Multi-objective design of PV-Wind-Diesel-Hydrogen-Battery systems

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Abstract

This paper presents, for the first time, a Triple Multi-Objective design of isolated hybrid systems minimizing, simultaneously, the total cost throughout the useful life of the installation, pollutant emissions (CO₂) and Unmet Load.

For this task, a Multi Objective Evolutionary Algorithm (MOEA) and a Genetic Algorithm (GA) have been used in order to find the best combination of components of the hybrid system and control strategies.

As an example of application, a complex PV-Wind-Diesel-Hydrogen-Battery System has been designed, obtaining a set of possible solutions (Pareto Set).

The results achieved demonstrate the practical utility of the developed design method.

Keywords: Hybrid Systems. Multi-Objective Design. Multi-Objective Evolutionary Algorithms, Genetic Algorithms.

1. Introduction

When carrying out a design taking into account several objectives simultaneously, it is typical that some of them are in conflict with some others [1].

This paper shows the design of a hybrid PV-Wind-Diesel-Hydrogen-Battery installation for the generation of electric energy (Fig. 1, wind turbines could be connected either at DC bus, as shown in the figure, or at AC bus), considering simultaneously three objectives (cost, pollutant emissions and Unmet Load) which are usually in conflict, since when one of them gets improved, the others get

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worse. The design of a hybrid system, considering the three mentioned objectives, poses a very complex problem of optimization.

In the specialized technical literature [2-8], the design of these systems is usually done by searching the configuration and/or control that renders the lowest total cost throughout the useful life of the installation, considering a fixed value for the Unmet Load, previously decided by the designer, and in some cases, the pollutant emissions are also limited or economically evaluated.

Therefore, the result obtained will depend on the Unmet Load value selected, on the limitation of the Pollutant Emissions and/or on the subjective assignation of costs to the Pollutant Emissions.

Using these techniques, the solutions can be very far from the global optimum.

However, some Multi-Objective design methods already exist and they have been applied successfully in several fields of Engineering [1]. Given the complexity of this kind of problems, because of the large number of variables that are usually considered and of the mathematical models applied, classical optimization techniques may consume excessive CPU time or even be unable to take into account all the characteristics associated to the posed problem.

Because of this, during the last three decades, heuristic techniques have been applied [8]. One of the most used heuristic techniques has been the Multi-Objective Evolutionary Algorithms.

Multi-Objective Evolutionary Algorithms (MOEA’s) stand out for this task, being applied in numerous research works [9].

One of the most important characteristic of this kind of algorithms is the concept of Pareto Optimality [9]; thanks to it, as a result of the optimisation process, a set of possible solutions is obtained after a searching process in which the objectives involved in the design are evaluated independently. From the obtained solutions, the designer can choose those which he/she thinks to be more appropriate depending on the values of the objectives considered.

From the MOEA’s developed until now, the ‘state of the art’ [9] about this subject indicates that the Strength Pareto Evolutionary Algorithm (SPEA, SPEA2) [10, 11] is not only one of the most efficient algorithms but also the one that gives the best results. Because of this, in the study explained in this paper, the SPEA is applied to the Multi-Objective design of hybrid systems.

In a previous work, the authors showed the optimization of Multi-Objective design of isolated hybrid systems minimising the total cost throughout the useful life of the installation and the pollutant emissions (CO₂) [12].

This paper starts by showing the mathematical model of the components, followed by the description of the objective functions and the basic concepts related to the problems of Multi-Objective optimisation and the Evolutionary Algorithms applied to it. Finally, the results and conclusions obtained from the Multi-Objective design of a PV-Wind-Diesel-Hydrogen-Battery system are shown, thus verifying the good behaviour of the SPEA as a design tool.
2. Mathematical model of the components

A more detailed mathematical model of the components of the hybrid system (PV panels, wind turbines, diesel generator, electrolyzer, fuel cell, hydrogen tank and batteries) and the control strategy can be found in previous works [7, 12, 13, 14].

A brief description of such mathematical models is shown in forthcoming subsections.

2.1. Current from the PV generator

The input data could be the monthly average daily radiation on the horizontal surface or the peak sun hours. Using the Rietveld equation [15], the design tool converts the input data into the average clearness index for each month of the year, obtaining the clearness index for each day of the year and calculating the global hourly irradiation $G$ (kWh/m$^2$) according to the Graham model [16].

Alternatively hourly irradiation data can be read from a file in which the global irradiation on horizontal surface for each hour of the year and for the geographic place of the design, are included.

The power supplied by the panels, during the hour $i$, is calculated by equation (1).

$$ P_{re,pv,i} = G_i \cdot I_{sc} \cdot F_{loss} \cdot U_{DC} $$

where $I_{sc}$ is the shortcut current of the PV generator, $F_{loss}$ is the factor that takes into account the losses of power given by the PV panels due to shadows, dirt, etc and $U_{DC}$ is the DC voltage.

2.2. Batteries

The design tool allows calculating the charge condition of the batteries and the maximum admissible current by using two different models: The Ah model [17] or the KiBaM model [18].

On the other side, there are several models to predict the expected life-span of batteries [19], which depends on the conditions of operation, on the charge/discharge regime and on temperature. Calculating the expected life-span of batteries is important, as it influences the total cost of the system.

With this design tool, it is possible to choose between two different methods in order to estimate the life-span of batteries:

- The first alternative is to estimate it through Cycles to Failure, (HOMER program [20] uses this method), considering, in this case, that the battery life-span depends on the Depth of Discharge (DOD) of the charge/discharge cycles, as seen in Fig. 2. Applying this method it is possible to define the Equivalent Full Cycles as the number of Cycles to Failure multiplied by
the DOD. The Average of Equivalent Full Cycles will be the value used to calculate the life of batteries.

- The other method - which can also be applied using the design tool shown in this paper - for estimating battery life-span is more complex and precise; it is the Cycles Counting method known as “rainflow”, based on Downing’s algorithm [21] which is used by the HYBRID2 program [22]. The method of Cycles Counting is based on counting the charge/discharge cycles. The number of cycles corresponding to each range of the DOD (split in m intervals) for a year is counted. For example, breaking up the DOD in 10 intervals, \( N_1 \) will be the number of cycles between 0 and 10% of the DOD, \( N_2 \) will be the number of cycles between 10% and 20% of the DOD, etc. For each interval there will be a number of Cycles to Failure \( (CF_i) \) obtained from Fig.2. Battery duration, in years, can be calculated using equation (2).

\[
Life_{bat} = \frac{1}{\sum_{i=1}^{m} \frac{N_i}{CF_i}}
\]  

(2)

2.3. Current from the wind turbine

To estimate the current generated by the wind turbine, the design tool uses the power curves supplied by the manufacturer for each wind turbine [23].

Fig. 3 shows a curve of this kind. Besides, it is necessary to know the hourly values of the wind, which are read from a file which is included the wind speed for each hour of the year and for the geographic place where the design is carried out. To calculate the output of the wind turbine in each of the 8,760 hours, the applied methodology is briefly described as follows [23].

The method has two steps:

First. The hourly wind speed at the hub height is calculated by using equation (3).

\[
v_{hub,i} = V_{data,i} \cdot \frac{\ln \frac{z_{hub}}{z_0}}{\ln \frac{z_{data}}{z_0}}
\]  

(3)

Where:

- \( z_{hub} \) = the hub height of the wind turbine [m]
- \( z_{data} \) = the anemometer height [m]. This is the height in which the wind data has been read.
- \( z_0 \) = the surface roughness length [m]
\( v_{\text{hub},i} \) = wind speed at the hub height of the wind turbine, during the hour \( i \) [m/s]

\( v_{\text{data},i} \) = wind speed at anemometer height, during the hour \( i \) [m/s]

Second. Using the power curve of the wind turbine, the power output is calculated. With the speed at the hub of the wind turbine, and using its power curve, it is obtained the power that the wind turbine provides in hour \( i \), \( P_{\text{re,w},i} \).

### 2.4. Inverter

The inverter has been modelled in a realistic way, considering the efficiency variable as a function of apparent power output (% of rated apparent power in VA) (example in Fig. 4).

### 2.5. Diesel generator fuel consumption

The fuel consumption of the Diesel generator, \( Cons_G \) (l/h) is modelled as dependant on the output power:

\[
Cons_G = B_G \cdot P_{N,G} + A_G \cdot P_G
\]  

(4)

where \( P_{N,G} \) (kW) is the nominal power, \( P_G \) (kW) is the output power of the Diesel Generator, \( A_G \) and \( B_G \) are the coefficients of the consumption curve, defined by the user (l/kWh).

The efficiency \( \eta_G \) (kWh/l) is calculated using equation (5).

\[
\eta_G = \frac{P}{Cons_G} = \frac{1}{A_G + B_G \cdot P_{N,G} / P}
\]  

(5)

The efficiency in % of the Lower Heating Value (LHV) of gas-oil (\( \eta_{G\%} \) (%)) is calculated from equation (6).

\[
\eta_{G\%} = \frac{\eta_G \text{(kWh/l)}}{LHV_{\text{GAS-OIL}} \text{(kWh/l)}} \cdot 100 = \frac{100 \cdot P}{Cons_G \cdot LHV_{\text{GAS-OIL}}}
\]  

(6)
Where \( LHV_{\text{GAS-OL}} \) is between 10 and 11.6 kWh/l. In this work it is considered \( LHV_{\text{GAS-OL}} = 11.55 \) kWh/l. Skarstein and Ullen [24] propose \( A_G = 0.246 \) l/kWh and \( B_G = 0.08145 \) l/kWh. The efficiency (\% of \( LHV_{\text{GAS-OL}} \)) curve in this case is shown in Fig. 5.

### 2.6. Fuel cell hydrogen consumption.

The hydrogen consumption of the fuel cell, \( Cons_{FC} \) (kg/h) is modelled as dependant on the output power:

\[
\text{If } P/P_{N,FC} \leq P_{\text{max,ef}}:
\]

\[
Cons_{FC} = B_{FC} \cdot P_{N,FC} + A_{FC} \cdot P_{FC}
\]

(7)

\[
\text{If } P/P_{N,FC} > P_{\text{max,ef}}:
\]

\[
Cons_{FC} = B_{FC} \cdot P_{N,FC} + A_{FC} \cdot P_{FC} \left( 1 + F_{ef} \left( \frac{P}{P_{N,FC}} - P_{\text{max,ef}} \right) \right)
\]

(8)

where \( P_{FC} \) is the output power (kW), \( P_{N,FC} \) (kW) is the nominal output power, \( A_{FC} \) and \( B_{FC} \) are the coefficients of the consumption curve (kg/kWh), \( P_{\text{max,ef}} \) (% of \( P_{N,FC} \)) is the output power that has the maximum efficiency and \( F_{ef} \) is the factor to consider the high consumption above \( P_{\text{max,ef}} \).

The efficiency in % of the LHV of hydrogen (\( LHV_{\text{H2}} \)) is calculated using equation (9).

\[
\eta_{FC\%} = \frac{100 \cdot P}{Cons_{FC} \cdot LHV_{\text{H2}}}
\]

(9)

where \( LHV_{\text{H2}} = 33.3 \) kWh/kg. The hydrogen consumption parameters considered in section 5 are the same for all the fuel cells (they are defined by the user): \( A_{FC} = 0.05 \) kg/kWh, \( B_{FC} = 0.004 \) kg/kWh, \( P_{\text{max,ef}} = 0.2 \) and \( F_{ef} = 1 \). The efficiency corresponding to these values is shown in Fig. 6.

### 2.7. Electrolyzer electrical consumption.

The electrical consumption (\( Cons_E \) (kW)) is modelled as dependant on the hydrogen mass flow:

\[
Cons_E = B_E \cdot Q_{N,E} + A_E \cdot Q
\]

(10)
where $Q_{N,E}$ is the nominal hydrogen mass flow (kg/h), $Q$ is the hydrogen mass flow (kg/h), $A_E$ and $B_E$ are the coefficients of the consumption curve (kW/kg/h).

The efficiency in % of the Higher Heating Value of hydrogen ($HHV_{H2}$) is calculated using equation (11).

$$\eta_{E\%} = \frac{100 \cdot Q \cdot HHV_{H2}}{Cons_E}$$

(11)

where $HHV_{H2} = 39.4$ kWh/kg. The electrical consumption parameters considered in section 5 of this work are the same for all the electrolyzers (they are defined by the user): $A_E = 40$ kW/kg/h, $B_E = 20$ kW/kg/h. The efficiency (% of Higher Heating Value of Hydrogen) corresponding to these values is shown in Fig.7.

3. Objective Functions

The objective functions to be minimized are:

- The Total Net Present Cost: $NPC$ (€).
- The CO$_2$ Emissions: $E$ (kg/year).
- The Unmet Load: $UL$ (kWh/year).

3.1. Costs

The costs objective function is the Total Net Present Cost of the system ($NPC$), which includes the cost of the initial investment plus the discounted present values of all future costs throughout the total life of the installation. The life of the system is usually considered to be the life of the PV panels - which are the elements that have a longer lifespan.

In the following paragraph, the costs taken into account are indicated. A more detailed description of its calculation can be found in [7, 12, 13, 14].

- Cost for purchasing the PV panels, the wind turbine, the batteries, the inverter, the charge regulator, the Diesel generator, the electrolyzer, the fuel cell and the hydrogen tank.
- Costs of maintenance of the components.
- Costs of replacing the components throughout the life of the system.
- Costs of operation and maintenance of components throughout the life of the system.
• Cost of the fuel consumed throughout the life of the system.

Some of the costs depend on the control strategy selected amongst those possible [7, 13, 14].

It has been considered that at the end of the life of the system, the remaining value of the elements is recovered.

3.2. Pollutant emissions

In order to measure the pollutant emissions, kg of CO₂ is considered; it represents the largest percentage of all emissions when fuel is burnt [25], and it is the main cause of the greenhouse effect. It is considered that the total amount of kg of CO₂ produced by the hybrid system throughout one year (E) is the correct measure of the pollutant emissions and, therefore, it can be used as the objective to be minimized.

The developed algorithm has as input data the number of kg of CO₂ produced per litre of fuel consumed by the Diesel generator. This value depends upon the characteristics of the Diesel generator and of the characteristics of the fuel, and it usually falls in the 2.4-2.8 kg/l range [25].

3.3. Unmet load

The Unmet Load (UL) is defined as the amount of non-served energy in one year, and it is usually measured in kWh/yr. In percentage it can be defined as follows:

\[
UL(\%) = \frac{UL \text{ (kWh/yr)}}{\text{Total Annual electrical Load (kWh/yr)}} \times 100
\]  

(12)

The maximum Unmet Load allowed is an input of the developed design tool.

The possible solutions (combinations of elements of the system and control strategies) that give a rate of Unmet Load higher than the maximum allowed by the user, are discarded.

4. Multi-Objective Optimization Evolutionary Algorithm

In this section, the Multi-Objective design problem is mathematically formulated, and the basic concepts used by the Multi-Objective Evolutionary Algorithms (MOEA’s) are defined.

Finally, it is also described the applied MOEA (SPEA), that searches the best combination of components minimizing NPC, Pollutant Emissions and Unmet Load. The design tool also uses a Genetic Algorithm (GA) to find the best control for each combination of components, and it is also described.

A Multi-Objective optimisation problem can be defined as follows [8]:

Minimise or maximise the objective functions included in the vector

\[ F(x) = [f_1(x), f_2(x), \ldots, f_k(x)] \]  

(13)

Satisfying the \( m \) restrictions of inequality and the \( p \) restrictions of equality:

\[ g_i(x) \geq 0 \quad i = 1, 2, \ldots, m \]  
\[ h_i(x) = 0 \quad i = 1, 2, \ldots, p \]  

(14)

Where \( x \) is a vector whose elements are the decisive variables of the problem.

Concepts related to Pareto optimality are regularly used in most MOEA’s. Because of this, the concepts of Pareto Dominance, Pareto Optimality, Pareto Optimal Set and Pareto Front are defined, as they appear in [9].

- **Pareto Dominance**: A vector \( u = (u_1, u_2, \ldots, u_k) \) is said to dominate \( v = (v_1, v_2, \ldots, v_k) \) (denoted by \( u \preceq v \)) if and only if \( u \) is partially less than \( v \), i.e., \( \forall i \in \{1, 2, \ldots, k\}, u_i \leq v_i \wedge \exists i \in \{1, 2, \ldots, k\}: u_i < v_i \).

- **Pareto Optimality**: A solution \( x \in \Omega \) is said to be Pareto optimal with respect to \( \Omega \) if and only if there is no \( x' \in \Omega \) for which \( v = F(x') = (f_1(x'), f_2(x'), \ldots, f_k(x')) \) dominates \( u = F(x) = (f_1(x), f_2(x), \ldots, f_k(x)) \).

- **Pareto Optimal Set**: For a given MOP \( F(x) \), the Pareto optimal set (\( P^* \)) is defined as:

\[ P^* := \{ x \in \Omega \mid \exists x' \in \Omega : F(x') \preceq F(x) \} \]  

(15)

- **Pareto Front**: For a given MOP \( F(x) \) and Pareto optimal set \( P^* \), the Pareto front (\( PF^* \)) is defined as:

\[ PF^* := \{ u = F(x) = (f_1(x), f_2(x), \ldots, f_k(x)) \mid x \in P^* \} \]  

(16)

4.2. MOEA applied to the design of PV-Wind-Diesel-Hydrogen-Battery Systems.

The implemented Multi-Objective algorithm is based on SPEA and SPEA2 [10, 11]. This algorithm is in charge of finding the designs which manage to, simultaneously, minimise the NPC of the system, the Pollutant Emissions (\( E \)) and the Unmet Load (\( UL \)). It has been developed using the C++ programming language.
The characteristics of the MOEA that has been applied in this study are described as follows.

### 4.2.1. Codification of solutions

The program uses two different Evolutionary Algorithms. The main algorithm is the MOEA algorithm and codifies the components of the system. The secondary algorithm is a Genetic Algorithm that codifies the control strategy. For each combination of components in the main algorithm (Multi-Objective), the secondary algorithm (Mono-Objective) runs to find its best control strategy (lowest NPC).

### 4.2.2. Main algorithm (MOEA)

The Main Algorithm (MOEA) can search for the configuration of PV panels, wind generators, hydro turbine, batteries, AC generator, fuel cell, electrolyzer and inverter that minimizes the three objectives mentioned. This is the general case, if all these elements are selected [13, 14]. However, in the computational results presented in this paper the system contains only some of these elements (PV-Wind-Diesel-Hydrogen-Batteries system).

In the general case the codification of the variables used by the main algorithm is done through a vector made up of 11 integers:

$$\begin{array}{cccccccc}
| & a & | & b & | & c & | & d & | & e & | & f & | & g & | & h & | & i & | & j & | & k & |
\end{array}$$

(17)

where,

- $a$ is the number of PV panels in parallel
- $b$ is the type of PV panel
- $c$ is the number of wind turbines
- $d$ is the type of wind turbine
- $e$ is the type of hydro turbine
- $f$ is the number of batteries in parallel
- $g$ is the type of battery
- $h$ is the type of AC generator (usually Diesel)
- $i$ is the type of fuel cell
- $j$ is the type of electrolyzer
- $k$ is the type of inverter
Regarding the inverter, it can be forced to supply the maximum power demanded by the AC load, which is an option of the design tool. In this case, the inverter selected will be the one with the lowest power whose output is higher than the AC load maximum. If this option is not used, the type of inverter will be a variable to be optimized, being possible that an inverter whose output is bigger than the maximum AC consumption is not needed; in this case, higher net load will be supplied by the AC generator.

The charge regulator, the battery charger and the H₂ tank do not take part in the combination of components optimized by the main algorithm. This is so because, for each possible combination calculated by the main algorithm, the optimal size of these components is determined once the secondary algorithm has obtained the best control strategy.

The fitness function of the combination $i$ of the main algorithm is assigned according to its rank in the population. The rank is obtained sorting the solutions out according to the number of solutions by which they are dominated: first the non-dominated solutions (dominated by cero solutions), then the dominated by one solution, then the dominated by two solutions, and so on.

The solutions that are dominated by the same number of solutions must have the same fitness, which will be the average fitness of these solutions. All the non-dominated solutions must have the same fitness, all the solutions dominated by 1 must have the same fitness, and so on:

$$fitness_{\text{MAIN}} = \frac{\sum x \left( \frac{(N_m + 1) - i}{\sum (N m + 1) - j} \right)}{(b - a + 1)}$$

(18)

where $N_m$ is the number of solutions of the main algorithm; $i$ is the rank of the solution of which it is calculated its fitness; $j$ are all the solutions of the main algorithm ($j = 1 \ldots N_m$); $k$ are all the solutions dominated by the same number of solutions as the solution $i$ ($k = a \ldots b$).

### 4.2.3 Secondary algorithm (GA)

There are 12 control variables of the hybrid system and all of them are optimized by the secondary genetic algorithm: $P_{\text{min gen}}, P_{\text{min FC}}, \text{SOC}_{\text{min}}, P_{\text{critical gen}}, \text{SOC}_{\text{stp gen}}, P_{\text{critical FC}}, \text{SOC}_{\text{stp FC}}, H_2\text{TANK}_{\text{stp}}, P_{\text{lim charge}}, P_{\text{1 gen}}, P_{\text{1 FC}},$ and $P_2.$ All these control variables were explained in [13, 14]. In some cases some of these variables are not selected to be optimized because they are non-sense (for example, $P_{\text{min gen}}$ will not be a control variable of the system if there is no diesel generator in the system) or because the user does not want to optimize them.

The secondary algorithm is a genetic algorithm (GA) that searches for the best control strategy for each combination of components in the main algorithm. This GA is mono-objective (minimisation of the
costs). The GA uses an integer codification, using a vector in which the information concerning the control strategy is stored.

Codification of the control variables is done through a vector that consists of twelve positions, corresponding with the twelve control variables.

The fitness function of the combination $i$ of the Secondary Algorithm is (rank 1 for the best individual, the one with lowest $NPC$, and rank $N_{sec}$ for the worst solution):

$$fitness_{SECi} = \sum_{j} \frac{(N_{sec}+1) - i}{\sum_{j}[(N_{sec}+1) - j]}$$

where $N_{sec}$ is the number of solutions of the secondary algorithm; $i$ is the rank of the solution of which its fitness is calculated; $j$ are all the solutions of the main algorithm ($j = 1 \ldots \ldots N_{sec}$).

4.2.4. **Steps of the algorithm**

In this section the algorithm that has been applied to perform the Multi-Objective design of the hybrid system is described.

In the following paragraphs, the steps taken to get the algorithm are indicated (see Fig. 8).

1. **Initialisation of the population of the main algorithm.**

   In this first step, it is generated a random set of $N_m$ possible solutions (or individuals) from the main algorithm (vectors codifying the combination of components), which will act as the initial population.

2. **Evaluate the secondary algorithm**

   For each vector $N_m$ of the main algorithm, the secondary algorithm is executed, in order to find the best control strategy:

   1. $N_{sec}$ vectors are obtained randomly from the secondary algorithm. These vectors have been described in 4.2.3, each one representing a possible control strategy.

   2. Each vector of the secondary algorithm together with the vector of the main algorithm codifies a hybrid system that is simulated and $NPC$ is obtained. The secondary algorithm searches for the best control strategy to minimize $NPC$, so the $N_{sec}$ vectors are evaluated by means of their aptitude (equation (19)).

   3. The best vectors (fittest) have a greater probability of reproducing themselves, crossing with other vectors. In each cross of two vectors, two new vectors are obtained (descendents). Descendents are then evaluated and the best of them replace the worst individuals of the previous generation (iteration).
4. To find the optimal solution and not to stay in local minimal, some solutions randomly change some of their components (mutation).

5. The individuals (vectors) obtained from reproduction and mutation are evaluated, making the next generation.

6. The process continues (from 2.2 to 2.5) until a determined number of generations \(N_{\text{gen,sec_max}}\) have been evaluated, obtaining the optimal control strategy.

3. **Sorting out according to the number of solutions they are dominated by.**

   The vectors of the main algorithm are sorted out by the number of solutions they are dominated by (taking into account \(NPC, E\) and \(UL\)), calculating their fitness by equation (18).

4. **Reduction of the Non-dominated Pareto Set.**

   In order to prevent a number of non-dominated solutions \(N_{\text{non,dom}}\) similar to the number of solutions \(N_m\) (avoiding solutions too near each other in the Pareto Set which does not contribute to variety), the program takes into account two inputs indicated by the user:

   a. The maximum \(NPC\) for the non-dominated solutions, in percentage over the minimum \(NPC\) of the non-dominated solutions, \(NPC_{\text{over}}\) (%). If a non-dominated solution has a \(NPC\) greater than the minimum \(NPC\) of the non-dominated solutions incremented by the percentage indicated by the designer \(NPC_{\text{over}}\), this solution is discarded.

   b. The maximum number of non-dominated solutions allowed \(N_{\text{max}}\). If the size of the non-dominated Pareto Set is greater than the admissible maximum, as indicated by the designer \(N_{\text{max}}\), its size is reduced by means of the truncation technique. This reduction technique selects the solution which has the minimum distance to another solution. The distance between two non-dominated solutions \(i\) and \(j\) is:

\[
D_{i-j} = \sqrt{\left(\frac{NPC_i - NPC_{j}}{NPC_{\text{max}}}\right)^2 + \left(\frac{UL_i - UL_{j}}{UL_{\text{max}}}\right)^2 + \left(\frac{E_i - E_{j}}{E_{\text{max}}}\right)^2}
\]

(20)

Where \(NPC\), \(UL\) and \(E\) are, respectively, the total net present cost (€), the unmet load (kWh/year) and the total amount of kg of CO\(_2\) produced by the hybrid system throughout one year (kg/year). The values denoted by “\(\text{max}\)” are the maximum values of the non-dominated solutions.

After knowing the two solutions \(i\) and \(j\) that have the minimum \(D_{i-j}\), then it is selected the one \((i\ or\ j)\) that has the shortest distance to another solution in the set. With this reduction method, solutions at the extremes of the Pareto Front will never be eliminated. This process is repeated as many times as required, eliminating solutions, until the size of the Pareto Set drops to the value specified by the designer \(N_{\text{max}}\).
5. **Stopping criterion.**

If the maximum number of generations indicated by the user \( N_{\text{gen\_main\_max}} \) has been reached, execution stops. Otherwise, selection, crossing and mutation will go on.

6. **Application of the selection, crossing and mutation operators.**

The solutions that will participate in the single point crossing operator [26] are selected (selection operator) from this very set using the roulette method. After crossing those solutions it is obtained a new population that will substitute the original. Finally, the mutation operator [26] is applied. Return to step 2.

7. **Solution selection.**

At this point, there exists a set of solutions which defines the Pareto frontier of non dominated solutions. Among them, the designer will select as the best solution the one that satisfies the associated objectives taken into account as well as other criteria which are considered relevant (O&M costs, etc.).

5. **Computational results: Multi-Objective optimization of a hybrid system.**

By using the developed program, a PV-Wind-Diesel-Hydrogen-Batteries system located in Zaragoza (latitude 41.65°) Spain, has been studied. The load profile considered is shown in Fig. 9 (AC load). The daily load profile is represented by a sequence of powers, each considered as constant over a time-step of 1 hour.

The irradiation on horizontal surface and wind speed data at 10 m height are shown in Figs. 10 and 11. The system has a 48V DC voltage and a 230V AC voltage. The power factor of the AC load is \( \cos \phi = 0.9 \). The wind speed hourly data (at 10 m height) and the irradiation in the area of the town are given by the average hourly values for the last few years.

The maximum Unmet Load allowed is 10% of the total annual load.

The nominal interest rate considered is 4% annually.

The annual general inflation rate is 3%. This rate is applied in order to calculate the cost of replacement of elements of the system when they reach the end of their own lifespan; it is also used to calculate the remaining value of the elements at the end of the lifetime of the system.

El interés nominal y la tasa de inflación influyen considerablemente en el NPC del sistema, no obstante, estos valores deben estimarse. Se podrían realizar varias optimizaciones multi-objetivo teniendo en cuenta distintos escenarios de interés nominal e inflación.
However, some elements have their own annual inflation rate, different from the general inflation rate (to be taken into account in order to estimate their cost when they finish their useful life and must be replaced).

The complete system lifespan estimated is 25 years.

The components considered in the optimization are explained in the following sections.

5.1. PV generators.

PV generators (sets of PV panels in series and in parallel) have been considered instead of data for discrete panels, so the number of panels in parallel will always be 1 and this number will not be optimized. There are 12 possible different PV generators, shown in table 1. Each hybrid system will include one of them. The panels have an inclination of 60° (in order to minimize the unmet load in winter time, because load in winter time is considered more important in this example), 0° azimuth and 0.2 albedo. Their lifespan is 25 years and the nominal voltage is 48 V DC. The loss factor $F_{\text{loss}}$ considered is 1.2.

5.2. Wind Turbines.

There are 6 possible different wind generators, shown in table 2. The power curve of the type 4 is shown in Fig. 3. It has been considered that the number of wind generators must be 1, so this number will not be optimized. The type of ground roughness considered is class 2.5 (0.2 m roughness length). The height above sea level is 247 m. The height of the hub is 10 m, the nominal voltage is 48 V DC and the lifespan is 20 years for all of the wind turbines considered.

In order to calculate the replacement cost (when the wind turbine has reached its lifespan), the annual inflation rate considered for wind turbines costs is -4% (these costs may be increased at a rate different from that of generic inflation figures, and in this case, it is expected that the prices will decrease a 4% annual) and the expected limit of the maximum variation of the wind turbines costs is -20% (this limit will be achieved in 4.4 years; after that, the wind turbines will be assumed to see their prices increased in line with general inflation).

5.3. Batteries.

Battery banks (sets of batteries in series and in parallel) have been considered instead of data for discrete batteries, so the number of batteries in parallel will be always 1 and this number will not be optimized. There are 7 possible different battery banks, shown in table 3. The minimum State of Charge ($SOC_{\text{min}}$) recommended by the manufacturer for all of them is 30%, and the self discharge coefficient is 3% monthly. It has been considered that all of them have 48 V DC nominal voltage and 12 years of
floating life. All of them have the same curve of Cycles to Failure vs. Depth of Discharge (Fig. 2). The battery model considered is Ah model [17] and the lifespan for the batteries is estimated by the Cycle Count (Rainflow method), according to Downing's Algorithm [21].

The annual inflation rate for battery banks costs considered is the same as the one considered for the wind turbines.

5.4. Diesel generators.

There are 6 possible different Diesel generators, shown in table 4. The fuel (gas-oil) price is 1.2 €/l with 10% annual inflation rate. The expected CO$_2$ emissions are 2,489 kg CO$_2$/l. Fuel Consumption Parameters considered are the same for all the Diesel generators: $A = 0.246$ l/kWh and $B = 0.08145$ l/kWh [24].

The efficiency curve is shown in Fig. 5.

The minimum output power recommended by the manufacturer is 30% of the rated power and the lifespan is 7,000 h. for all the Diesel generators considered.

5.5. Fuel cells.

There are 6 possible different fuel cells, shown in table 5. The minimum output power recommended by the manufacturer is 10% of the nominal power and the lifespan is 15,000 h. for all of them.

The hydrogen consumption parameters considered are the same for all the fuel cells: $A_{FC} = 0.05$ kg/kWh, $B_{FC} = 0.004$ kg/kWh, $P_{\text{max,ef}} = 0.2$ and $F_{\text{ef}} = 1$. The efficiency (% of Lower Heating Value of hydrogen) corresponding to this hydrogen consumption is shown in Fig. 6.

The annual inflation rate considered for wind turbines costs is -20% (these costs may be expected to increase at a rate different from that of generic inflation figures, in this case it is expected that the prices will decrease at 20% annual) and the limit expected of the maximum variation of the hydrogen components costs is -60% (this limit will be achieved in 4.1 years; after then, the hydrogen components will be assumed to see their prices increased in line with general inflation).

5.6. Electrolyzers.

There are 7 possible different electrolyzers, shown in table 6. The minimum input power is 10% of the nominal power and the lifespan is 10 years for all the electrolyzers considered.

The electrical consumption parameters considered are the same for all the electrolyzers: $A_E = 40$ kW/kg/h, $B_E = 20$ kW/kg/h.

The efficiency (% of Higher Heating Value of Hydrogen) is shown in Fig.7.
5.7. Inverters.

There are 5 possible different inverters: 0/ 2.2/ 3.3/ 4.5 and 5.5 kVA, with prices 0/ 2,300/ 3,200/ 4,300 and 5,200 € respectively. The lifespan is 10 years and the efficiency depends on the output power (Fig. 4).

5.8. Other data.

The rectifier, the battery charge regulator and the hydrogen tank are selected at the end of the simulation of each combination of components and control variables.

The cost of the rectifiers is 200 €/kW, the lifetime is 10 years and the efficiency is 90%. The cost of the batteries charge regulator is 30 € + 4 €/A and the lifetime is 10 years.

The specific cost of the hydrogen tank is 1,000 €/kg, the maximum capacity allowed is 10 kg. The lifespan expected is 20 years and the annual O&M cost is 50 €/yr.

5.9. Results.

Several executions of the design program have been worked out, determining the best values of the parameters, evaluating convergence and computational time for the algorithms. The parameters used in this case are the following (they are entered by the user):

Main algorithm (MOEA): Number of Generations \( N_{\text{gen\_main\_max}} = 20 \). Population \( N_m = 300 \). Maximum size of the Pareto Front is \( N_{\text{max}} = 50 \). Crossing probability is 0.9. Mutation rate is 0.01. The maximum \( NPC \) for the non-dominated solutions is 60% over the lowest \( NPC \) of the non-dominated solution \( (NPC_{\text{over}} = 60\%) \).

In this case, only 7 of the 11 possible positions of the vector are optimized (section 4.2.2): \( b \) (type of PV generator), \( c \) (type of wind turbine), \( g \) (type of battery bank), \( h \) (type of AC generator), \( i \) (type of fuel cell), \( j \) (type of electrolyzer) and \( k \) (type of inverter). Number of possible combinations of components is \( 12 \cdot 6 \cdot 7 \cdot 6 \cdot 6 \cdot 7 \cdot 5 = 635,040 \).

However, the number of combinations evaluated by the main algorithm is less than (number of generations \( \cdot \) population) \( 20 \cdot 300 = 6,000 \).

Secondary algorithm (GA): Number of Generations \( N_{\text{gen\_sec\_max}} = 20 \). Population \( N_{\text{sec}} = 100 \). Crossing probability is 0.9. Mutation rate is 0.01. The control variables to be optimized are 10: \( P_{\text{min\_gen}} \), \( P_{\text{min\_FC}} \), \( \text{SOC}_{\text{min}} \), \( \text{P}_{\text{critical\_gen}} \), \( \text{SOC}_{\text{tsp\_gen}} \), \( \text{H}_2\text{TANK}_{\text{tsp}} \), \( P_{\text{lim\_charge}} \), \( P_{\text{I\_gen}} \), \( P_{\text{I\_FC}} \) and \( P_2 \). Each variable can take 5 values, the number of combinations of the control strategy is \( 5^{10} = 9,765,625 \).
However, the number of combinations of the control strategy evaluated by the secondary algorithm is less than \((\text{number of generations} \cdot \text{population}) = 20 \cdot 100 = 2,000\).

With a Pentium IV 3.4 GHz, 1 GB RAM, about 50 evaluations per second can be performed. The number of combinations of components and control strategies is \(635,040 \cdot 9,765,625 = 6.2 \cdot 10^{12}\). Evaluating all the combinations would take 3,933 years. This fact demonstrates that an enumerative technique (classical technique) is not adequate to solve this kind of optimization problems.

Genetic algorithms are suitable for this kind of problem because evaluating all the combinations is impossible. The number of combinations evaluated by the design tool, using genetic algorithms, is less than \(6,000 \cdot 2,000 = 1.2 \cdot 10^7\). This task has taken 68 hours.

The evolution of the 3D Pareto Front can be observed in Fig. 12 (first and last Pareto Fronts).

In Figs. 13, 14 and 15, the different 2D representations of the last Pareto Front (20th generation of the main algorithm) are shown.

There are 35 solutions in the Pareto Set of the last generation. As an example, in table 7, three solutions of the Pareto Front can be observed in detail: Solution 1, solution 9 and solution 31.

In Figs. 16-25, the hourly simulation through the year for solution 31 can be observed.

Fig. 19 shows that the Diesel Generator starts working in June, when the load becomes higher. Hydrogen tank capacity in this case is the maximum allowed (10 kg).

Fig. 20 shows that the hydrogen tank is full before March.

In Fig. 24, it can be observed that, in March and April, there is Excess Energy, which could be stored in the hydrogen tank if the maximum hydrogen tank capacity allowed was higher.

However, it can be seen that storing energy in the hydrogen tank is much more inefficient than storing energy in batteries, so when the renewable sources produce more energy than is demanded, the surplus power is used to charge the batteries as much as possible and, if there is still more energy left, then this spare energy can also produce hydrogen in the electrolyzer (\(P_{\text{charge}}\) in solution 31, has a high value).

Fig. 22 shows that, many times, energy supplied by the batteries is higher than energy consumed by the AC load, as energy supplied by batteries includes inverter losses.

In Fig. 25 the unmet load is shown, being higher in summer. Unmet load in winter time is near 0, due to the step inclination of PV panels, among several other reasons.

6. Conclusions

In this paper it has been applied, for the first time, the Strength Pareto Evolutionary Algorithm to the Multi-Objective design of hybrid systems of electrical energy generation, minimising, simultaneously, three objectives: cost, pollutant emissions and unmet load.
The problem of design is very complex. The classical optimisation techniques are not able to solve the problem of optimization consuming a reasonable CPU time. Nevertheless, the SPEA obtains a set of non dominated solutions with little computational effort.

La herramienta de diseño realiza la optimización multi-objectivo, seleccionando diversas soluciones que componen el paréntóptimo. Cada una de las soluciones está compuesta por una determinada combinación de componentes físicos (generador fotovoltaico, aerogeneradores, generador Diesel, baterías, electrolizador, pila de combustible y tanque de hidrógeno, inversor, regulador de carga, rectificador), así como una estrategia de control del sistema.

An application example has been explained, the design of a PV-Wind-Diesel-Hydrogen-Battery system in Zaragoza. The results state the practical value this method has for the designer, making it possible to select any of the solutions obtained by the algorithm. En este ejemplo, el paréntóptimo ha obtenido 35 soluciones, entre las que el diseñador puede elegir la que más le interese, teniendo en cuenta, para cada una de ellas, el NPC, las emisiones de CO₂ y la energía no servida. Dado el elevado coste del gasoil, así como su elevada tasa de inflación, muchas de las soluciones del paréntóptimo disponen del mayor generador fotovoltaico de los considerados en la optimización, así como del mayor aerogenerador de entre los considerados. Otras soluciones disponen del mayor aerogenerador y de generadores fotovoltaicos más pequeños, dado el elevado coste de los paneles fotovoltaicos. Debido a los elevados costes de los componentes del hidrógeno, el almacenamiento de energía sobrante en la mayoría de las soluciones se realiza únicamente mediante baterías. Algunas soluciones incorporan tanto almacenamiento en baterías como en hidrógeno, pero en esos casos la estrategia de control óptima da prioridad al almacenamiento en baterías, como en el caso de la solución nº 31.

Acknowledgments

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Fig. 2. Battery Cycles to Failure vs. Depth of Discharge
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Evaluation of the control strategy for each of the vectors of the main algorithm. The secondary algorithm is executed $N_m$ times.

$i = 1 \ldots N_m$

Each vector of the main algorithm has its best control. Sort the solutions obtained out according to the number of solutions they are dominated by.

Random generation of $N_m$ vectors from the main algorithm $N_{gen\_main} = 1$

Selection, crossing and mutation of the main algorithm vectors. $N_{gen\_main} = N_{gen\_main} + 1$

The best control (rank 1) is the one represented by the vector of the secondary algorithm with lowest NPC.

$\text{i} = i + 1$

$\text{i} < N_m + 1$?

Simulation of the system. Evaluation of the $N_{sec}$ vectors of the secondary algorithm: Calculate NPC for each one and sort by NPC.

Selection, crossing and mutation of the secondary algorithm vectors. $N_{gen\_sec} = N_{gen\_sec} + 1$

$N_{gen\_sec} < N_{gen\_sec\_max} + 1$?

The best control (rank 1) is the one represented by the vector of the secondary algorithm with lowest NPC. $\text{i} = i + 1$

$\text{i} < N_m + 1$?

$\text{NO}$

Random generation of $N_{sec}$ vectors of the secondary algorithm from the vector $\text{i}$ of the main algorithm.

$N_{gen\_sec} = 1$

$\text{YES}$

Selection, crossing and mutation of the secondary algorithm vectors.

$N_{gen\_sec} = N_{gen\_sec} + 1$?

$\text{NO}$

Reduction. $N_{gen\_sec} = N_{gen\_sec} - 1$

$\text{YES}$

$N_{gen\_sec} > N_{gen\_sec\_max}$?

$\text{NO}$

$\text{YES}$

$N_{gen\_main} < N_{gen\_main\_max}$?

$\text{NO}$

END: PARETO SET

Fig. 8. Flowchart.
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<table>
<thead>
<tr>
<th>Nominal Peak Power of the PV generator (kWp)</th>
<th>0</th>
<th>0.5</th>
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<th>1.5</th>
<th>2</th>
<th>2.5</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
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<tbody>
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<td>Shortcut current (A)</td>
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<td>15.2</td>
<td>22.8</td>
<td>30.4</td>
<td>38</td>
<td>45.6</td>
<td>60.8</td>
<td>76</td>
<td>91.2</td>
<td>106</td>
<td>122</td>
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<tr>
<td>O&amp;M cost (€/yr)</td>
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<td>30</td>
<td>33</td>
<td>37</td>
<td>40</td>
<td>44</td>
<td>50</td>
<td>60</td>
<td>70</td>
<td>80</td>
<td>90</td>
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<tr>
<td>Acquisition cost (k€)</td>
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<td>6</td>
<td>9</td>
<td>11.7</td>
<td>14.5</td>
<td>17</td>
<td>22</td>
<td>26</td>
<td>30</td>
<td>35</td>
<td>40</td>
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Table 2. Wind turbines

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<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
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<tbody>
<tr>
<td>Max output power (W)</td>
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<td>275</td>
<td>640</td>
<td>1760</td>
<td>3500</td>
<td>6500</td>
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<tr>
<td>Wind speed at max output power (m/s)</td>
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<td>14</td>
<td>14</td>
<td>14</td>
<td>14</td>
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<td>0</td>
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<td>Output power (W) at 4 m/s</td>
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<td>75</td>
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<td>Output power (W) at 6 m/s</td>
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<td>75</td>
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<td>2000</td>
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<td>1900</td>
<td>3700</td>
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<td>1260</td>
<td>2500</td>
<td>5000</td>
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<td>1500</td>
<td>3100</td>
<td>6000</td>
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<td>1480</td>
<td>3000</td>
<td>5800</td>
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<td>50</td>
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Table 3. Battery banks
## Table 4. Diesel AC Generators

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<th>Rated output power (kVA)</th>
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<td>Acquisition cost (€)</td>
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<td>1514</td>
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<td>2800</td>
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## Table 5. Fuel cells

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<td>Acquisition cost (€)</td>
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## Table 6. Electrolyzers

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<th>3</th>
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<td>O&amp;M cost (€/yr)</td>
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<td>45</td>
<td>50</td>
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Table 7. Three solutions of the Pareto Set (last generation)

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<th>SOL.1</th>
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<td>Peak power of the PV Generator (kWp)</td>
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<td>Wind Turbine</td>
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<td>Type 6</td>
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<td>Wind Turbine peak power (kW)</td>
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<td>6.5</td>
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<tr>
<td>Nominal Capacity of Battery bank (kWh)</td>
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<td>44.3</td>
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<tr>
<td>Diesel Generator rated power (kVA)</td>
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<td>Electrolyzer nominal power (kW)</td>
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<td>0</td>
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<td>Fuel Cell nominal power (kW)</td>
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<tr>
<td>Hydrogen tank capacity (kg)</td>
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<tr>
<td>Inverter nominal power (kVA)</td>
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<td>Charge Regulator current (A)</td>
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<tr>
<td>Rectifier power (kW)</td>
<td>678</td>
<td>495</td>
</tr>
<tr>
<td>Dispatch strategy:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>- SOC&lt;sub&gt;min&lt;/sub&gt; (%)</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>- P&lt;sub&gt;lim_charge&lt;/sub&gt; (W)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>- P&lt;sub&gt;1_gen&lt;/sub&gt; (W)</td>
<td>31284</td>
<td>28809</td>
</tr>
<tr>
<td>- P&lt;sub&gt;1_Fc&lt;/sub&gt; (W)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>- P&lt;sub&gt;2&lt;/sub&gt; (W)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>- Priority P&lt;sub&gt;1&lt;sup&gt;2&lt;/sup&gt;&lt;/sub&gt; (Gen. or Fuel Cell)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>- P&lt;sub&gt;min_gen&lt;/sub&gt; (VA)</td>
<td>570</td>
<td>1200</td>
</tr>
<tr>
<td>- P&lt;sub&gt;min_Fc&lt;/sub&gt; (W)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>- P&lt;sub&gt;critical_gen&lt;/sub&gt; (W)</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>- SOC&lt;sub&gt;stp_gen&lt;/sub&gt; (%)</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>- H&lt;sub&gt;2&lt;/sub&gt;TANK&lt;sub&gt;stp&lt;/sub&gt; (kg)</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Annual Electrical Energy delivered by PV generator (kWh/yr)</td>
<td>8610</td>
<td>8610</td>
</tr>
<tr>
<td>Annual Electrical Energy delivered by Wind turbine (kWh/yr)</td>
<td>8571</td>
<td>8571</td>
</tr>
<tr>
<td>Annual Battery Through-output Energy (kWh/yr)</td>
<td>5714</td>
<td>5620</td>
</tr>
<tr>
<td>Annual Electrical Energy consumed by Electrolyzer (kWh/yr)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Annual Electrical Energy delivered by Fuel Cell (kWh/yr)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Annual Overall load Energy (kWh/yr)</td>
<td>14039</td>
<td>14039</td>
</tr>
<tr>
<td>Annual Excess energy (kWh/yr)</td>
<td>1720</td>
<td>1962</td>
</tr>
<tr>
<td>Batteries replacement cycle (yr)</td>
<td>9.62</td>
<td>4.92</td>
</tr>
<tr>
<td>Annual Hours of Diesel operation</td>
<td>1241</td>
<td>1267</td>
</tr>
<tr>
<td>Annual Hours of Electrolyzer operation</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Annual Hours of Fuel Cell operation</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Unmet annual Load (kWh/yr)</td>
<td>644.1</td>
<td>74.8</td>
</tr>
<tr>
<td>Unmet Load (%)</td>
<td>4.5</td>
<td>0.5</td>
</tr>
<tr>
<td>CO&lt;sub&gt;2&lt;/sub&gt; Emissions (kg CO&lt;sub&gt;2&lt;/sub&gt;/yr)</td>
<td>1353</td>
<td>2421</td>
</tr>
<tr>
<td>Total Net Present Cost of the system (€)</td>
<td>147026</td>
<td>184571</td>
</tr>
</tbody>
</table>
Nomenclature and abbreviations

\(a\)  
integer that matches the code that identifies the number of PV panels in parallel (or PV generators in parallel)

\(A_E\)  
coefficient of the Electrolyzer electricity consumption curve \([\text{kW/kg/h}]\).

\(A_{FC}\)  
coefficient of the Fuel Cell hydrogen consumption curve \([\text{kg/kWh}]\).

\(A_G\)  
coefficient of the Diesel generator fuel consumption curve \([\text{l/kWh}]\).

\(b\)  
integer that matches the code that identifies a certain type of PV panel or PV generator

\(B_E\)  
coefficient of the Electrolyzer electricity consumption curve \([\text{kW/kg/h}]\).

\(B_{FC}\)  
coefficient of the Fuel Cell hydrogen consumption curve \([\text{kg/kWh}]\).

\(B_G\)  
coefficient of the Diesel generator fuel consumption curve \([\text{l/kWh}]\).

\(c\)  
integer that matches the code which identifies a certain wind turbine model.

\(\cos\varphi\)  
power factor of the AC load.

\(CF\)  
cycles to failure.

\(CF_i\)  
number of cycles to failure of the battery in the interval \(DOD_i\).

\(Cons_E\)  
electrical energy consumption of the Electrolyzer \([\text{kW}]\)

\(Cons_{FC}\)  
hydrogen consumption of the Fuel Cell \([\text{kg/h}]\)

\(Cons_G\)  
fuel consumption of the Diesel generator \([\text{l/h}]\)

\(d\)  
integer that matches the code that identifies the number of wind turbines

\(DOD\)  
depth of discharge of the battery \([\%]\)

\(DOD_i\)  
interval between 2 values of \(DOD\)

\(e\)  
integer that matches the code which identifies a certain hydro turbine model.

\(E\)  
Total amount of kg of CO\(_2\) produced by the hybrid system throughout one year \([\text{kg/year}]\).

\(f\)  
integer that matches the code that identifies the number of batteries in parallel (or groups of batteries banks in parallel)

\(F_{ef}\)  
fuel cell consumption factor to consider the high consumption above \(P_{\text{max,ef}}\).

\(fitness_{\text{main}}\)  
fitness of a solution of the main algorithm (combination of components)

\(fitness_{\text{sec}}\)  
fitness of a solution of the secondary algorithm (control strategy)

\(F_{\text{loss}}\)  
factor that takes into account the losses of power given by the PV panels due to shadows, dirt, etc.

\(g\)  
integer that matches the code that identifies a certain type of battery or batteries bank

\(GA\)  
Genetic Algorithm.

\(h\)  
integer that indicates the code that matches the size of the AC generator (Diesel usually) used in the system.

\(H_2TANK_{\text{sp}}\)  
Setpoint for the amount of H\(_2\) stored in the tank, value optimized by the program \([\text{kg}]\)

\(HHV_{\text{H2}}\)  
Higher Heating Value of hydrogen \([39.3 \text{kWh/kg}]\)

\(i\)  
integer that matches the code that identifies a certain fuel cell.

\(j\)  
integer that matches the code that identifies a certain electrolyzer.
**$k$** integer that matches the code that identifies a certain inverter.

\[ LHV_{\text{GAS-OIL}} \] Lower Heating Value of gas-oil [kWh/l]

\[ LHV_{\text{H}_2} \] Lower Heating Value of hydrogen [33.3 kWh/kg]

**MOEA** Multi-Objective Evolutionary Algorithm.

\[ N_i \] Number of cycles of the battery in the interval \( DOD_i \) in 1 year.

\[ N_{\text{max}} \] maximum size allowed of the Pareto Set (non-dominated solutions).

\[ N_{\text{gen \_main}} \] number of generations of the main algorithm

\[ N_{\text{gen \_main \_max}} \] maximum number of generations of the main algorithm

\[ N_{\text{gen \_sec}} \] number of generations of the secondary algorithm

\[ N_{\text{gen \_sec \_max}} \] maximum number of generations of the secondary algorithm

\[ N_\text{pop} \] population of the main algorithm: number of solutions (vectors) of the main algorithm.

\[ N_{\text{non \_dom}} \] number of non-dominated solutions.

**NPC** Net Present Cost of the system [€]

\[ NPC_{\text{over}} \] maximum NPC for the non-dominated solutions, in percentage over the minimum NPC of the non-dominated solutions [%].

\[ N_{\text{sec}} \] population of the secondary algorithm: number of solutions (vectors) of the secondary algorithm

\[ P_{\text{critical \_gen}} \] power under which the diesel generator, instead of providing exactly the necessary value required to satisfy demand, provides the nominal power (or the possible maximum without losing energy), using the surplus energy to charge the batteries until a certain level of charge called \( SOC_{\text{ap \_gen}} \) [W]

\[ P_{\text{FC}} \] output power of the Fuel Cell [kW]

\[ P_{\text{G}} \] output power of the AC Generator [kW]

\[ P_{\text{lim \_disch}} \] Discharge limit power [W]

\[ P_{\text{max \_ef}} \] fuel cell output power that has the maximum efficiency (% of \( P_{\text{N \_FC}} \)) [%]

\[ P_{\text{min \_gen}} \] minimum operational power of the Diesel generator optimized by the program [W]

\[ P_{\text{min \_FC}} \] minimum operational power of the Fuel Cell optimized by the program [W]

\[ P_{\text{N \_FC}} \] nominal power of the Fuel Cell [kW]

\[ P_{\text{N \_G}} \] nominal power of the Diesel generator [kW]

\[ P_{\text{re \_pv \_i}} \] power supplied by the PV panels, during the hour \( i \) [W]

\[ P_{\text{re \_w \_i}} \] power supplied by the wind turbine, during the hour \( i \) [W]

\[ PI_{\text{FC}} \] Intersection point of the cost of supplying energy with the batteries and the cost of supplying energy with the fuel cell. Value optimized by the program [W]

\[ PI_{\text{gen}} \] Intersection point of the cost of supplying energy with the batteries and the cost of supplying energy with the AC generator. Value optimized by the program [W]

\[ P2 \] Intersection point of the cost of supplying energy with the fuel cell and the cost of supplying energy with the AC generator. Value optimized by the program [W]
$Q_{N,E}$ Electrolyzer hydrogen mass flow (kg/h)

$Q_{N,E}$ Electrolyzer nominal hydrogen mass flow (kg/h)

$SOC$ State of Charge of the batteries [% of $C_n$]

$SOC_{min}$ minimum State Of Charge of the battery bank [% of nominal capacity]

$SOC_{set_gen}$ $SOC$ set point of the batteries [% of nominal capacity]

SPEA Strength Pareto Evolutionary Algorithm

$UL$ Annual Unmet load [kWh/year]

$UL$ (%) Unmet load as a percentage of the overall load [%]

$v_{hub_i}$ Wind speed at the hub height of the wind turbine, during the hour $i$ [m/s]

$v_{data_i}$ Wind speed at anemometer height, during the hour $i$ [m/s]

$z_0$ The surface roughness length [m]

$z_{data}$ The anemometer height [m]. This is the height in which the wind data has been read.

$z_{hub}$ The hub height of the wind turbine [m]

$\eta_{E%}$ electrolyzer efficiency (in % of the Higher Heating Value of hydrogen, $HHV_{H2}$) [%]

$\eta_{F%}$ fuel cell efficiency (in % of the Lower Heating Value of hydrogen, $LHV_{H2}$) [%]

$\eta_G$ Diesel generator efficiency [kWh/l]

$\eta_{G%}$ Diesel generator efficiency (in % of the Lower Heating Value of gas-oil, $LHV_{GAS-OIL}$) [%]