# Energy Management System for a Stand-Alone Multi-Source Grid Wind Turbine / PV/ BESS/ HESS/ Gas Turbine/ Electric Vehicle Using Genetic Algorithm

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**Abstract-** One of the most important goals of smart grids is the ability to improve grid situational awareness and enable rapid changes in energy production, because renewable sources are intermittent and depend on non-controllable operating conditions. An energy management system (EMS) is then needed, particularly when multiple resources are involved, to achieve the best allocation of energy and to optimize the efficiency of systems, energy production and storage components. This work proposes an EMS for distributed generation (DG) in an AC island microgrid. The suggested microgrid (MG) consists of a fuel cell, an electrolyzer, a hydrogen tank, a wind turbine, a gas turbine, a battery energy storage system, a load, and an electric vehicle. A new energy management strategy based on genetic algorithm (GA) was proposed, another fuzzy logic strategy was also proposed in order to compare the results with those of GA-based management. The specificity of this work consists in taking into account the ageing of the batteries in the optimization process as well as the operating cost of the different elements of the studied microgrid, complicated hybrid system composed of several storage and generation elements, which has not been studied before. The simulation results show that the proposed strategy, based on the genetic algorithm, is able to reduce the cash flow of the system, while finding the best power distribution between the different elements that compose the hybrid energy system (HES) and ensuring, despite the strong variations of the produced energy, the electrical energy needs of the load. The proposed algorithm is also able to minimize the use of storage elements and extend the life of the HES.

**Keywords** Battery Energy Storage System; Genetic algorithm; Hybrid Energy System; Renewable Energy Sources; Hydrogen Energy Storage System; Distributed Energy Resources; Fuzzy Logic Control.

## 1. Introduction

In recent years, the idea of using microgrids in the distribution of electrical energy has attracted great interest, as they have a high capacity to foster and enhance the integration of the renewable energy sources. In addition, they allow for improved power quality and improved system efficiency. Distributed energy resources provide consumers with a flexible scale of energy use, the electrical system must be transformed into small and integrated distributed energy systems.

Micro-grids are now recognized as a critical factor in transitioning to more intelligent and greener power systems. Because renewable sources are intermittent and are dependent on non-controllable operating conditions, an EMS is necessary, particularly when there are many resources, to ensure the best power flow between the various elements of the HES, meeting the demand of the load at all times, and minimizing the system's cash flow.

Several management strategies have been discussed in the literature and vary depending on the composition of the HES and its objectives. Energy management systems have been developed on three bases: either mathematical models, human expertise or simulations [1]. For example, a rule-based method was proposed in [2], the optimization process depends on predefined rules and constraints are respected, but optimization is not necessarily ensured. In [3, 4], the previously described strategy was enhanced by introducing a fuzzy logic controller which evaluates the rules to apply in the strategy. Examples of predictive EMS have been presented in [5, 6, 7, 8]. The predictive EMS has been proposed to optimize system costs. However, it is necessary to commit and allocate units performing activities, a priori to improve the robustness of the microgrid. A dynamic programming has been used in [9, 10] for optimizing power management. The obtained results confirm the efficiency of this approach. Both linear and integer linear programming were used in [11, 12], for finding the optimal power flow in the system. These methods provide satisfactory performance. However, its principal disadvantage is the necessity of using a mathematical problem solver. In [13, 14], the optimal energy management for a hybrid energy system composed of PV/battery/electric vehicle is achieved with quadratic programming. This approach provides satisfactory performance. However, its application is restricted to convex objective functions. A genetic algorithm is used in [15] for optimal sizing of units, in an isolated microgrid, considering emission reduction and maximizing renewable energy penetration. A predictive building EMS based on mixed integer quadratic programming was proposed in [16], to optimize cost. However, RESs were not used. An energy management based on quadratic programming was proposed in [17], the problem was formulated in a relaxed form by the Lagrange multiplier. But this method generally requires more simplifications of the problem and a convex or concave objective function.

In this work, we have proposed two predictive energy management strategies with the objective of optimizing energy performance and minimizing system operating costs. The first predictive strategy, for energy management, proposed is the one using genetic algorithms, based on nature's reproduction phenomena that implement crossover, mutation and selection and allow, through appropriate coding, to find good solutions to complex optimization problems in a limited time. The second strategy is the one based on rules, that guarantees the respect of the imposed constraints but presents certain limits which we will expose. The two methods will be evaluated and compared mainly in terms of energy and economic performance criteria.

The main objective of this study is to optimize system operating costs and improve energy management while maintaining a balance between energy production and consumption and ideal operating conditions.

In this paper, the microgrid configuration is presented in Section 2. Methodology is discussed in Section 3. Energy management strategy using genetic algorithm is presented in Section 4. Fuzzy logic strategy is described in Section 5. Results and discussion are presented in Section 6. Finally, the paper is concluded in the final section.

## 2. Microgrid Configuration

The studied microgrid is comprised of PV and wind turbine generator, gas turbine, BESS, load, electric vehicle and HESS, as presented in Fig.1:

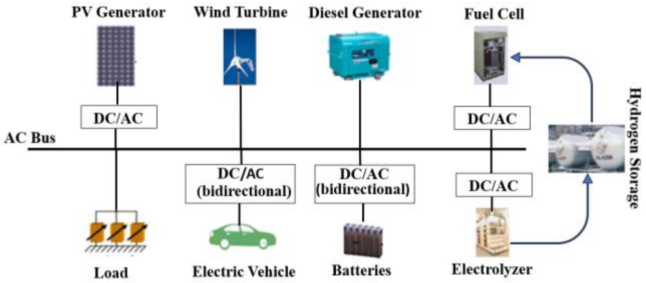



**Fig. 1**. The topology of the considered MG.

### *2.1 Battery Energy Storage System (BESS)*

The BESS discharges only when the generation from RESs is not sufficient to power the load, according to the Battery's State Of Charge (SOC), and is recharged only from PV and wind sources, when generation is in excess [9, 21].

The SOC is calculated by Eq. (1):

$$\mathrm{SOC(t)} = \frac{C_{batt}(t)}{C_{batt}^{ref}} \quad (1)$$

Where $C_{batt}(t)$ is the capacity of the Battery at time t and $C_{batt}^{ref}$ is the reference capacity.

The SOC of the batteries, at time t, can also be calculated using Eq. (2):

$$\mathrm{SOC(t)} = \mathrm{SOC(t-1)}\,\frac{P_{PV}(t) + P_{wt}(t) - P_{load}(t)}{C_{batt}^{ref}} \times \Delta t \quad (2)$$

With :

$P_{wt}$: The wind turbine power.
$P_{pv}$: The PV generator power.
$P_{load}$: The load power.

### *2.2 Wind Turbine Generator*

The calculation of the wind energy is given by equation (3):

$$E_k = 0{,}5 \times m \times v^2 \quad (3)$$

The power delivered to the turbine rotor from the wind will be deduced from Eq. (4):

$$P_{wt} = \frac{1}{2} \times k_m \times (v^2 - v_0^2) \quad (4)$$

Where:

v and $v_o$ are respectively the wind speed before and after the turbine.

$$k_m = \rho \times A \times \frac{v + v_0}{2} \quad (5)$$

The power of the turbine is finally obtained by equation (6). [19, 20]:

$$P_{wt} = \frac{1}{2} \times \rho \times A \times v^3 \times C_p \quad (6)$$

$C_p$ is the rotor coefficient.

Figure 2 illustrates the wind power profile produced for 24H.

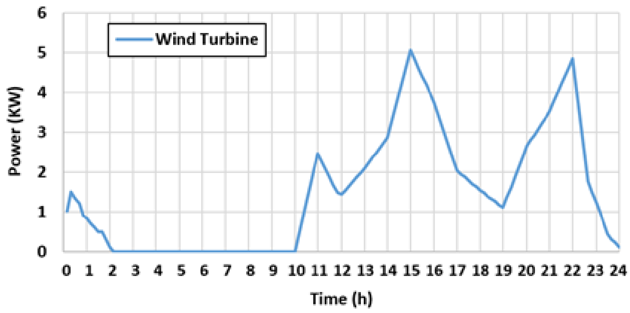



**Fig. 2.** Wind generation hourly data.

### 2.3 Photovoltaic System

The photovoltaic power calculation is mainly performed using a simplified solar panel model, which is an electrical circuit equivalent to a diode of photovoltaic cells and that mainly considers the solar radiation Gin (in W/m²), the ambient temperature T (in °C) and the different characteristics of the panels considered, as given by Eq. (7) [18].

$$P_{pv}(G_{in}, T) = N_{pv} \frac{G_{in}}{G^R}\left(P_{pv,max} + \eta_{p,max}\left(T + G_{in}\frac{NOCT - 20}{800} - T_j^R\right)\right) \quad (7)$$

Where:

$N_{pv}$ : Number of; PV modules.
$G^R$ : Solar irradiation reference [W/m²].
$\eta_{p,max}$ : Power variation with temperature [W /°C].
NOCT : Normal operating temperature of the cell [C].
$T_j^R$ : Module temperature at standard conditions [°C].

The solar inverter efficiency is supposed equal to 1. The PV generation curve is shown in Fig.3:

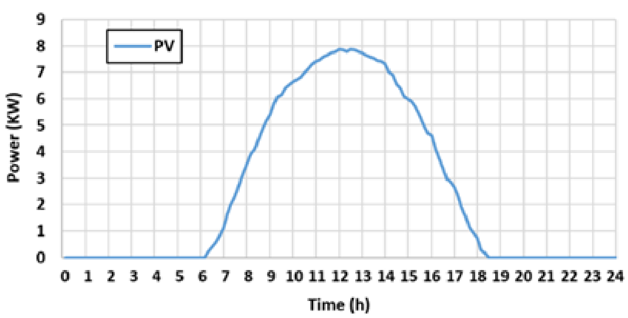



**Fig. 3.** Hourly production data of the PV generator.

### 2.4 Load

Figure 4 shows the daily load curve for a 9-person household:

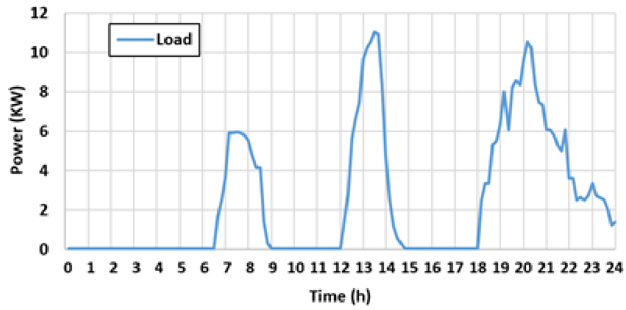



**Fig. 4.** The daily load power.

The maximum daily power demand of the load is 11.2 kW.

### 2.5 Gas Turbine

The gas turbine is composed of a synchronous machine with permanent magnets supplying AC current and a power conditioner system. It is used to supply the needed energy in case of insufficiency of the energy supplied by the RESs or the storage systems. The gas turbine should not be used for generation of less than 50% and greater that 90% of its nominal power ($P_{gt,nom}$), for reasons of its efficiency [21]. As shown by the Eq. (8):

$$0.5 \times P_{gt,nom} \le P_{gt}(t) \le 0.9 \times P_{gt,nom} \quad (8)$$

A simplified first order linear model to model the electrical energy generated by the gas turbine, with a 10 seconds response time, was used. Eq. (9):

$$P_{gt}(t) = \frac{1}{1 + \frac{\tau_{gt}}{3}} \times P_{gt,nom} \quad (9)$$

$P_{gt}$ is the power generated by the gas turbine, $P_{gt,nom}$ is the nominal power.

### 2.6 Hydrogen Energy Storage System (HESS)

The HESS is composed of a hydrogen tank, a fuel cell and an electrolyzer. In case of overproduction and the batteries are completely recharged, the excess of energy is utilized to produce hydrogen through electrolysis of water, which is subsequently stocked in the hydrogen storage tank for use by fuel cells, during the periods when there is a deficit of energy, to satisfy the energy demand of the load. The energy stored in the hydrogen tank is defined by Eq. (10) [19]:

$$Q_{H2}(t) = Q_{H2}(t_0) + \int (P_{elec} - P_{fc}).dt \quad (10)$$

Where:

$Q_{H2}(t)$ is the energy equivalent of the stored.
$P_{fc}$ is the fuel cell power.

$P_{elec}$ is the electrolyzer power.

To fit this equation to the discrete model, it must be discretized as follows, Eq. (11):

$$Q_{H2}(k) = Q_{H2}(0) + \sum_{i=1}^{k}(P_{elec}(i) - P_{fc}(i)).\Delta t \qquad (11)$$

At the beginning of the day. The storage tank contains 10 kWh of energy equivalent to hydrogen ($Q_{H2}$ (0)).

The level of hydrogen storage in the tank (NH) is expressed in percentage as shown in Eq. (12):

$$NH\,(i) = 100 \times \frac{Q_{H2}\,(i)}{Q_{H2,max}} \qquad (12)$$

### *2.7 Electric Vehicle*

The electric vehicle battery is considered as a backup energy storage system that can be used to achieve power balance and minimize the cash flow of the system. In case of excess production, if the BESS is completely recharged and the hydrogen tank is at its maximum level, we can charge the battery of the electrical car with that excess of energy (in the limits imposed by the state of charge of the car battery). In case of under-production and the BESS is fully discharged and the hydrogen tank is at its low level and to prevent the gas turbine from starting, the battery of the electrical car is utilized to meet the energy deficit. In the two cases, the electrical car's battery can be used only in the time periods when it is connected to the microgrid. In our case, the car is connected to the micro-grid from midnight to 8am and from 5am to 12am.

## 3. Methodology - Approach and Optimization Problem

The optimization model of the microgrid EMS is performed over a 24-hour period with a 10-minute step. The determining variable are the PV power production "$P_{pv}$", the wind power generation "$P_{wt}$", the load requirement "$P_{load}$", the BESS power "$P_{BESS}$", the power of the gas turbine "$P_{gt}$", the electrolyzer power "$P_{elec}$", the fuel cell power "$P_{fc}$", and the electric vehicle's battery power "$P_{bcar}$".

Where $P_{BESS}$ and $P_{bcar}$ are the charging/discharging power of the BESS and the car battery system respectively.

### *3.1 The cost minimization of the objective function*

The objective function is to ensure the optimal use of the BESS, fuel cells and gas turbine. The objective function is defined as followed:

$$\min\,(CF(t)) = \min \sum_{0}^{T}\big(BrC(t) + CG(t) + CH(t)\big) \qquad (13)$$

With :

BrC: The battery replacing cost ($).
CH and CG: The operating costs of the hydrogen system and the gas turbine respectively ($).
T: Number of simulation steps (10 min) for a time interval of 24 hours (T= 144).

The index of performance is the cash flow sum, CF, given as the inflows and outflows cash difference, provided by the activity.

The replacement cost of the battery at each time step, calculated in Eq. (16), is the replacing cost of the lost capacity over the time period (Δt). Eq. (14) and Eq. (15) define the State Of Health (SOH) variation over the time interval. The Batteries investment Cost "BiC", given by Eq. (17):

$$\Delta SOH_{BESS}(x_i, x_j, t) = SOH_{BESS,x_i}(t - \Delta t) - SOH_{bESS,x_j}(t) \qquad (14)$$

$$\Delta SOH_{BESS}(x_i, x_j, t) = Z.\,[SOC_{BESS,x_j}(t + \Delta t) - SOC_{BESS,x_i}(t)] \qquad (15)$$

$$\sum_{t,SOH=1}^{t,SOH=SOH_{BESS}^{min}} BrC(t) = BiC \qquad (16)$$

$$BrC(x_i, x_j, t) = BiC \times \left[\frac{\Delta SOH_{BESS}(x_i, x_j, t)}{1 - SOH_{BESS}^{min}}\right] \qquad (17)$$

Where :

- Z is the aging coefficient of the battery.
- $x_i$ and $x_j$ are the state of charge at time t and t+Δt respectively.

The following Eq. (18) represent the operating cost of the hydrogen system:

$$CH(t) = C_{fc} \times (a_{fc} \times P_{fc} + b_{fc}) \times \Delta t \qquad (18)$$

With:

- $a_{fc}$, $b_{fc}$ are the operating cost parameters of the fuel cell and $c_{fc}$ is the cost by kWh generated by the fuel cell.
- $b_{fc}$ is assumed to be negligible (=0) and $a_{fc}$ is considered equal to 1

To represent the operating cost of the gas turbine, a quadratic function is used:

$$CG\,(t) = C_{gt} \times \left(a_{gt} \times P_{gt}^2 + b_{gt} \times P_{gt} + c_{gt}\right) \times \Delta t \qquad (19)$$

With:

- $a_{gt}$ and $c_{gt}$ considered negligible, $b_{gt}$ is assumed equal to 1.
- $a_{gt}$, $b_{gt}$ and $c_{gt}$ are the gas turbine operating cost parameters and $C_{gt}$ is the cost by kWh generated by the gas turbine.

### *3.2 Constraints*

Balance constraint: Constraint, Eq. (20), is defining the power flow in the system according to the principle of power conservation. This constraint requires that the power sum of the various system components as well as the load demand must be null at each instant [20, 21]:

$$P_{load} + P_{pv} + P_{wt} + P_{gt} + P_{fc} + P_{elec} + P_{BESS} + P_{bcar} + P_{sc} = 0 \quad (20)$$

The equality and inequality power distribution problem constraints are given by the following equations:

$$SOC_{BESS}^{min} \leq SOC_{BESS}(t) \leq SOC_{BESS}^{max} \quad (21)$$

$$SOC_{bcar}^{min} \leq SOC_{bcar}(t) \leq SOC_{bcar}^{max} \quad (22)$$

$$P_{BESS}^{min} \leq |P_{BESS}(t)| \leq P_{BESS}^{max} \quad (23)$$

$$P_{bcar}^{min} \leq |P_{bcar}(t)| \leq P_{bcar}^{max} \quad (24)$$

$$\Delta SOC_{BESS}^{min} \leq \Delta SOC_{BESS} \leq \Delta SOC_{BESS}^{max} \quad (25)$$

$$\Delta SOC_{bcar}^{min} \leq \Delta SOC_{bcar}(t) \leq \Delta SOC_{bcar}^{max} \quad (26)$$

$$SOH_{BESS,}(t) \geq SOH_{min,} \quad (27)$$

$$SOH_{bcar,}(t) \geq SOH_{min,} \quad (28)$$

$$NH_{min,} \leq NH(t) \leq NH_{max,} \quad (29)$$

$$P_{gt}^{min} \leq P_{gt}(t) \leq P_{gt}^{max} \quad (30)$$

Where:

$$P_{BESS}(t) = ((SOC_{BESS}(t+\Delta t) - SOC_{BESS}(t)).V_{dc}.C_{refBESS})/\Delta t \quad (31)$$

$$P_{bcar}(t) = ((SOC_{bcar}(t+\Delta t) - SOC_{bcar}(t)).V_{dc}.C_{refbcar})/\Delta t \quad (32)$$

The constraints, Eq. (21) and Eq. (22), protect the BESS and the electric vehicle batteries from deep charging and overcharging, by ensuring that the batteries operate in a range of predetermined values experimentally or as specified by the manufacturer.

Eq. (25), Eq. (26), Eq. (27) and Eq. (28) represent the constraint on the variation limits of the SOC and the power variation of the BESS and the car battery.

Eq. (27) and Eq. (28) are the constraints on the SOH of the batteries.

Constraint, Eq. (29), represents the limits related to the hydrogen energy storage levels.

Constraint, Eq. (30), represents the ideal operating range, with better efficiency, of the gas turbine. However, it is not considered as a strict constraint, i.e., policies that do not meet this constraint, $P_{gt}(t) \geq P_{gt}^{max}$ or $P_{gt}(t) \leq P_{gt}^{min}$ , are not discarded, but instead a performance penalty is imposed on the performance criterion:

$$CG(t) = C_{gtPen} \times (a_{gt} \times P_{gt}^2 + b_{gt} \times P_{gt} + c_{gt}) \times \Delta t \quad (33)$$

$C_{gt,Pen}$ is the cost penalty per kWh.

## 4. Genetic Algorithm – EMS Strategy

Genetic algorithms are evolutionary stochastic optimization algorithms inspired by the mechanisms of natural evolution (selection, adaptation, reproduction, recombination, mutation) developed by Charles Darwin. These algorithms are considered efficient and robust for solving complicated problems, efficient because they are developing a potential population of solutions rather than a unique one, and robust because of their ability to solve nonlinear and discontinuous problems. The optimization based on the genetic algorithm consists in searching for the best solution of a problem in the sense of one or more criteria chosen while respecting the characteristics of the system and the constraints imposed on it [22].

This section presents an EMS based on genetic algorithm for optimal and efficient energy management in an isolated microgrid and for optimizing the performance of power system, energy generation and storage components.

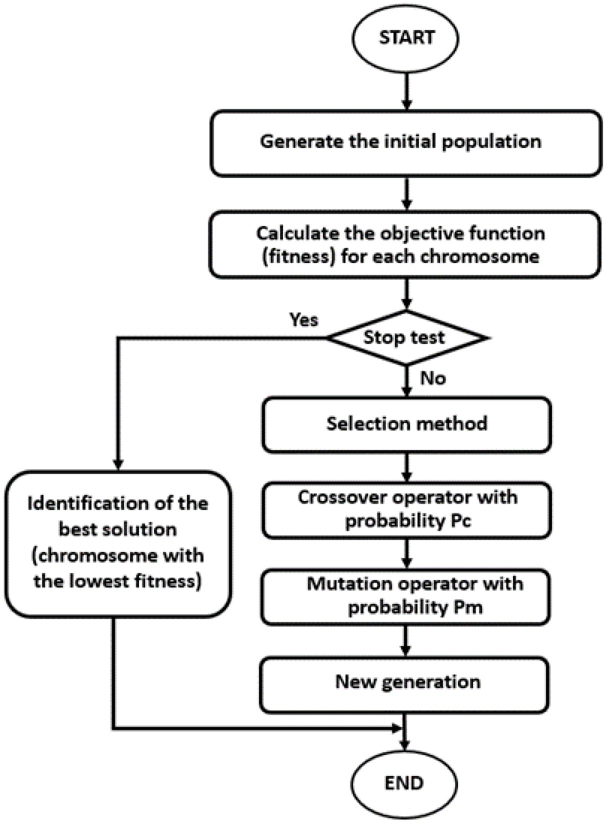



**Fig. 5.** Activity diagram of the genetic algorithm.

The genetic algorithm, described in Fig.5, begins with the generation of an initial population of S individuals (chromosomes), for which their objective function values are calculated and individuals are selected using a selection procedure. The chromosomes that will be the subjects of the crossover operator are selected using a crossover probability Pc.

Their results can be mutated by a mutation operator with a mutation probability Pm. The individuals resulting from these genetic operators will be inserted by a method of insertion in the new population of which we evaluate the value of the objective function of each of its individuals. A stop test will be carried out to check the quality of the individuals obtained. If the test is verified, then the algorithm stops with an optimal solution.

In our case the adopted coding of chromosome is numerical, each chromosome (individual) represents a sequence of possible SOC transitions, discreet SOC values of the battery energy storage system shifted by one step (δSOC) and composed of 145 genes (SOC(t)), temporal values sampled in this system according to the sampling step (Δt) for the time period of 24 hours .The first gene (SOC(t=0s)) and the last gene (SOC(t=T)) of each individual (chromosome) must be equal to 50%.

An initial population of fixed size S is formed by a finite set of solutions, in the search space, in order to accelerate the convergence of the genetic algorithm.

The selection principle adopted for our case is the one based on the roulette selection. In a maximization optimization problem, we associate to each individual "i" a probability of selection, noted " $Prob_i$ ", calculated on the basis of its value " $CF_i$ "of the objective function (Eq. (34)). Each individual is then reproduced with the probability " $Prob_i$ ", some individuals (the good solutions) will then be more reproduced:

$$\mathrm{Prob_i} = 1 - \frac{\mathrm{CF_i}}{\sum \mathrm{CF_i}} \tag{34}$$

The crossover operator adopted for our case is the one with one crossover point, which consists in dividing each of two father individuals into two randomly chosen. Child 1, the first reproduced individual, consists of the first parent's first part, and the second parent's second part, while Child 2 consists of the second parent's first part, and the first parent's second part. A local fitness " $CF_i$ " is calculated for each scenario.

The mutation operator adopted consists in modifying the values of the genes of the chromosomes according to a probability of mutation Pm. In our case, we apply this probability to the whole individual by deciding not to apply the crossover to both parents, i.e. the children will be identical to the parents (child 1 is constituted by the same genes of the first parent and child 2 is constituted by the same genes of the second parent).

After the mutation step, an insertion method is used to generate a new population. During the construction of this population, it is necessary to establish a compromise between the produced solutions and the producing solutions (the parents) by using an insertion mechanism. The strategy of evolution of the adopted population is based on a generational method, which replaces the parents by the children already created by the operators of crossover and mutation. In other words, and following precise information, it is necessary to decide what must remain and what must disappear by saving at each generation a fixed size of the population S.

The stopping test, Stest, plays a primordial role in the judgment of the individual's quality. Its goal is to assure us the optimality of the final solution obtained by the genetic algorithm. In our case and to avoid a robust computation time, the stopping criterion of the genetic algorithm is defined by an absolute maximum number of 50 generations.

$P_{BESS}$ is estimated at each stage of charge variation "$\Delta SOC_{BESS}$", then $P_{gt}$, $P_{elec}$, $P_{fc}$ and $P_{bcar}$ are calculated, by priority of each component, following the flowchart below:

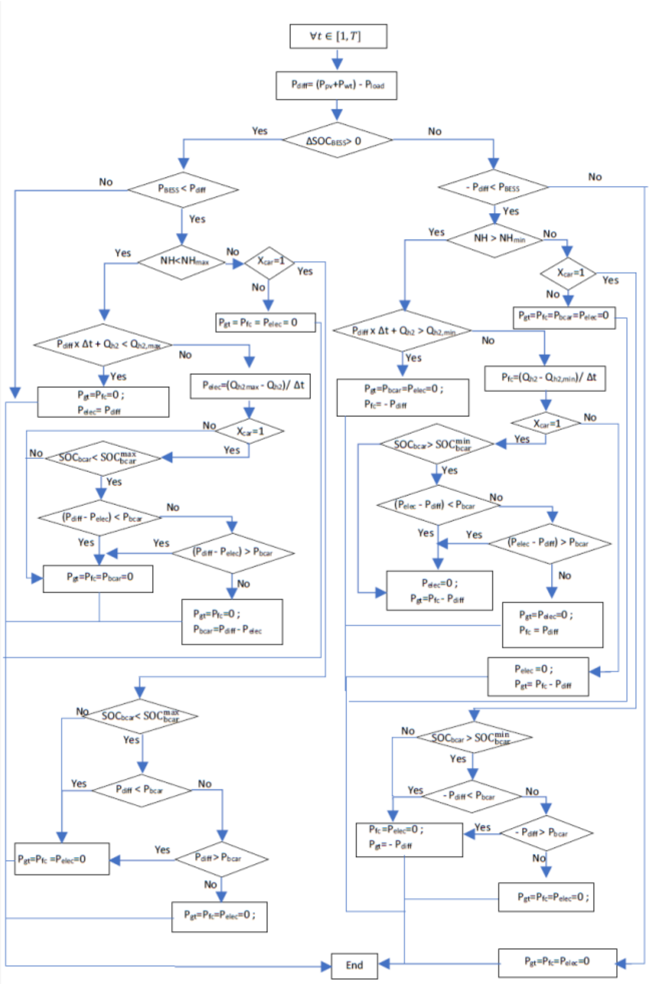


**Fig. 6.** The flowchart of Priority rules for the use of system components.

$X_{car}$ represents the connection status of the electric vehicle to the microgrid, connected or not, at each time step

## 5. Fuzzy Logic Strategy

Fuzzy logic is very similar to human logic. In non-linear systems, fuzzy control has higher adaptability, flexibility and shorter settling times compared to other traditional controllers [23] [24].

By simulating judgment and reasoning under uncertainty, Fuzzy Logic Control (FLC) is used to address optimization challenges that are difficult to solve with traditional control approaches. The FLC structure developed in this work is illustrated in Fig.7.

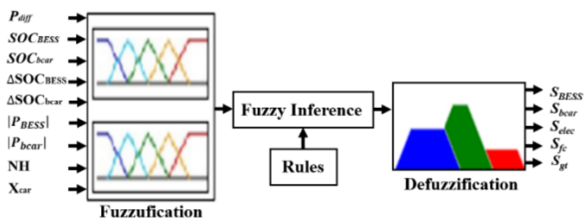



**Fig. 7.** Supervision system with Fuzzy Logic

The fuzzy controller adopted for the EMS uses 9 input variables which are: the power difference " $P_{diff}$ " between the power produced by the SERs and the power demanded by the load, the SOC of the BESS and the car battery "$SOC_{BESS}$, $SOC_{bcar}$", the variation of SOC between two sample periods "$\Delta SOC_{BESS}$, $\Delta SOC_{bcar}$", the power of the BESS and the car battery, in absolute value, "$|P_{BESS}|$, $|P_{bcar}|$", the hydrogen storage level in the tank "NH" and the connection state of the electric vehicle to the microgrid at each time step " $X_{car}$". The output variables of the system are the state, ON/ OFF, of the control signals of the switches:

- $S_{BESS}$: located between the BESS and the AC bus.
- $S_{bcar}$: located between the car battery and the AC bus.
- $S_{gt}$: located between the gas turbine and the AC bus.
- $S_{fc}$: located between the fuel cell and the AC bus.
- $S_{elec}$: located between the electrolyzer and the AC bus.

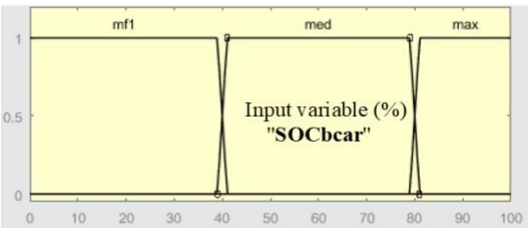
$P_{diff}$ is calculated using the following equation:

$$P_{Diff} = (P_{PV} + P_W) - P_{Load} \tag{35}$$

### *5.1 Choice of The Membership Functions*

Fuzzy logic control provides a better comprehension of power management. In fact, it is considered as an enhancement of deterministic rules. The FLC does not deal with mathematical equations but instead uses inferences with multiple rules [25]. These rules can be developed in two ways, based on human expertise and profile knowledge, using data generated by the genetic algorithm or using dynamic programming values.

The input variables "$SOC_{BESS}$, $SOC_{bcar}$, $\Delta SOC_{BESS}$, $\Delta SOC_{bcar}$, $|P_{BESS}|$, $|P_{bcar}|$, NH" can be: Minimum "min", Medium "med" or Maximum "max". Similarly, the power difference, $P_{diff}$, can be: Negative "N", Zero "Z" or Positive "P". $X_{car}$ variable can be "ON" or "OFF". Finally, the states of the switches $S_{BESS}$, $S_{bcar}$ , $S_{elec}$ , $S_{fc}$ ,$S_{gt}$ can be closed "OFF" or opened "ON". Each of these fuzzy sets is designated by a trapezoidal membership function. The membership functions chosen for the state of the input and output variables are shown in Fig 8 and Fig 9.

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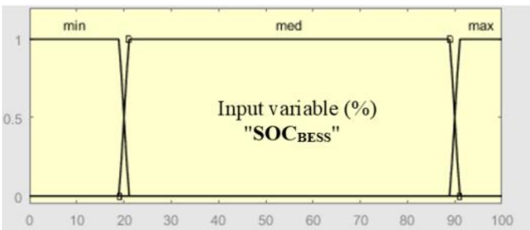


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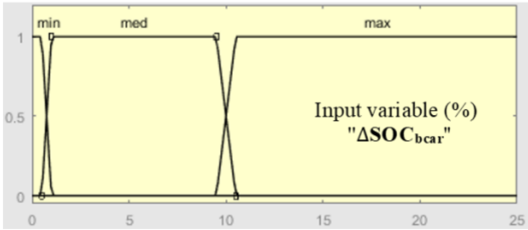


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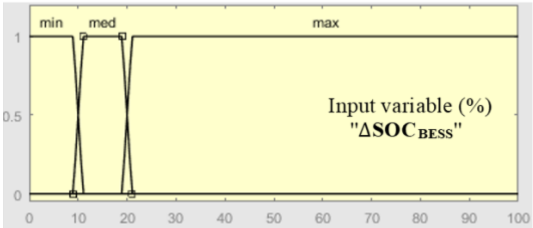


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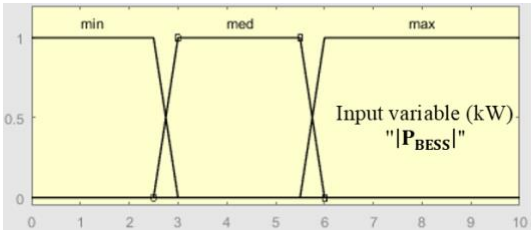


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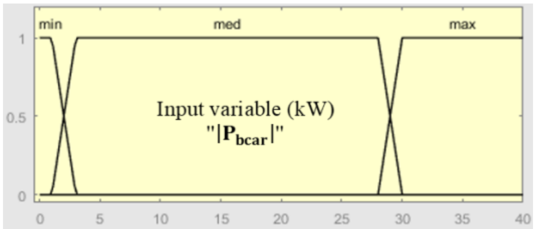
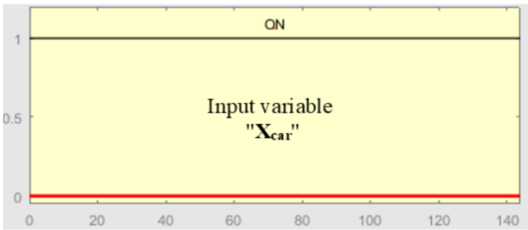
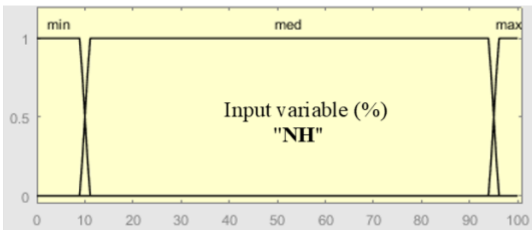


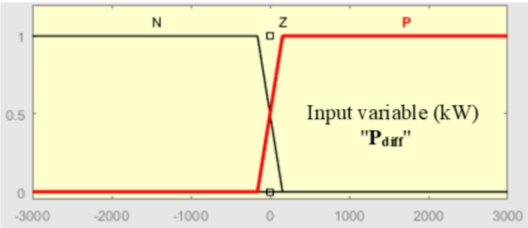

(f)




(g)




(h)




(i)

**Fig. 8.** Block diagram for the input membership functions FLS based EMS (a) "$SOC_{BESS}$", (b) "SOCbcar", (c) "$\Delta SOC_{BESS}$", (d) "$\Delta SOC_{bcar}$", (e) "$|P_{BESS}|$", (f) "$|P_{bcar}|$", (g) "NH", (h) "$X_{car}$", (i) "$P_{diff}$" .

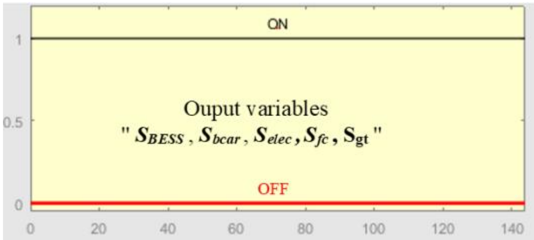



**Fig. 9.** Block diagram for the ouput membership function FLS based EMS $S_{BESS}$, $S_{bcar}$ , $S_{elec}$ , $S_{fc}$ ,$S_{gt}$ .

### 5.2 *Choice of Inference Rules*

The tuning strategy depends essentially on the adopted inferences, which associate the input variables with the output linguistic variable using a set of rules. The linguistic description of the inference adopted in our system is as follows:

➢ If $P_{diff}$ is N **and** ($SOC_{BESS}$ is med or $SOC_{BESS}$ is max) **and** $|P_{BESS}|$ is med **and** $\Delta SOC_{BESS}$ is med **then** $S_{BESS}$ is ON **and** $S_{bcar}$ , $S_{elec}$ , $S_{fc}$ , $S_{gt}$ are OFF.

➢ If $P_{diff}$ is N **and** ($SOC_{BESS}$ is min **or** $|P_{BESS}|$ is min **or** $|P_{BESS}|$ is max **or** $\Delta SOC_{BESS}$ is max **or** $\Delta SOC_{BESS}$ is min) **and** (NH is med **or** NH is max) **then** $S_{fc}$ is ON **and** $S_{BESS}$, $S_{bcar}$ , $S_{elec}$ , $S_{gt}$ are OFF.

➢ If $P_{diff}$ is N **and** ($SOC_{BESS}$ is min **or** $|P_{BESS}|$ is min **or** $|P_{BESS}|$ is max **or** $\Delta SOC_{BESS}$ is max **or** $\Delta SOC_{BESS}$ is min) **and** NH is min **and** $X_{car}$ is ON **and** (($SOC_{bcar}$ is med **or** $SOC_{bcar}$ is max) and $|P_{bcar}|$ is med and $\Delta SOC_{bcar}$ is med) then $S_{bcar}$ is ON and $S_{BESS}$ , $S_{elec}$ , $S_{fc}$ ,$S_{gt}$ are OFF.

➢ If $P_{diff}$ is N **and** ($SOC_{BESS}$ is min **or** $|P_{BESS}|$ is min **or** $|P_{BESS}|$ is max ) **and** NH is min **and** $X_{car}$ is OFF **or** ($SOC_{bcar}$ is min **or** $|P_{bcar}|$ is min **or** $|P_{bcar}|$ is max **or** $\Delta SOC_{bcar}$ is min **or** $\Delta SOC_{bcar}$ is max) **then** $S_{gt}$ is ON **and** $S_{BESS}$ , $S_{elec}$ , $S_{fc}$ , $S_{bcar}$ are OFF.

➢ If $P_{diff}$ is Z **then** $S_{BESS}$, $S_{bcar}$ , $S_{elec}$ , $S_{fc}$ ,$S_{gt}$ are OFF

➢ If $P_{diff}$ is P **and** ($SOC_{BESS}$ is med **or** $SOC_{BESS}$ is min) **and** $|P_{BESS}|$ is med **and** $\Delta SOC_{BESS}$ is med **then** $S_{BESS}$ is ON **and** $S_{bcar}$ , $S_{elec}$ , $S_{fc}$ , $S_{gt}$ are OFF.

➢ If $P_{diff}$ is N **and** ($SOC_{BESS}$ is max **or** $|P_{BESS}|$ is min **or** $|P_{BESS}|$ is max **or** $\Delta SOC_{BESS}$ is max **or** $\Delta SOC_{BESS}$ is min) **and** (NH is med **or** NH is min) **then** $S_{fc}$ is ON **and** $S_{BESS}$, $S_{bcar}$ , $S_{elec}$ , $S_{gt}$ are OFF.

➢ If $P_{diff}$ is N **and** ($SOC_{BESS}$ is max **or** $|P_{BESS}|$ is min **or** $|P_{BESS}|$ is max **or** $\Delta SOC_{BESS}$ is max **or** $\Delta SOC_{BESS}$ is min ) **and** NH is min **and** $X_{car}$ is ON **and** (($SOC_{bcar}$ is med **or** $SOC_{bcar}$ is min) and $|P_{bcar}|$ is med **and** $\Delta SOC_{bcar}$ is med) **then** $S_{bcar}$ is ON **and** $S_{BESS}$ , $S_{elec}$ , $S_{fc}$ ,$S_{gt}$ are OFF.

## 6. Simulation Results and Discussion

The system parameters and the simulation values are shown in Table 1:

**Table 1.** The values of the simulation parameters and the studied system characteristics

| | |
|---|---|
| T (h) | 24 |
| $\Delta$T (min) | 10 |
| $\delta SOC_{BESS}$ (%) | 10 |
| Pc | 0.8 |
| Pm | 0.001 |
| Stest | 50 |
| S | 100 |
| $SOC0_{BESS}$ (%) | 50 |
| $SOCT_{BESS}$ (%) | 50 |
| $SOC_{BESS}^{max}$ (%), $SOC_{BESS}^{min}$ (%) | 90, 20 |
| $SOC_{bcar}^{max}$ (%) , $SOC_{car}^{max}$ (%) | 80, 4 |
| $\Delta SOC_{BESS}^{max}$ (%), $\Delta SOC_{bcar}^{max}$ (%) | 20.00 |
| $\Delta SOC_{BESS}^{min}$ (%), $\Delta SOC_{bcar}^{min}$ (%) | 10, 0.10 |
| $V_{dc}$ (V) | 48.00 |
| $SOH_{min}$ (%) | 70.00 |
| $C_{BESS}^{ref}$ (Ah) | 100.00 |
| $C_{bcar}^{ref}$ (Ah) | 500.00 |
| $P_{BESS}^{max}$ (kW), $P_{BESS}^{min}$ (kW) | 5.760, 2.880 |
| $P_{bcar}^{max}$ (kW), $P_{bcar}^{min}$ (kW) | 28.80, 0.1440 |
| $NH_{max}$ (%) , $NH_{min}$ (%) | 95.00 , 10.00 |
| NHO(%) | 65.00 |
| $P_{gt}^{max}$ (kW), $P_{gt}^{min}$ (kW) | 6.00, 3.30 |
| $P_{gtnom}$ (kW) | 6.660 |
| $C_{fc}$ (€/kwh) | 0.120 |
| $C_{gt}$ (€/kwh) | 0,2570 |
| $C_{gtPen}$ (€/kwh) | 2.570 |
| $C_{sc}$ (*F*) | 50.00 |
| $Q_{H2max}$ (kWh) | 10.00 |
| Techno PV | Poly-crystalline S.P |
| $P_{pv}^{max}$ (kW) | 9.00 |
| Techno Battery | Lith-ium-ion |
| BiC (€) | 140 |
| Z | 0.170×10-4 |
| $P_{wt}^{max}$ (kW) | 6.00 |
| Nominal wind speed (V) | 12m/s |
| Wind turbine nominal speed (Ω) | 153.4 rad/sec |
| Density of the air (ρ) - WT | 1.225 Kg/m3 |

The distribution curves obtained using the GA and the FLC are shown in Fig.10 and Fig.11:

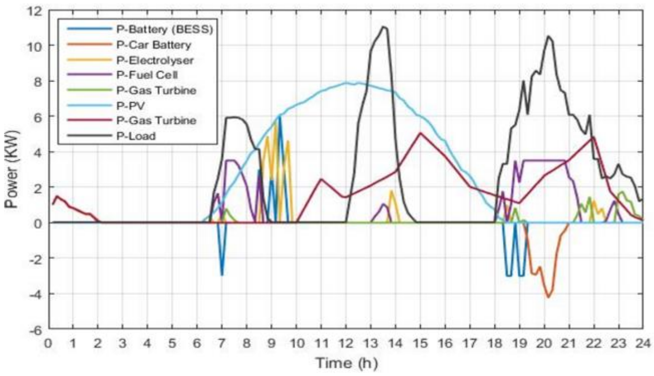



**Fig. 10.** System power flow using GA.

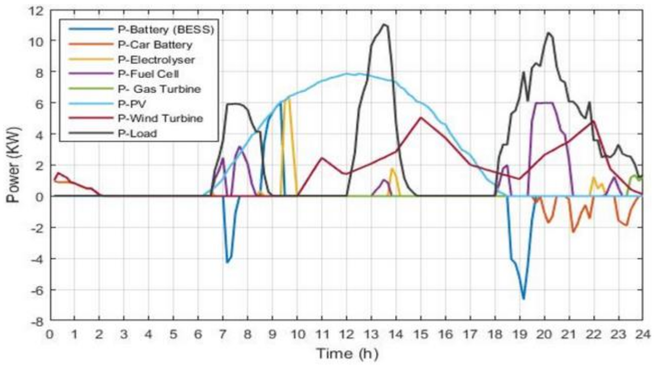



**Fig. 11.** System power flow using FLC.

With the genetic algorithm, the energy management is controlled better than the fuzzy logic strategy. In fact, the genetic algorithm-based strategy allows to optimally manage the battery SOC, discharge the batteries only when renewable sources production is not sufficient to meet the needs of the load, minimizes the gas turbine usage and reduces the cost while meeting all the constraints. A lowest cash flow is expected with the genetic algorithm-based management compared to the fuzzy logic strategy

The variation in battery SOC for the two methods proposed is presented in Fig.12:

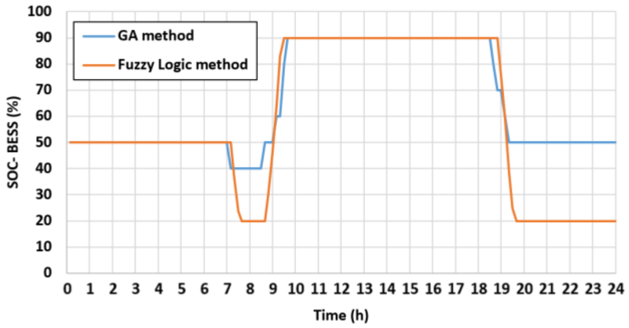



**Fig. 12.** SOC of the BESS.

With the management using the genetic algorithm, the starting SOC at t=0 ($SOC0_{BESS}$=50%) equals to the terminal SOC at t=T ($SOCT_{BESS}$=50%), giving additional flexibility to start the next day, but using the fuzzy logic approach, the final SOC of the BESS is at its lowest level ($SOCT_{BESS}=SOC_{BESS}^{min}$).

The SOC of the hydrogen tank, stored energy, for both proposed strategies are shown in Fig.13. With genetic algorithm approach, the stored energy level in the reservoir by the end of the day reaches 3.3 kWh, thus not attaining its minimum value of 1 kWh, giving more flexibility for starting the following day. With the fuzzy logic strategy approach, the tank is at its lowest level by the end of the day.

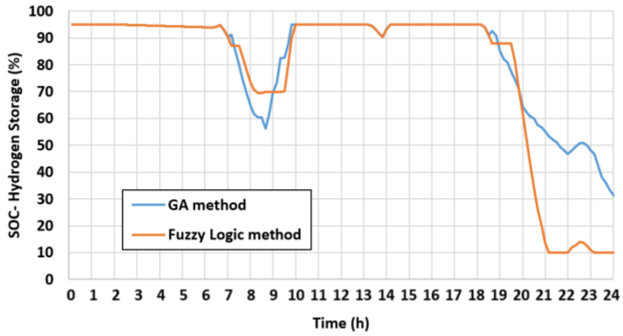



**Fig. 13.** SOC of the HESS storage tank.

Figure 14 shows the SOC variation of the electric vehicle's battery. With the two methods (GA & FLC), the state-of-charge value at the end of the operating time periods is higher than the minimal value $SOC_{bcar,}^{min}$ (40%,).

In case of under-production, the electric car battery is recharged with excess energy after the BESS and hydrogen tank are charged (in the limits set by the electric car battery's SOC). When there is insufficient production and if the BESS is discharged and the hydrogen tank is at its minimum level, the electric vehicle batteries can be utilized (discharged), during the periods when it is connected to the microgrid, to avoid starting the gas turbine.

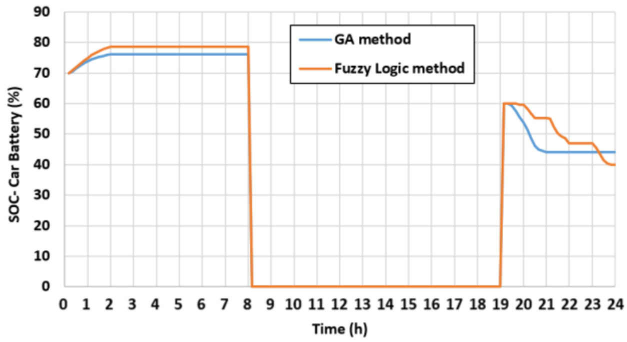



**Fig. 14.** SOC of the car battery.

The final objective function value is presented in Table 2.

**Table 2.** The final objective function value

| | Fuzzy logic algorithm | Genetic algorithm |
|---|---|---|
| Final Value (€) | **1.17** | **0.98** |

By the end of the day, the cash flow with the method based on the genetic algorithm is lower than that found with the fuzzy logic strategy. On the other hand, the computation time with the genetic algorithm is about 4 seconds, which is a little higher than with the fuzzy logic strategy (1.2 second).

Figure15 shows the 24-hour cash flow variation using the GA and FLC:

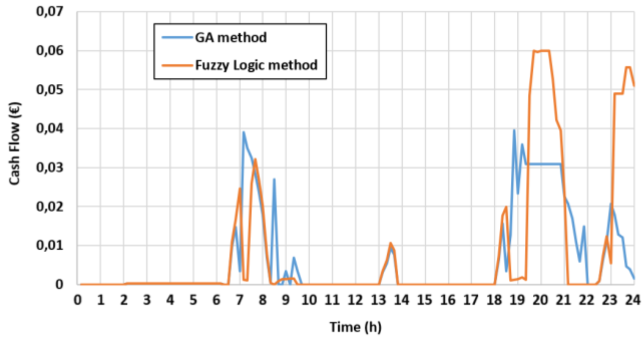



**Fig. 15.** Cash flow.

We also simulated a predictive energy management strategy based on Dynamic Programming (DP) and rule-based method, for the same system studied in this work and with the same constraints. The final value of the objective function, at the end of the day, is about 1.1€ with DP and about 1.33€ with the rule-based strategy. The computation time of the DP-based strategy is about 2.5 seconds and that of the rule-based method is about 1 second [9].

The following table summarizes some characteristics of the different energy management approaches based on GA, DP, rules and fuzzy logic, based on the different simulations performed and conclusions reached:

**Table 3.** Comparison of algorithms – predictive energy management

| | Simplicity | Calculation time | Robustness | Cost minimization |
|---|---|---|---|---|
| Genetic algorithm | ✖ | ✖ | ✔ | ✔ |
| Rule-based method | ✔ | ✔ | ✖ | ✖ |
| Dynamic programming | ✖ | ▬ | ✔ | ▬ |
| Fuzzy logic control | ▬ | ✔ | ✖ | ▬ |

In general, the results obtained show a fairly high cost sensitivity depending on the methods and algorithms used. Therefore, optimal scheduling is a sensitive issue and choosing the right approach is critical to ensure optimal energy management.

## 7. Conclusion

This work proposes a new predictive control system using genetic algorithm for an isolated microgrid, a complicated hybrid system composed of various storage and generation components composed mainly of wind and PV generators, gas turbine, BESS , HESS, load and electric vehicle. The genetic algorithm-based strategy was applied to find the lowest cash flow and to optimize power system performance and achieve peak shaving. The particularity of this work consists in considering the ageing of the batteries in the optimization process as well as the operating cost of the different elements of the studied microgrid. The proposed strategy's performance has been tested and validated by the various simulations and previous results and confirmed by comparison with the results of the fuzzy logic management approach. The final value of the objective function, at the end of the day, is about 0.98€ with GA and about 1.17€ with the fuzzy logic strategy, the computation time of the GA-based strategy is about 2.5 seconds and that of the fuzzy logic method is about 1 second. The GA-based method provides a significantly better cash flow, saving over 22.5% of the electricity bill, but with a slightly longer calculation time than the fuzzy logic strategy.

Future work will include new methods for real-time optimal EMS by also incorporating forecast errors on generation and consumption profiles, which was not considered in this study, making the implementation of the optimization approach closer to the operational reality.

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