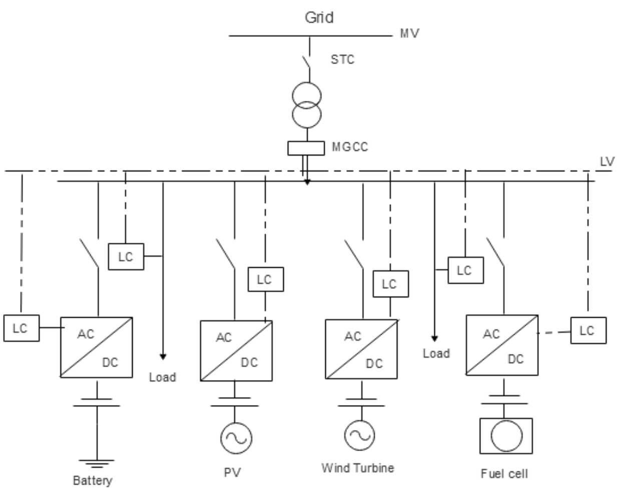

Fig. 2. The structure of the adopted MG system

PV panels

PV panels are based on photovoltaic cells (made out of crystalline silicon) that can transform sunlight into electric current (Meliani *et al.*, 2021). Nowadays, they are seen as the principal energy source. For PV power output calculation, the equation (1) is needed (Faisal & Koivo, 2011):

$$P_{\mathrm{PV}} = P_{\mathrm{STC}} \times (G_{\mathrm{ING}}/G_{\mathrm{STC}}) \times [1 + k(T_c - T_r)] \quad (1)$$

where PPV is the energy output of the module at irradiance GING, GINC is the incident irradiance, GSTC is the irradiance at STC, PSTC is the module maximum power at standard test conditions (STC), T_c is the cell temperature, k is the temperature coefficient of power, and T_r is the reference temperature. Operating temperature of solar PV cells is estimated using the equation (2) presented in Migan (2013):

$$T_c = T_{\mathrm{air}} + (NOCT - T_{\mathrm{soc}}) * G/G_{\mathrm{soc}} \quad (2)$$

T_{air} is the ambient temperature whereas NOCT is the rated operating cell temperature. G_{soc} and T_{soc} are the irradiance during standard operating conditions and ambient temperature, respectively. In this paper, the Solarex, MSX-83 is supposed to be employed (Solarex, Frederick, MD, USA). Its output features are represented in Table 3 (Solar Electric Supply, 2017).

Table 3
Characteristics of the output

Parameters	Value
P_{pv}, n Max power	83 W
Maximum voltage power	17.1 V
NOCT	47°C
G_{SOC}	800 W/m^2
G_{STC}	1000 W/m^2
Current at maximum power	4.85 A
T_{SOC}	20°C
T_{stc}	25°C
Approximate effect of temperature on power, k	0.5 %/°C

Wind turbine

The energy output generated from turbines may be characterized as a wind speed function that maybe calculated using the equation (3) (Vestas, 2017):

$$P_{\mathrm{wind}} = \begin{cases} 0 & U_Z \le U_{ci} \text{ or } U_Z > U_{co} \\ \dfrac{U_Z - U_d}{U_r - U_{ci}} \cdot P_t & U_{ci} \le U_Z \le U_r \\ P_t & U_r \le U_Z \le U_{co} \end{cases} \quad (3)$$

P_t and P_{wind} are the rated wind power of the turbine and the potential wind energy output, respectively. U_{ci}, U_r, U_Z, U_{co}, are the input wind speed, the rated wind speed, the wind speed at the hub height of Z, and the output wind speed of the wind turbine selected, respectively (Faisal *et al.*, 2020). All parameters used in the given equation (3) were chosen on basis of the V90-3.0 MW wind turbines manufactured by Vestas, they are listed in Table 4 (Vestas, 2017).

Table 4
Parameters of the V90-3.0 MW wind turbines

Parameter	Value
Z, Hub height	105 m
U_r	15 m/s
U_{ci}	3.5 m/s
U_{co}	25 m/s
P_t	3 MW

Storage system

Batteries provide a means of storing excess energy, once the demand for energy is satisfied, in case there is insufficient energy from the PV panels and the wind field for later use. The battery's SOC is characterized by its available capacity in percent. The following equation (4) can be used to calculate the SOC of a battery:

$$\mathrm{SOC} = C \times 100/C_{\mathrm{Ref}} \tag{4}$$

where C is battery capacity and C_{Ref} is the battery reference capacity. Based on size, efficiency ($> 90\%$), cost, capacity, storage lifetime and charging time (Graditi *et al.*, 2016).

Fuzzy logic-based charging and discharging model of batteries

Fuzzy logic is a general purpose logic, unlike Boolean logic, in which the truth variable values are real numbers from 0 to 1, instead of being true or false (Garcia-Gutierrez, 2021). Logic considers a variety of numerical factors to reach a suitable solution (Zadeh, 1965). Such formalization takes place by means of operations called fuzzy subsets which are characterized by a membership function μ as in equation (5), where V is a reference frame:

$$\mu : x \in V \to \mu(x) \in [0, 1] \tag{5}$$

The fuzzy logic method is widely applied in data processing, automation and computer science. The various characteristics of Boolean logic can be found in fuzzy logic, such as OR, AND, addition, etc. This approach helps in making decisions according to a certain rules that are predefined or learned, instead of numerical calculations. However, the input data must be represented in such a way that it retains its meaning while still allowing for manipulation before the rule base can be used (El Bourakadi *et al.*, 2020). Once the linguistic and fuzzy parameters are defined, the complete inference system can be considered as a fuzzy inference system development (El Bourakadi *et al.*, 2020). The application of this system in a controlling problem comprises many phases (Figure 3, presents the concept).

- Fuzzification engine: Converts the system inputs, clear numbers, into fuzzy sets. It classifies input signals to 5 stages (e.g. small, medium negative, large positive, large negative, medium positive). In general, input parameters are decided according to the user's requirements, while MFs are not limited in number.
- Inference engine: simulates the process of human rationality through fuzzy inferences on inputs and IF-THEN rules. The fuzzy output sets of each rule is aggregated into a single fuzzy output set.
- Defuzzification engine: Converts the fuzzy set generated by the inference engine into a crisp output. There are different defuzziication options, the common ones are centroid and average of maxima.

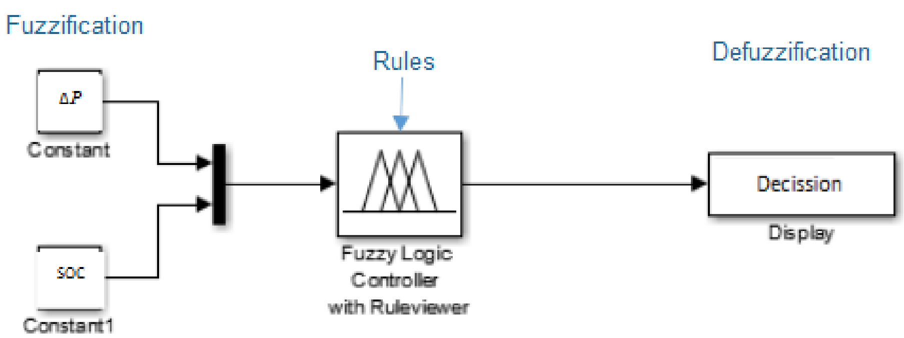

Fig. 3. Fuzzy logic concept

Fuzzy logic controller structure

In this paper, a FLC-based energy management controller is suggested to take a decision on the power sale or purchase from the main network and the charging-discharging of the batteries. To sum up, Figure 4 describes the different steps of the energy management strategy used to address the problem.

The Mamdani fuzzy inference system (FIS) is used in this research, while the battery SOC and the difference between the power generated by the RES and the demanded load (ΔP) are considered. Therefore, the inputs are ΔP and the SOC of batteries. The output is the decision I from among four options that should be used: take energy from the distributed network, discharge the batteries, charge the batteries, and feed the excess to the grid. In the safe operating zone between 20% and 80%, the battery will be charged or discharged based on the difference between the reference SOC and the current SOC, the load demand and the power availability of the grid and distributed sources. At 20% SOC, the battery will be charged permanently despite the load demand and the SOC will not cross the 80% maximum threshold. The FLC input, ΔP, which is the difference in power demand from the load PL and the overall available power PT from distributed sources and the grid, it can be found through the following equations (6) and (7):

$$\Delta P(t) = P_T(t) - P_L(t) \tag{6}$$

with

$$P_T(t) = P_{\mathrm{PV}}(t) + P_W(t) \tag{7}$$

where ΔP can either be positive (if the output of RE is higher than the load) or negative (if the load is higher than the RE output). For example, when ΔP is negative, it is necessary to complete the energy need from the grid or from batteries if the batteries are discharged.

In simulation, four functions represented ΔP first input: VS (Very Small), MS (Medium Small), ML (Medium Large), VL (Very Large). For SOC, five functions were supposed:

- VS (Very Small) from 0% to 30%;
- MS (Medium Small) from 25% to 35%;
- Normal (N) from 30% to 70%;
- ML (Medium Large) from 65% to 75%;
- VL (Very Large) from 75% to 100%.

The output decisions are represented by four functions: MGS (Microgrid Supply), DB (Discharge Batteries), CB (Charge Batteries), and SE (sell energy to the grid). Figure 6 shows the MFs that have been designed considering the MG and the power demand of the load.

There are 20 rules defined to simultaneously smooth the current for controlling the battery charge-discharge to realize the global charge-discharge controller strategy, because there are four functions representing ΔP and five representing the SOC. Table 5 represents the controller conditions. The decisions in

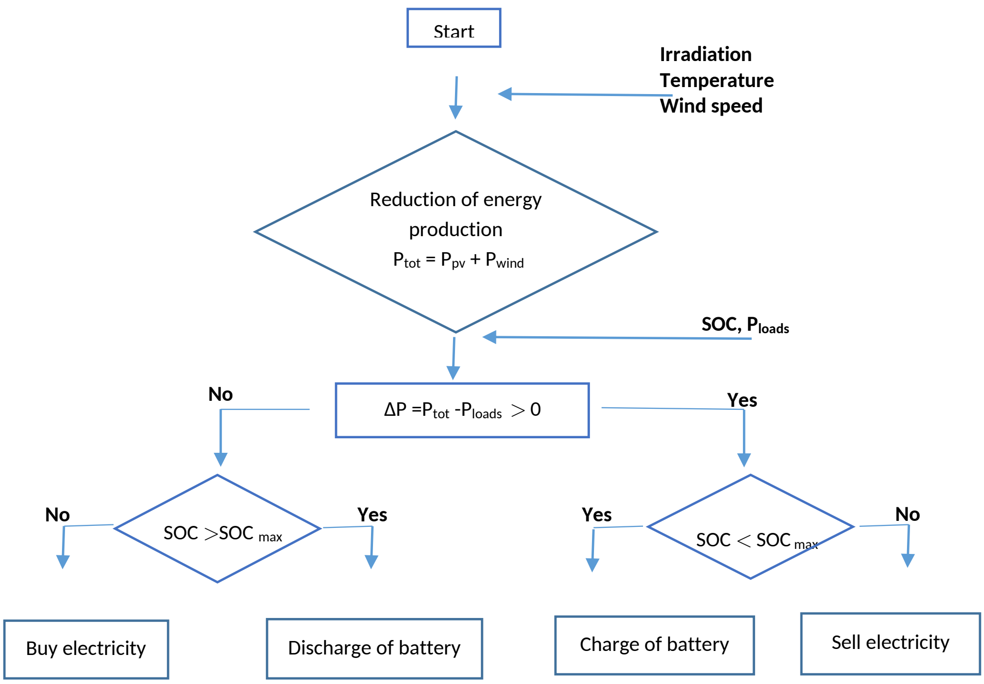

Fig. 4. Flowchart proposed

Table 5
Rules of the fuzzy controller

Decision		ΔP			
		VS	MS	ML	VL
SOC	VS	VS	VS	VS	VS
	MS	VS	VS	ML	ML
	N	MS	MS	ML	ML
	ML	MS	MS	ML	VL
	VL	N	N	ML	VL

each mix were selected to ensure proper use of batteries by guaranteeing no $< 20\%$ discharged or $> 80\%$ charged batteries. Table 6 summarizes these rules. However, the purpose behind setting up the rules as a matrix is making the operating point closer to the maximum power point with less fluctuation while raising or lowering the usage rate based on which direction the maximum peak occurs.

Table 6
Presentation of the rules block on fuzzy system

1. If (SOC is VS) & (ΔP is VS) then (Decision is MGS)
2. If (SOC is VS) & (ΔP is MS) then (Decision is MGS)
3. If (SOC is VS) & (ΔP is ML) then (Decision is CB)
4. If (SOC is VS) & (ΔP is VL) then (Decision is CB)
5. If (SOC is MS) & (ΔP is VS) then (Decision is MGS)
6. If (SOC is MS) & (ΔP is MS) then (Decision is DB)
7. If (SOC is MS) & (ΔP is ML) then (Decision is CB)
8. If (SOC is MS) & (ΔP is VL) then (Decision is CB)
9. If (SOC is N) & (ΔP is VS) then (Decision is DB)
10. If (SOC is N) &(ΔP is MS) then (Decision is DB)
11. If (SOC is N) & (ΔP is ML) then (Decision is CB)
12. If (SOC is N) & (ΔP is VL) then (Decision is CB)
13. If (SOC is ML) & (ΔP is VS) then (Decision is DB)
14. If (SOC is ML) & (ΔP is MS) then (Decision is DB)
15. If (SOC is ML) & (ΔP is ML) then (Decision is CB)
16. If (SOC is ML) & (ΔP is VL) then (Decision is SE)
17. If (SOC is VL) & (ΔP is VS) then (Decision is DB)
18. If (SOC is VL) & (ΔP is MS) then (Decision is DB)
19. If (SOC is VL) & (ΔP is ML) then (Decision is SE)
20. If (SOC is VL) & (ΔP is VL) then (Decision is SE)

According to the analysis, when there isn't enough total energy from RES to supply the load, the battery needs to switch to discharge mode. However, when the load demand decreases below the available energy, then the battery can switch to charge mode. Thus, according to Table 6 the fuzzy rules are explained as follow:

Rule 1: If (SOC is VS) and (ΔP is VS) then (Decision is MGS): This means that if the SOC is low and the load demand is low, then power should be taken from the main grid.

Rule 8: If (SOC is MS) and (ΔP is VL) then (Decision is CB): Meaning that if the SOC is small medium to be discharged and the load demand is very high, then the battery can work in charge or discharge mode.

Rule 20: If (SOC is VL) and (ΔP is VL) then (Decision is SE): Meaning that if both SOC and ΔP are very large, and the battery is already overcharged, then the excess of energy will be sold to the main distributed network.

According to the rules, when the SOC is below the limit, the battery will be on mode charge and will prevent overcharging. But if the battery is full, it would not accept the load to protect the overcharge. However, if ΔP is Large Positive, there is a large excess of energy. So, it is better to sell the surplus energy because if the batteries are charged, the limit can be exceeded ($> 80\%$).

Simulation and results

In this section, the results and discussion of the numerical analyses are presented. First, the curve results are shown, and then the FIS performance is discussed. For the input parameters ΔP and SOC, an actual weather data of wind speed, temperature, and irradiation of the FEZ city were used. For load demand profile, the data of Aghajani & Yousefi (2019) was used. The forecasting study was based on time series model, with the help of Zaitun Time Series software, and the following profiles are chosen (see Figure 5): the PV power profile and the wind power profile, of one summer and one winter day.

Each row of plots represents one rule in total there is 20. If power should be taken from the values will change and generate a new output response. If the example in Figure 6 is considered, the SOC is around 28.5% which is in the area of medium low, while ΔP is in the very small rang with a value of 28.1%, so as a result in this case, power must be taken from the grid. The line in the output plot provides a defuzzified value, the decision value in this example equals to 0.623. The graph at the bottom right illustrates how the output of every rule is combined to get an aggregated output, and then defuzzified. The model treats all the possibilities with all different rules that were set, and collects all plot results in a 3D surface as shown in Figure 6.

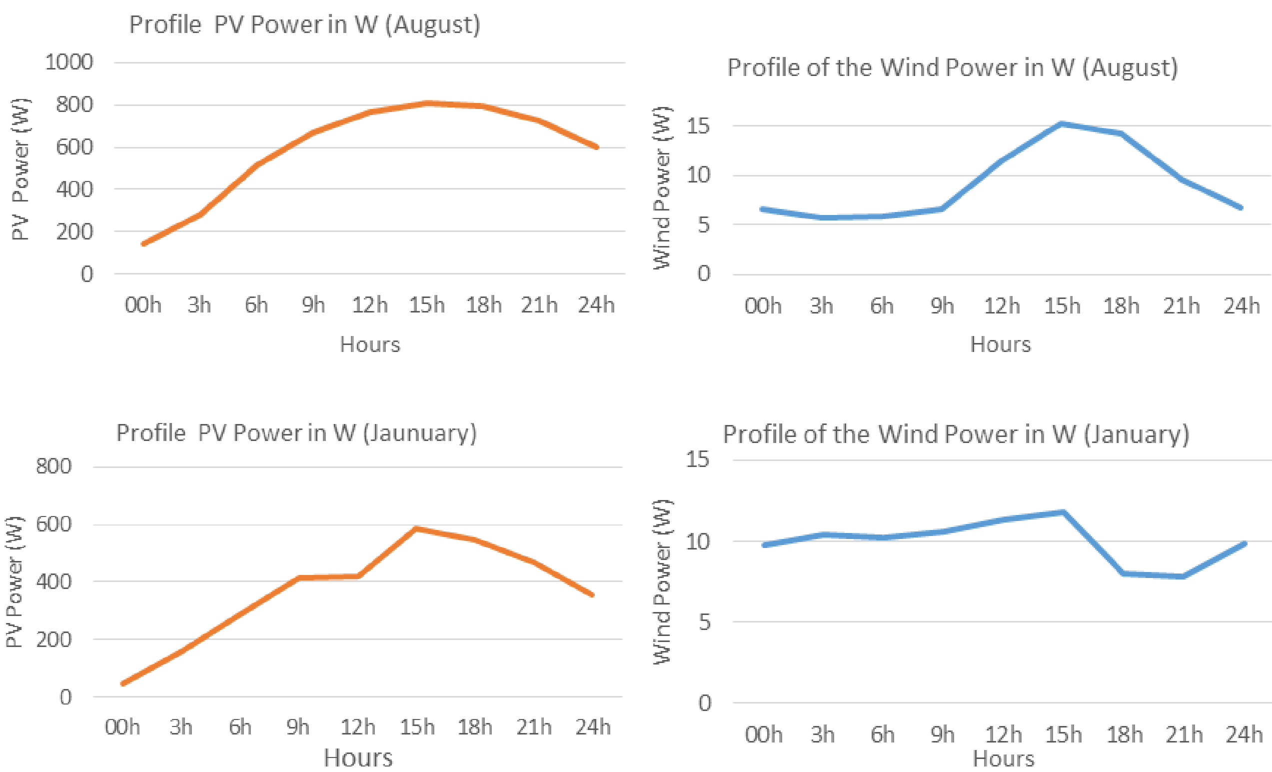

Fig. 5. Representation of the profile of: the load demand, temperature, solar irradiance, and wind speed

Fig. 6. The fuzzy rule viewerinterface from MATLAB

The computation of fuzzy control action signal includes multiple steps. Those steps can be mixed together, given different inputs, in order to create the rule's visualization surface or control surface, since the system has two inputs (ΔP and SOC) and one output I. Figure 7, represent the FIS 3D surface current with variation of SOC and ΔP, simulated by Matlab. This interface's shape demonstrates the way the output values vary with any combination of the two input values. In addition, this shows the surface of how the output is varied with different variations of the error and error change values.

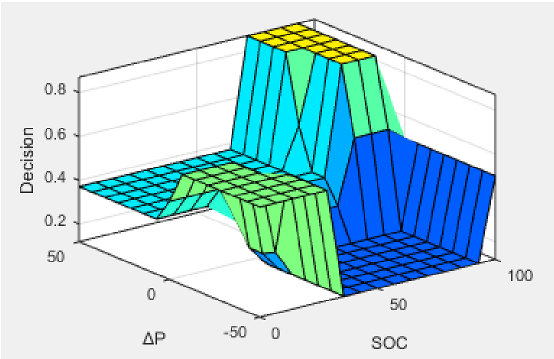

Fig. 7. The 3D FIS surface inference systems

Conclusions

In this study the MG is supported by RES (i.e. PV and wind turbine) combined together to enhance the system efficiency. For this systema batteries for storage unit are suggested. The power generated by the RES were forecasted using the Zaitun Time Series software. Then, the FLC technique is applied to make a decision out of four options to match the economic objectives and to minimize the cost and benefit ratio. The obtained results of the simulation were quite favorable. Employing the FLC for decision making has provided a better capability for controlling different operations to get the maximum profit and a minimalcost. The maximum discharge rate and maximum battery SOC have been taken into account for correct usage.

Therefore, our main objective in this research is to enhance the BESS performance and thereby to provide the MG with reliable operation through an adequate control over battery's SOC. The fuzzy optimized model considered with two main entries 20 rules (ΔP and SOC) and one output (Decision I). The obtained results prove that the controller works with a designed mechanism to either charge or discharge the battery. The model developed is not dependent on any mathematical features, and it may be easily implemented in any DC system with multiple devices with only output power and minimum alternating current constraints under suitable rules. However, the discharge setting rules must be properly defined based on the DC loads and power sources available.

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