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Optimal sizing of a Hybrid Renewable Energy System: importance of data selection with highly variable renewable energy sources

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Abstract

The replacement of fossil fuels for producing energy with renewable sources is crucial to limit the climate change effects. However, the unpredictable nature of renewables, like sun and wind, complicates their integration within the power systems. This problem can be faced with the introduction of Hybrid Renewable Energy Systems (HRESs) where several energy sources can be incorporated. A key aspect is the assessment of the HRES configuration, which is fundamental to obtain a feasible system from both technical and economic points of view. In this paper, a novel Mixed Integer Linear Programming (MILP) optimization algorithm has been developed to design a tool capable of assessing the optimal sizing of a HRES. The algorithm has been applied to a real case study of a mountain hut located in South-Tyrol (Italy) with a hybrid system composed by solar, wind and diesel generators together with a battery storage. The algorithm compares several scenarios providing the optimal configurations of the HRES, which are characterized by different costs and energy deficits. This tool helps engineers to identify the best trade-off between costs and energy deficits in the planning phase of a HRES, still granting the demand of the users as well as the constraints.

Keywords: Hybrid Renewable Energy Systems, Mixed Integer Linear Programming, Solar Energy, Wind Energy, Diesel Engine, Battery Storage.

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Nomenclature

PV system

α	Absorptivity of the cell [-]
β	Efficiency loss coefficient of the solar cell [$^{\circ}\text{C}^{-1}$]
η_{BOS}	Balance of system efficiency [-]
η_c	Cell efficiency [-]
$\eta_{\text{n,c}}$	Rated efficiency of the cell in STC [-]
τ	transmissivity of the cell [-]
A_{eff}	Net cell opening area [m^2]
E_{PV}	Energy delivered by the PV system [kWh]
G	Global Irradiance on the panel tilted surface [kWh/m^2]
$NOCT$	Nominal Operating Cell Temperature of the PV panel [$^{\circ}\text{C}$]
T_A	Ambient temperature [$^{\circ}\text{C}$]
T_C	Cell temperature [$^{\circ}\text{C}$]

Wind turbine system

$\rho_{\text{air}(STC)}$	Air density in STC [kg/m^3]
ρ_{air}	Air density [kg/m^3]
E_{WT}	Energy delivered by the wind system [kWh]
P_R	Rated power delivered by the wind turbine in STC [kW]
$P_{\text{WT}(STC)}$	Power delivered by the wind turbine in STC [kW]
P_{WT}	Power delivered by the wind turbine [kW]

W_{cut-in} Cut in speed of the wind turbine [m/s]

$W_{cut-out}$ Cut out speed of the wind turbine [m/s]

W_{hub} Wind speed at hub height [m/s]

W_h Wind speed measured at the anemometer height [m/s]

W_R Wind speed corresponding to the rated power [m/s]

z_0 Surface roughness [m]

z_{hub} Hub height [m]

Diesel generator

η_{gen} Efficiency of the diesel generator [-]

ρ_{fuel} Fuel density [kg/m³]

E_{Mot} Energy delivered by the Diesel generator [kWh]

F_C Fuel consumption [g/s]

LHV_{fuel} Lower Heating Value [MJ/kg]

P_{el} Electrical power [kW]

P_r Rated power [kW]

Battery storage

σ Self discharge rate [-]

B_C Battery capacity [kWh]

E_{batt} Energy delivered or stored [kWh]

MILP model

C_{Batt} Total NPC of a battery unit [€]

C_{PV} Total NPC of a PV unit [€]

C_{WT} Total NPC of a WT unit [€]

N_{Batt} Total number of batteries units [-]
 N_{Diesel} Total number of diesel generators [-]
 N_{PV} Total number of PV panels [-]
 N_{WT} Total number of wind turbines [-]

NPC of the HRES

C_{fuel} Fuel cost [€]
 C_{IN} Initial capital cost [€]
 $C_{O\&M}$ Operation and maintenance cost [€]
 C_R Replacement cost [€]
 D_f Discount factor [-]
 f Inflation rate [-]
 i Real discount rate [-]

Other abbreviations

BOS Balance of System
 E_{Load} Energy absorbed by the load [kWh]
 GHG Greenhouse gas
 $HRES$ Hybrid Renewable Energy System
 $MILP$ Mixed Integer Linear Programming
 NPC Net Present Cost
 STC Standard Test Conditions

1. Introduction

The continuous development of Renewable Energy Systems (RES) has become a key aspect in many Countries all over the World with the aim of guaranteeing a clean and sustainable development, as well as to contrast the effects of the climate change. Even though the replacement of fossil fuels with renewables for producing energy is nowadays crucial, the use of traditional sources is continuously increasing. In such a context, the use of non-fossil fuels is still low for preventing this continuous growth [1]. One of the main reasons that limits the replacement of fossil fuels with renewables is their fluctuating and unpredictable nature, which complicates the integration within the power systems [2]. The characteristics of solar and wind energies may lead to an excess of energy production that would be wasted if the balance between the load requirements and the generated energy does not match. For instance, a global amount of curtailed electrical energy of 940.8 billion kWh was estimated in the year 2013 [3].

Locations that have few connections with the national grid, or those that have not been electrified so far, are typical examples where the introduction of renewables would be crucial for decreasing the environmental burden. When considering the electrification of rural areas through mini-grids, the lack of methodologies related to the assessment of the energy needs can lead to an inefficient system design. Gambino et al. [4] proposed a solution that takes into account both specific needs and context conditions, characterizing a community to be electrified. They developed a methodology that can be applied per each different case based on data collection methods, aiming to achieve a high accurate description of the electricity consumption. Hybrid Renewable Energy Systems (HRESs) are currently being developed in order to exploit the sources available in a determined area instead of adopting solutions based on convectional generators or power grid extensions, thus resulting in a more profitable use of these sources on both environmental and economic points of view [5, 6]. HRESs are outlined by different configurations: for instance, they can be composed by photovoltaic (PV) panels coupled with batteries [7], wind turbines paired with batteries [8], PV panels mated with wind turbines [9] or by coupling PV panels and wind turbines together with a Pumped Hydro Energy Storage (PHES) [10]. In addition, other configurations can be PV-wind-battery [11, 12], PV-wind-hydrogen [13], PV-wind-battery-diesel generator [14], PV-Wind-Combined Heat and Power (CHP) [15], PV-wind-biomass [16] and PV-biogas generator-PHES with battery storage [17]. Further examples can be found in [18].

When considering the installation of an off-grid HRES, one of the main chal-

38 lenges is the evaluation of the optimal design, which is related to the selection of
39 the optimal number and size of the system components [19]. To achieve this goal,
40 optimization techniques that are divided into mathematical and metaheuristic
41 methods have to be used [20]. Mathematical methods are suitable for solving
42 linear problems and allow engineers to obtain the exact optimal solution. On
43 the other hand, metaheuristic methods find the optimal solution iteratively, thus
44 requiring lower computational efforts: however, they provide an approximate
45 solution that is not always the exact one [21]. Among the first ones, Linear Pro-
46 gramming (LP) and Mixed Integer Linear Programming (MILP) have been widely
47 applied to the HRESs optimization. Morais et al. [22] used this technique to com-
48 pute the optimal operation scheduling of an isolated system constituted by PV
49 panels, wind turbines and a fuel cell coupled with a storage. Ferrer et al. [23] de-
50 veloped a MILP model, which has been applied to a case study in Peru, in order
51 to optimize hybrid off-grid PV-wind systems. The model computes the optimal
52 solution considering various consumption points with the aim of minimizing the
53 objective function that represents the initial investment cost of the system. Mal-
54 heiro et al. [24] used a MILP model to design an isolated PV-wind-diesel with a
55 battery storage where its Levelized Cost Of Energy (LCOE) has been used as ob-
56 jective function. Among the second ones, Genetic Algorithm (GA) and Particle
57 Swarm Optimization (PSO) methods have been widely employed to compute the
58 optimal sizing of HRESs. Zhao et al. [25] used a GA for a multi-objective opti-
59 mization of a system composed by PV panels, wind turbines and a diesel engine
60 coupled with a battery storage. The multi-objective optimization aimed to mini-
61 mize the life-cycle cost, as well as the system pollutant emissions, and maximize
62 the penetration of renewables. Stoppato et al. [26] developed a PSO model to op-
63 timize the cost of a PV-PHES system in a rural village located in North Nigeria.

64 However, HRESs have been also investigated by means of commercial soft-
65 ware like HOMER. For instance, HOMER has been used in [27], [28] and [29]
66 to study an off-grid PV-wind-hydro system coupled with a battery storage and a
67 back-up diesel generator, while in [30] it was used to assess the optimal planning
68 of a hybrid system composed by PV panels, diesel generators and a battery stor-
69 age as well. Along the same line, the IHOGA [31] software was developed by the
70 University of Zaragoza and applies optimization models, based on GA, to anal-
71 yse HRESs as discussed in [32] and [33]. In several cases, the techno-economic
72 optimization of a HRES is based on simplified assumptions that provide an opti-
73 mal result but, if the external conditions vary, they can lead to either under-sized
74 or over-sized systems. The most common assumptions regard the load profile,
75 which is considered to be the same per each day of the year, and the shape of

76 both solar and wind energies. Indeed, the selection of the optimal configuration
77 of a HRES cannot be assumed as unique for an application where the daily load
78 profile and the sources shape vary. For this reason, an assessment of possible
79 optimal solutions can help engineers to choose the best configuration that meets
80 the system needs.

81 In this work, a MILP optimization model has been developed with Matlab[®]
82 [34] and applied to a case study of a mountain hut, located in the Italian region
83 of South-Tyrol (Italy), in order to assess the optimal sizing of a PV-wind-diesel
84 generator system together coupled with a lead-acid battery storage. The paper
85 analyses the possibility of electrifying the hut through a HRES: in this case, the
86 high level of complexity related to the system optimization regards the strong
87 variability of the load, as well as the high level of fluctuations of both sun and
88 wind sources. The main novelty of the work is the methodology adopted to assess
89 how the configuration of a HRES, thus the optimal sizing, can vary depending on
90 the variability of both load and renewables, thus allowing engineers to analyse
91 several realistic cases corresponding to a specific time span. Specifically, the op-
92 timization code has been run considering different possible boundary conditions
93 and the design of the system takes into account all these variations. In addi-
94 tion, the effect of the reference time span selected for the optimization process
95 is studied and discussed. The MILP model also shows how the optimal output,
96 thus the sizing of the system, can change according to the parameters involved
97 in the process change, providing a complete tool that can be adapted to different
98 applications and targets.

99 The paper is structured as follows: Section 2 presents the case study, the
100 models of the various components related to the HRES and the MILP model as
101 well. Section 3 shows the results of the simulations and Section 4 reports the
102 conclusions of the work.

103 **2. Research and Methods**

104 *2.1. Problem definition and goal of the work*

105 Most of the works available in literature that deal with the optimal sizing of
106 the HRESs provide results in a time span of 24 hours. They are based on the
107 shapes of both load profile and energy production from renewables. In other
108 works [35, 36], standard hours are selected with the aim of representing the
109 whole dataset properly, thus providing results that can be compatible and ex-
110 tendable to the entire time period. This strategy is particular suitable to lower
111 the computational efforts [37] in the calculation processes.

112 Sometimes, the daily fluctuations of the shapes of both load profile and re-
113 newable energy production do not allow engineers to choose a reference day or a
114 significant time span to extend the results since they complicate the computation
115 of the optimal system configuration, as well as the definition of the optimization
116 strategy. In these cases, an assessment of the various optimal configurations,
117 which depends on the dataset variability, is required in order to avoid a "wrong
118 design" of the system that otherwise would not meet the real needs of the load.

119 The problem addressed in this paper regards the assessment of the optimal
120 sizing of a HRES where the load profile, sun and wind curves present a high
121 daily variability in a considered time period. An algorithm has been developed
122 in order to analyse the daily configuration of the system, showing how the opti-
123 mization results can be significantly affected by the variability of both load and
124 renewable energies profiles. Firstly the developed model was run considering
125 each day of a specific time period and then the whole month. The main benefit
126 behind this methodology is the possibility of comparing and analysing several
127 results. Moreover, it provides a general figure of the system behavior in the con-
128 sidered time period, as well as detailed information about the trend of both load
129 and renewable energy sources per each day together with the system response.

130 The goal is to provide a tool capable of depicting various configurations of a
131 HRES, thus helping engineers to assess and choose the size that best meets the
132 energy demand using particular system requirements. The developed algorithm
133 that has been used in the present case study is described in Subsection 2.2.

134 2.2. Case study

135 The algorithm has been applied to a case study of a mountain hut located at
136 an altitude of 2,200 *m* a.s.l., precisely at a latitude of 46.819° and a longitude of
137 11.442° , in South-Tyrol (Italy) that is not connected with the national grid. The
138 opening period of the hut is related to the summer season, namely from May
139 to October, and its energy needs are satisfied through a diesel generator. The
140 fuel consumption has been estimated to be about 15,000 *l* per season, leading
141 to an emission of CO₂ close to 10 *tons*. The power absorbed by the load can
142 vary significantly in the daily hours and the days as well. Figure 1 shows the
143 maximum, minimum and average power absorbed by the load per each hour of
144 the day.

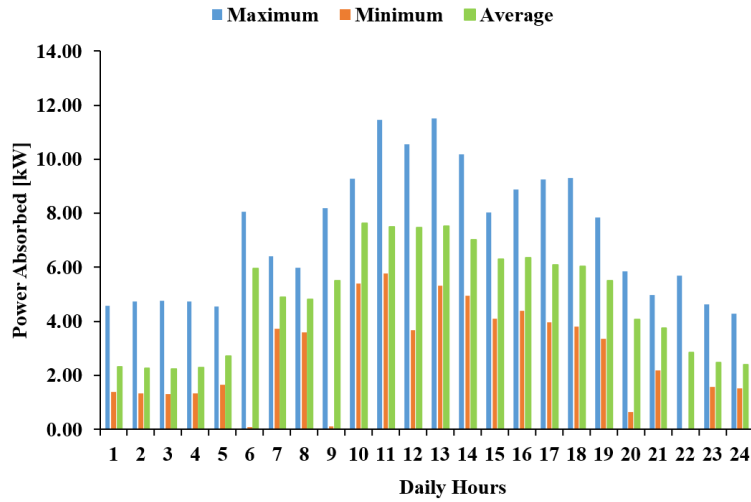


Figure 1: Maximum, minimum and average power absorbed by the load per day

145 The considered area is characterized by good sun and wind sources that could
 146 potentially supply all the energy needs to the hut. However, they are also out-
 147 lined by a high variability that complicates the sizing of the system. The max-
 148 imum, minimum and average recorded values of the Global Irradiance on the
 149 panel tilted surface (G), which is expressed in $[kWh/m^2]$, and the wind speed,
 150 which is expressed in $[m/s]$, are shown in Figures 2 and 3, respectively.

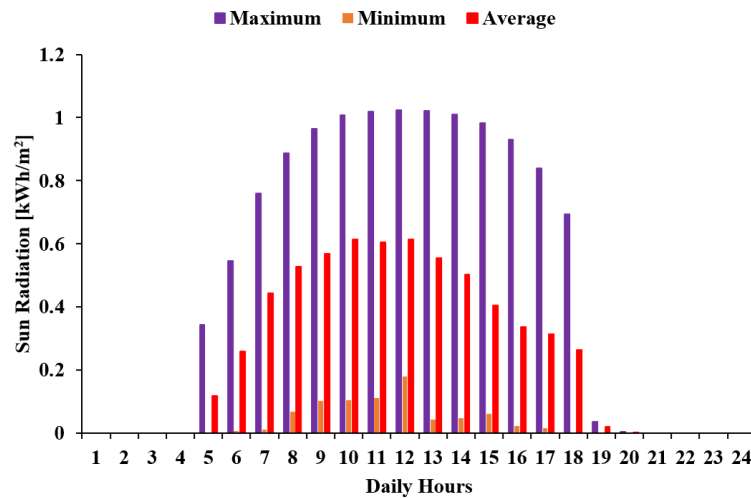


Figure 2: Maximum, minimum and average solar radiation per day

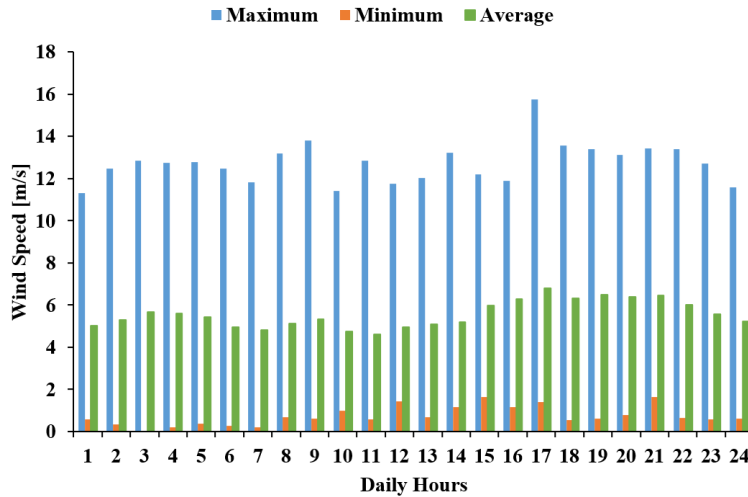


Figure 3: Maximum, minimum and average wind speed registered in the month of June

151 The data used to run the simulations have been collected through measure-
 152 ment campaigns and online tools. Precisely, the load profile and the wind speed
 153 were recorded in June 2018 through a power meter, which was installed in the
 154 main power line of the electrical control cabinet, and an anemometer. The month
 155 of June has been chosen since it is the one that presents the highest number of
 156 people in the hut. The data were recorded each minute in order to obtain, at
 157 the end of the measurements, the hourly averaged values of the absorbed power
 158 and wind speed. The global irradiance above the site in June 2018 were down-
 159 loaded from the Photovoltaic Geographical Information System (PVGIS) [38]. It
 160 is worth noticing that the power generated, delivered or absorbed by the bat-
 161 tery storage has been considered constant in each time interval: therefore, the
 162 produced power corresponds to the final energy production.

163 2.3. HRES components modeling

164 The location where the HRES will be installed is characterized by high solar
 165 and wind sources. Therefore, the HRES will be composed by PV panels, wind and
 166 a diesel generators coupled with the battery storage. Figure 4 shows the layout
 167 of the system. Sub-subsections 2.3.1, 2.3.2 and 2.3.3 describe the mathematical
 168 model of the PV system, wind turbines system and the diesel generator, respec-
 169 tively, while the one related to the battery storage is assessed in Sub-subsection
 170 2.3.4.

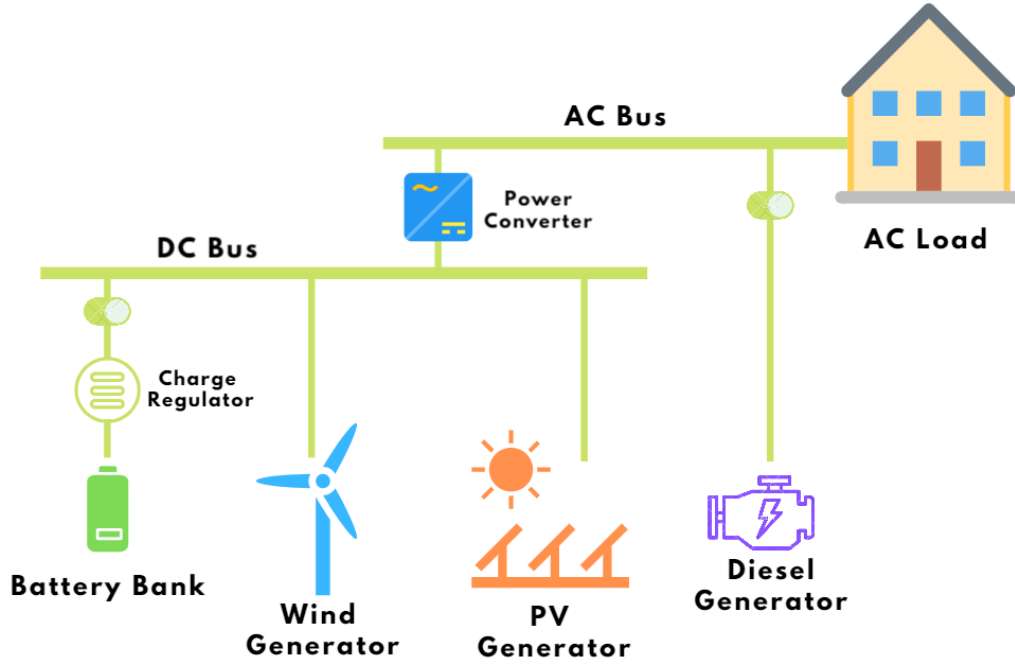


Figure 4: HRES layout

171 2.3.1. PV system modeling

172 The PV system has been modeled according to [39] considering a sharp poly-
 173 crystalline module [40], whose characteristics referring to Standard Test Condi-
 174 tions (STC) are listed in Table 1. The Direct Current DC power that is delivered
 175 by the PV system was computed through Eq. (1), where η_c is the cell efficiency,
 176 A_{eff} is the net cell opening area and G is the global irradiance on the panel tilted
 177 surface.

$$P_{PV-DC} = \eta_c A_{\text{eff}} G \quad (1)$$

178 In order to calculate the effective power delivered by the PV system, the losses
 179 related to the Balance Of System (BOS) were considered. These losses include
 180 several parameters that take into account the effective performance of the system
 181 components, such as the frequency converter, wirings, batteries, support racks
 182 and switches. The AC power delivered by the PV system is calculated through
 183 Eq. (2), considering the BOS efficiency η_{BOS} equal to 85%.

$$P_{PV-AC} = P_{PV-DC} \cdot \eta_{BOS} \quad (2)$$

Table 1: Characteristics of a sharp poly crystalline PV panel at STC

Parameter	Value	Unit of measure
Net cell opening area (A_{eff})	1.47	m^2
Cell efficiency at STC ($\eta_{m,c}$)	0.14	–
Power peak	240	W
Efficiency Loss Coefficient (β)	0.0044	$^{\circ}\text{C}^{-1}$

184 In this model, the performance of the panels were evaluated under real oper-
 185 ating conditions: in particular, the effect of the temperature and the solar radi-
 186 ation were considered for the evaluation of the cell efficiency η_c , as expressed by
 187 Eq. (3):

$$\eta_c = \eta_{n,c} \left[1 - \beta(T_C - 25) + 0.12 \log \frac{G}{1000} \right] \quad (3)$$

188 where $\eta_{n,c}$ is the rated efficiency of the cell in STC, β is the efficiency loss coef-
 189 ficient of the solar cell, with increasing temperature, expressed in [$^{\circ}\text{C}^{-1}$], and T_C
 190 is the cell temperature. Along the same line, Eq. (4) evaluates T_C , where T_A is
 191 the ambient temperature, NOCT is the Nominal Operating Cell Temperature of
 192 the PV panel, τ is the transmissivity of the cell and α is the absorptivity.

$$T_C = T_A + \frac{G}{800} (\text{NOCT} - 20) \left(1 - \frac{\eta_c}{\tau\alpha} \right) \quad (4)$$

193 2.3.2. Wind turbine system modeling

194 The power produced by a wind turbine depends on the wind speed at the
 195 hub. Knowing the wind speeds, the produced power is obtained directly from
 196 the power curve of the turbine supplied by the manufacturer. Generally, the
 197 anemometers are located at a lower height than the hub one: therefore, Eq. (5)
 198 calculates the effective wind speed considering the most used formulation for
 199 heights lower than 150 m . Eq. (5) computes the values at different heights taking
 200 into account the surface roughness of the installation site, whose typical values
 201 are reported in [41].

$$w_{hub} = w_h \cdot \frac{\ln \left(\frac{z_{hub}}{z_0} \right)}{\ln \left(\frac{z_{anem}}{z_0} \right)} \quad (5)$$

202 Knowing the wind speeds at the hub height, the power output of a wind turbine is
 203 computed by means of its power curve. As described by Eq. (6), the wind turbine
 204 starts to generate power when the value of the wind speed reaches the cut-in
 205 one w_{cut-in} . The power output increases with the increasing wind speed until its
 206 rated value P_R is reached, corresponding to a wind speed w_R . Starting from w_R
 207 to the cut-out speed $w_{cut-out}$, the power output does not increase anymore, thus
 208 remaining constant and equal to P_R . Beyond the value of $w_{cut-out}$, the turbine
 209 stops to generate power to prevent failures. Then, the power curve of a possible
 210 wind turbine to be installed in the analysed site is shown in Figure 5.

$$P_{WT(STC)} = \begin{cases} 0, & \text{if } w_t < w_{cut-in} \text{ or } w_t > w_{cut-out} \\ P_i, & \text{if } w_{cut-in} \leq w_t < w_R \\ P_R, & \text{if } w_R \leq w_t \leq w_{cut-out} \end{cases} \quad (6)$$

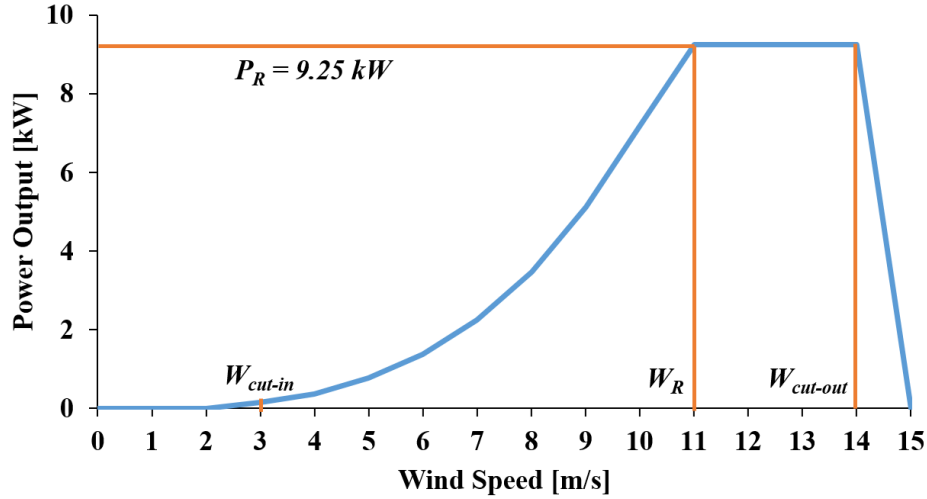


Figure 5: Possible power curve of a wind turbine eligible for the site of interest

211 It is worth noticing that the power output reported in Figure 5 considers an
 212 air density ρ of 1.225 kg/m^3 in STC (ρ_{STC}). In case of a different air density, Eq.
 213 (7) corrects the power output of the wind turbine P_{WT} . In this case study, an air
 214 density of 1.007 kg/m^3 has been considered [42].

$$P_{WT} = P_{WT(STC)} \cdot \frac{\rho_{air}}{\rho_{air(STC)}} \quad (7)$$

215 *2.3.3. Diesel generator modeling*

216 A diesel engine has been chosen as generator, which consists on a 3.5 kW
 217 engine described in [43]. A greater size of the generator has not been chosen due
 218 to the implicit goal of maximizing the use of renewable energies. A larger gen-
 219 erator would have added an additional constraint to limit the power output in
 220 determined cases. Certainly, this would have led to a better overall optimization,
 221 but also let the generator operate outside its best efficiency range, thus lower-
 222 ing the performance. The fuel consumption and the efficiency curves reported
 223 in [43] were used to model the power generated by the diesel engine. The fuel
 224 consumption of the generator is calculated with Eq. (8), which represents the
 225 fuel consumption curve of the engine fed by the diesel fuel. It depends on the
 226 generated electrical power P_{el} and a binary variable P_g that assumes the value of
 227 0 or 1 whether the diesel generator is turned off or on, respectively. The coeffi-
 228 cients ϕ and ψ have been obtained through laboratory tests and their respective
 229 values are equal to 0.087 g/kW and 0.127.

$$F_C = \phi \cdot P_{el} + \psi \cdot P_g \quad (8)$$

230 Figure 6 shows the fuel consumption curve experimentally obtained in [43].
 231 The fuel consumption is expressed in [g/s] (Y-axis) as a function of the electrical
 232 power (X-axis), which is expressed in [kW].

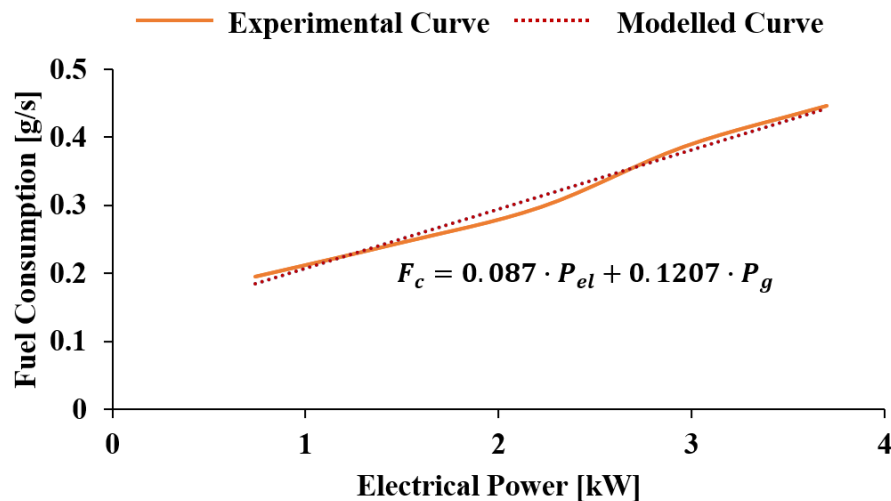


Figure 6: Fuel consumption curve of the diesel generator [43]

233 The efficiency of the diesel generator is calculated with Eq. (9), which corre-
 234 sponds to the ratio between the produced energy and the one provided by the
 235 fuel. The efficiency curve of the considered generator is shown in Figure 7.

$$\eta_{gen} = \frac{3.6 \cdot P_{el}}{\rho_{fuel} \cdot (F_C \cdot LHV_{fuel})} \quad (9)$$

236 LHV_{fuel} represents the Lower Heating Value (LHV) of the fuel and ρ_{fuel} is
 237 the fuel density equal to 42.6 MJ/kg and 0.828 kg/l, respectively.

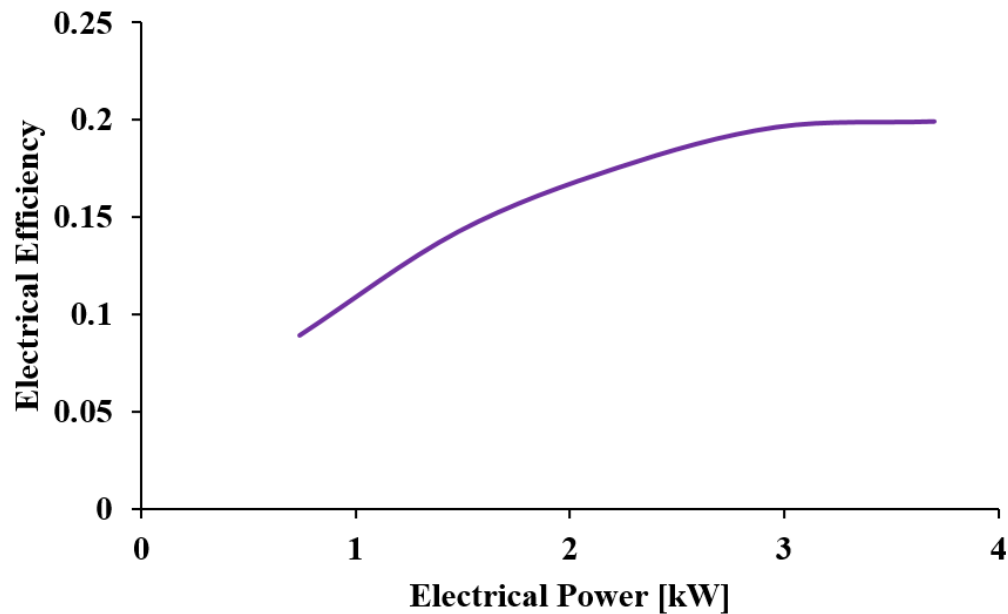


Figure 7: Efficiency curve of the diesel generator [43]

238 If a general motor is considered and the fuel consumption curve is not pro-
 239 vided by the manufacturer, a simplified fuel consumption curve, which correlates
 240 the generator rated power to the generated electrical power, can be used [44].

241 2.3.4. Battery storage modeling

242 The battery storage in a HRES plays a key role since it stores the excess of
 243 energy produced by renewable sources, as well as to deliver it to the load during
 244 the high demand. Lead-acid batteries are chosen to model the storage. This type
 245 of battery is more suitable for climates subjected to low temperatures, which can
 246 be sometimes lower than 0 °C also in summer seasons, as it occurs in this case

247 study. The energy that can be delivered or stored by the batteries at each time
 248 interval depends on the one that is already present in the battery E_{batt} , the self
 249 discharge rate σ and the energy balance between the generators and the load.
 250 During the discharging phases, the batteries supply the remaining energy to the
 251 load. This amount of energy is evaluated by means of Eq. (10). When the energy
 252 produced by the generators exceeds the load requirements, this overproduction
 253 can be stored in the batteries. The amount of the stored energy is expressed
 254 through Eq. (11).

$$E_{batt}(t) = E_{batt}(t-1) \cdot (1 - \sigma) + [E_{Load}(t) - (E_{PV}(t) + E_{WT}(t) + E_{Mot}(t))] \quad (10)$$

$$E_{batt}(t) = E_{batt}(t-1) \cdot (1 - \sigma) + [E_{PV}(t) + E_{WT}(t) + E_{Mot}(t) - E_{Load}(t)] \quad (11)$$

255 In order to simulate a real behavior of the batteries, the delivered energy
 256 cannot drop below the minimum State of Charge SOC_{min} , which is equal to the
 257 20% of the batteries capacity B_C .

258 2.4. MILP modeling

259 The Linear Programming (LP) is an optimization algorithm in which a linear
 260 objective function has to be minimized or maximized with respect to a defined
 261 time period and a temporal discretization through time steps. When only some
 262 variables have to be integer, the problem is called Mixed Integer Linear Program-
 263 ming (MILP) [45]. A MILP problem consists of: i) an objective function, ii) deci-
 264 sion variables and iii) constraints. The target of the MILP problem is to minimize
 265 an objective function choosing the best values of the decision variables that re-
 266 spect the established constraints. A flow chart that shows the MILP optimization
 267 steps is reported in Figure 8. Objective functions, decision variables and con-
 268 straints that constitute the problem are described in Sub-subsections 2.4.1, 2.4.2
 269 and 2.4.3, respectively.

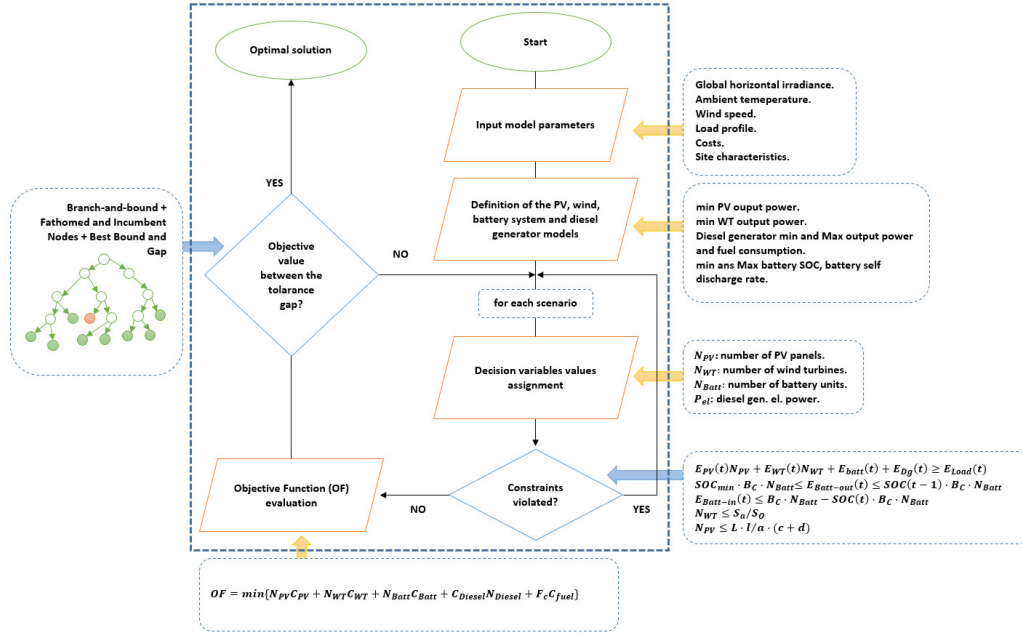


Figure 8: Flow chart of the MILP optimization algorithm

270 2.4.1. Objective function

271 The objective function of the MILP algorithm is the total Net Present Cost
 272 (NPC) of the system, which is the sum of the total NPC related to each element
 273 that constitutes a HRES. The total cost of an element embedded in a HRES can be
 274 defined as the sum of the initial capital cost C_{IN} , the operation and maintenance
 275 (O&C) cost $C_{O\&M}$ and the replacement one C_R . If the fuel is consumed, the
 276 supposed quantity of the fuel consumption in the lifetime of the generator F_c
 277 and its cost C_{fuel} must be included. In order to obtain the NPC, all the costs
 278 must be actualized at the present stage of the project. The objective function is
 279 expressed by Eq. (12).

$$\min(N_{PV}C_{PV} + N_{WT}C_{WT} + N_{Batt}C_{Batt} + C_{Diesel}N_{Diesel} + F_c C_{fuel}) \quad (12)$$

280 where N_{PV} , N_{WT} and N_{Batt} are the total number of PV panels, wind turbines
 281 and batteries units, respectively. N_{Diesel} is the number of diesel generators that in
 282 this case has been set equal to 1 and does not constitute a decision variable of this
 283 specific optimization problem. Nevertheless, it has been included in the problem
 284 in order to improve the flexibility of the algorithm when a different case study

285 is used. C_{PV} , C_{WT} , C_{Batt} and C_{Diesel} are the total NPCs of a single PV panel,
 286 wind turbine, battery and diesel generator respectively. F_c and C_{fuel} are the fuel
 287 consumption of the diesel generator and the fuel cost, respectively.

288 2.4.2. Decision variables

289 The decision variables determine the output of the objective function. The
 290 target of the MILP algorithm consists on minimizing the objective function, thus
 291 to find the values of the decision variables for reaching this target. In the analysed
 292 case, the decision variables are the following:

- 293 • N_{PV} : number of PV panels;
- 294 • N_{WT} : number of wind turbines;
- 295 • N_{Batt} : number of batteries units;
- 296 • $E_{Batt}(t)$: energy delivered or absorbed by the battery per each time inter-
 297 val;
- 298 • $E_{Dg}(t)$: energy delivered by the diesel generator per each time interval.

299 2.4.3. Constraints

300 The constraints are mathematically expressed in form of equalities and in-
 301 equalities, thus limiting the values that can be attributed by the algorithm to the
 302 decision variables. They are related to technological, economic or geometrical
 303 limitations. In this case study, technological and geometrical constraints are in-
 304 volved. Eq.s (13), (14) and (15) set the technological constraints, while Eq.s (16),
 305 (18) and (17) define the geometrical ones. Eq. (13) expresses the balance between
 306 the energy produced by the HRES and the load demand. The produced energy
 307 has to satisfy the load demand per each time interval. It is also assumed that
 308 the excess of the produced energy can be managed by the inverter connected to
 309 the PV modules and the pitch control system of the wind turbines, thus reduc-
 310 ing the power output by letting the generators operate in off-design conditions
 311 according to the power curves of the machines.

$$E_{Load}(t) \leq E_{PV}(t)N_{PV} + E_{WT}(t)N_{WT} + E_{Dg}(t) + E_{Batt}(t) \quad (13)$$

312 Eq.s (14) and (15) limit the energy that can be delivered or absorbed by the
 313 battery storage per each time interval. Eq. (14) sets both lower and upper limits
 314 of the energy delivered by the batteries per each time interval, thus establishing

315 that the energy delivered by the batteries cannot be lower than the minimum
 316 State Of Charge (SOC_{min}), which corresponds to 20% of the battery capacity
 317 (B_C). In addition, the maximum energy delivered per each time interval cannot
 318 exceed the SOC of the batteries, i.e. the effective amount of energy left in the
 319 batteries after their operation in the previous time interval.

$$SOC_{min} \cdot B_C \cdot N_{Batt} \leq E_{Batt-out}(t) \leq SOC(t-1) \cdot B_C \cdot N_{Batt} \quad (14)$$

$$E_{Batt-in}(t) \leq B_C \cdot N_{Batt} - SOC(t) \cdot B_C \cdot N_{Batt} \quad (15)$$

320 Eq. (16) limits the available ground area of the wind turbines in the installa-
 321 tion site: precisely, S_o is the one occupied by a wind turbine. It is worth noticing
 322 that the total area that can be occupied by the wind turbines $N_{WT} \cdot S_o$ cannot
 323 exceed the available area S_a .

$$N_{WT} \leq \frac{S_a}{S_o} \quad (16)$$

324 Eq. (17) limits the ground area that can be occupied by PV panels: namely,
 325 L and l are the larger and the smaller sides of the available ground area, respec-
 326 tively, a is the smaller side of the PV module, c is the projection of the larger side
 327 b of the panel on the ground and d is the distance between the rows of the PV
 328 panels. A clear description of these geometrical parameters is shown in Figure
 329 9.

$$N_{PV} \leq \frac{L \cdot l}{a \cdot (c + d)} \quad (17)$$

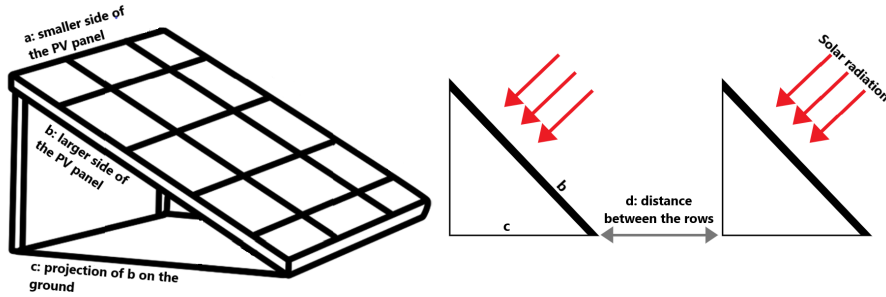


Figure 9: Dimensions of the PV panels

330 Eq. (18) reports the calculation process used to obtain the constraints deriving
 331 by Eq. (17).

$$\begin{cases} N_{PV} \leq \frac{l}{a} \cdot N_{rows} \\ N_{rows} = \frac{L}{c+d} \\ c = b \cdot \cos(\beta) \\ d = k \cdot \sin(\beta) \\ k = \frac{1}{\tan(61^\circ - \text{Latitude})} \end{cases} \quad (18)$$

332 where β is the tilt angle of the PV panel, b is the larger side of the PV module
 333 and k is a coefficient used to calculate the distance between two PV panels rows,
 334 which depends on the latitude where they are installed. Table 2 lists the values
 335 of the parameters used to limit the ground areas occupied by the PV panels and
 336 the wind turbines.

Table 2: Parameters adopted to limit the ground areas of PV panels and wind turbines

Parameter	Value	Unit of measure
S_a	100	m^2
S_o	25	m^2
L	10	m
l	10	m
a	0.994	m
b	1.652	m
β	30	degrees
Latitude	46.819	degrees

337 2.5. Economic analysis - NPC of the HRES

338 The MILP algorithm computes the optimal solution of the problem finding
 339 the values of the optimization variables that minimize the objective function,
 340 which is the minimum NPC of the system. Generally, the NPC of an investment
 341 allows the investors to choose the optimal option among different ones. The NPC
 342 is defined as the sum of the present value of all the costs minus the sum of the
 343 present value of all the benefits. Therefore, the NPC of a component considers
 344 its total cost that is composed by the initial capital cost C_{IN} , the operation and
 345 maintenance (O&M) cost $C_{O\&M}$, the replacement cost C_R and, eventually, the

346 fuel cost C_{fuel} taking into account the Time Value of Money (TVM) through a
 347 discount factor D_f . For sense of clarity, D_f is used to calculate the present value
 348 of the cash flow during the project lifetime and it is defined by Eq. (19).

$$D_f = \frac{1}{(1+i)^n} \quad (19)$$

349 Referring to Eq. (19), i is the real discount rate, which takes into account
 350 the money inflation as defined by Eq. (20), and n is the lifetime of the project
 351 expressed in years.

$$i = \frac{i_{nom} - f}{1 + f} \quad (20)$$

352 Referring to Eq. (20), i_{nom} represents the nominal discount rate that indicates
 353 the rate at which money can be borrowed, while f is the expected inflation rate.
 354 D_f decreases over the years, thus stating that a future cash flow is less worth
 355 than a present one. Considering an expected inflation rate of about 2%, D_f has
 356 been considered equal to 6%.

357 3. Results and comments

358 The goal of the work is to demonstrate that the choice of the dataset used to
 359 run the simulation has a crucial role on the results: therefore, all the outcomes
 360 of the calculations require a correct evaluation to avoid misunderstandings. In
 361 particular, simulations aim to show how the optimal solution varies depending
 362 on the assumptions made on the renewable energy sources profiles. The MILP
 363 optimization algorithm was used taking into account three different cases related
 364 to the HRES:

- 365 • **Case 1:** The simulation was run considering a time span of 24 hours. In this
 366 case, it is possible to analyse how the configuration of the HRES changes
 367 depending on the fluctuations of the power absorbed by the load and the
 368 power produced by the renewable sources as well. This case is important
 369 for analysing how the variability of the dataset can affect the optimal solu-
 370 tion. The reduction of the Greenhouse gases (GHGs) emissions derived by
 371 feeding the load with the HRES instead of only a diesel generator is also
 372 shown.
- 373 • **Case 2:** The simulation was run considering a time span of 1 month. In
 374 this case, the output of the analysis is a unique configuration that meets

375 the constraints per each hour of the month, thus satisfying the load re-
376 quirements. Furthermore, it is the most robust solution, but also the most
377 expensive. Indeed, the system will be oversized and the excess of the pro-
378 duced energy will be managed by the PV inverter and the pitch control
379 system of the wind turbines that can shift the operating point of PV panels
380 and wind turbines, respectively, to off-design conditions accordingly to the
381 required power output regulation. Also in this case, a reduction of GHGs
382 emissions is presented.

- 383 • **Case 3:** The simulation was run considering a time span of 24 hours, vary-
384 ing the constraint of the load requirements from 100% of the actual value to
385 50%, with steps of 10%. Indeed, it can be supposed that it is not always nec-
386 essary to satisfy the total hourly load described by the load profile curves,
387 applying a demand side management strategy. In these cases, a percent-
388 age of the load can be sometimes sacrificed since it is not essential. For
389 instance, loads like a cold storage can hold some hours without the elec-
390 trical supply. This case aims at demonstrating that a reduced percentage
391 of the load requirements lowers the dependency on the renewable energy
392 sources profiles, thus reducing the variability of the total NPC between the
393 most expensive and the cheapest solutions. As a result, the algorithm helps
394 engineers to reduce the total cost of the system, adopting a configuration
395 that is not oversized over the entire time period. Furthermore, a sensitivity
396 analysis has been performed in order to assess the effects of fuel and bat-
397 tery prices variations. Simulations have been run considering a fuel price
398 variation from 1.4 €/l to 3.8 €/l, with steps of 0.2 €/l, and a decreasing
399 battery price with steps of 5% until the 50% of its actual cost per kWh is
400 reached. This wide fuel price variation has been chosen to better point out
401 how the fuel price variation affects the HRES optimal sizing. For sense of
402 clarity, diesel prices can vary from 1.4 €/l in developing countries to 3 €/l
403 in remote areas characterized by a complicate fuel distribution system [46]
404 and [47].

405 Per each case, an economic analysis based on the NPC has been carried out. The
406 economic parameters used in the simulation are described in Table 3.

Table 3: Economic parameters used to run the simulation [44, 48, 49, 50, 51]

PV panels	C_{IN}	1,400	€/kW
	$C_{O\&M}$	0.081	€/kW (daily)
Wind turbines	C_{IN}	2,000	€/kW
	$C_{O\&M}$	0.095	€/kW (daily)
Batteries	C_{IN}	1,223	€/kWh
	$C_{O\&M}$	0.1	€/kWh (daily)
	C_R	612	€/kWh
Diesel generator	C_{IN}	550	€/kW
	$C_{O\&M}$	438	€/year
	C_{fuel}	2	€/l

407 **3.1. Case 1 and case 2**

408 Results of the first two cases are presented in Table 4. The MILP algorithm
 409 computes the optimal number of PV panels, wind turbines and battery units that
 410 minimizes the total NPC of the system per each day related to the considered
 411 time interval. The algorithm also computes the value of the energy delivered or
 412 absorbed by the batteries, thus optimizing the energy produced by the generators
 413 and minimizing the effect of the fluctuating renewable energy sources.

414 Table 4 lists the results obtained in Cases 1 and 2, showing that the optimal
 415 size of the system varies over the considered days and highlighting a noticeable
 416 difference between the solution characterized by the highest and the lowest NPC.

417 Results also show that the variability of the power absorbed by the load and
 418 the fluctuating nature of both sun radiation and wind speed strongly affects the
 419 output of the simulation. Moreover, it can be noticed how the results of the sim-
 420 ulation change according to the considered time span. When considering a time
 421 span of 24 hours, the algorithm sizes the system in order to optimize the energy
 422 produced by renewable energy sources, reducing the fuel consumption of the
 423 diesel generator and considering also the energy stored in the battery storage
 424 during the night hours when the sun radiation cannot contribute to the energy
 425 supply. As a consequence, the battery storage is completely discharged at the
 426 end of the day, contributing to a lower sizing and, eventually, to the impossi-
 427 bility of meeting the power demand if the first hours of the following day are
 428 characterized by low values of wind speeds. The simulation over the time span
 429 of the entire month (Case 2), as shown in the last line of Table 4, considers the

430 worst scenario in which there is a lack of both solar and wind production in the
431 different days: therefore, the result presents a bigger capacity of the battery stor-
432 age. Figures 10 and 11 show the simulation results considering the time period of
433 the 7th and the 17th of June 2018, respectively. These two days were selected in
434 order to highlight the behavior of the system when dealing with a different load
435 and with variable profiles of the sun radiation and the wind speed. It is worth
436 noticing that the negative values in the battery power profile indicate the periods
437 of the day during which the battery is charged, while the positive values refer
438 to the supply of power from the battery, namely the discharge phase. In the first
439 case, the optimal solution computed by the algorithm does not include the wind
440 turbines due to the lack of the wind source. The algorithm computes the optimal
441 solution relying significantly on the contribution of the diesel generator during
442 the daily hours characterized by a lack of the sun source. In the second case, the
443 optimal solution computed by the optimization algorithm includes the exploita-
444 tion of the wind source and a minimum contribution of the diesel generator is
445 required. In this case, the HRES is able to satisfy the load requirements relying al-
446 most entirely on renewable energy generators and batteries. In both cases, it can
447 be noticed how the PV production and the batteries operations are complemen-
448 tary. The system aims to charge the batteries with the excess of PV production
449 to use them when renewable resources cannot be exploited. For sense of clarity,
450 it is worth noticing that the trend of the energy supplied by the PV system does
451 not correspond exactly to the one reported in Figure 2 since a control system is
452 implemented to modulate the power delivered through the solar inverter. Sim-
453 ilarly, the wind turbine includes a pitch control functionality to modulate the
454 generated power when an excessive power production is achieved. Figure 12
455 shows the trend of the load profile, the energy produced by the HRES and the
456 SOC of the batteries in the entire month. It is worth noticing that the diesel gen-
457 erator operates when the energy cannot be supplied by both PV panels and wind
458 turbines, thus operating at its rated power to optimize the fuel consumption. The
459 diesel generator does not operate when solar and wind sources are abundant. In
460 this case, the entire energy needs are supplied by PV panels, the wind turbine
461 and the battery storage, either supplying energy when needed or absorbing its
462 overproduction. It can be also appreciated how a change of the simulation time
463 span from 24 hours to the entire month affects the simulation results related to
464 each single day computed in a scenario of 24 hours. For instance, considering
465 the 7th of June, the optimization algorithm has to compute the charge/discharge
466 operation of the battery pack and the power delivered by the diesel generator in
467 a day taking into account the previous operating conditions and the state of the

468 HRES. Therefore, results shown in Figures 10 and 12 differ one to each other.

Table 4: Comparison between different configurations of the HRES. Case 1 (results of each single day) and Case 2 (results of the whole month)

Day	N_{PV}	N_{WT}	Battery [kWh]	NPC_{TOT} [€]	NPC_{PV} [€]	NPC_{WT} [€]	NPC_{Bat} [€]	NPC_{Mot} [€]
1 st June	103	0	12	169,720	44,523	0	35,573	89,624
2 nd June	119	0	20	152,967	51,439	0	59,288	42,240
3 rd June	138	0	16	167,448	59,652	0	47,430	60,366
4 th June	169	0	21	151,011	73,052	0	62,252	15,706
5 th June	146	0	21	148,444	63,110	0	62,252	23,082
6 th June	89	0	17	103,946	38,471	0	50,395	15,080
7 th June	63	0	8	122,607	27,232	0	23,715	71,659
8 th June	93	0	12	147,277	40,200	0	35,573	71,504
9 th June	182	0	17	182,475	78,672	0	50,395	53,409
10 th June	74	0	8	98,311	31,987	0	23,15	42,608
11 th June	1	2	15	175,084	432	49,397	44,466	80,788
12 th June	72	0	8	125,813	31,123	0	23,715	70,975
13 th June	50	1	7	92,858	21,613	24,699	20,751	25,796
14 th June	105	0	17	176,568	45,387	0	50,395	80,786
15 th June	75	1	4	94,895	32,420	24,699	11,858	25,919
16 th June	189	1	13	160,185	81,697	24,699	38,537	15,251
17 th June	126	1	14	137,282	54,465	24,699	41,502	16,617
18 th June	73	1	5	86,342	31,555	24,699	14,822	15,266
19 th June	29	2	6	94,260	12,536	49,397	17,786	14,541
20 th June	60	0	22	150,473	25,936	0	65,217	59,321
21 st June	77	0	24	120,933	33,284	0	71,145	16,504
22 nd June	48	1	6	97,159	20,749	24,699	17,786	33,926
23 rd June	57	0	16	115,275	24,639	0	47,430	43,206
24 th June	74	0	18	129,388	31,987	0	53,359	44,041
25 th June	46	2	18	130,500	19,884	49,397	53,359	7,860
26 th June	49	2	4	115,954	21,181	49,397	11,858	33,518
27 th June	35	1	0	47,688	15,129	24,699	0	7,860
28 th June	26	1	4	82,272	11,239	24,699	11,858	34,477
29 th June	27	2	3	84,371	11,671	49,397	8,893	14,409
30 th June	106	2	23	171,258	45,820	49,397	68,181	7,860
Month	110	1	10	171,473	47,549	24,699	29,644	69,851

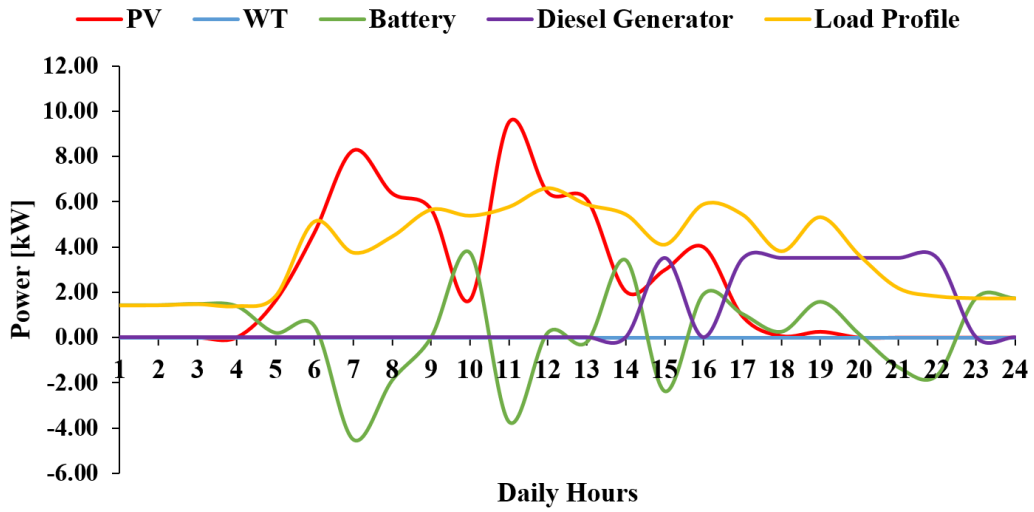


Figure 10: Simulation results of the 7th June 2018

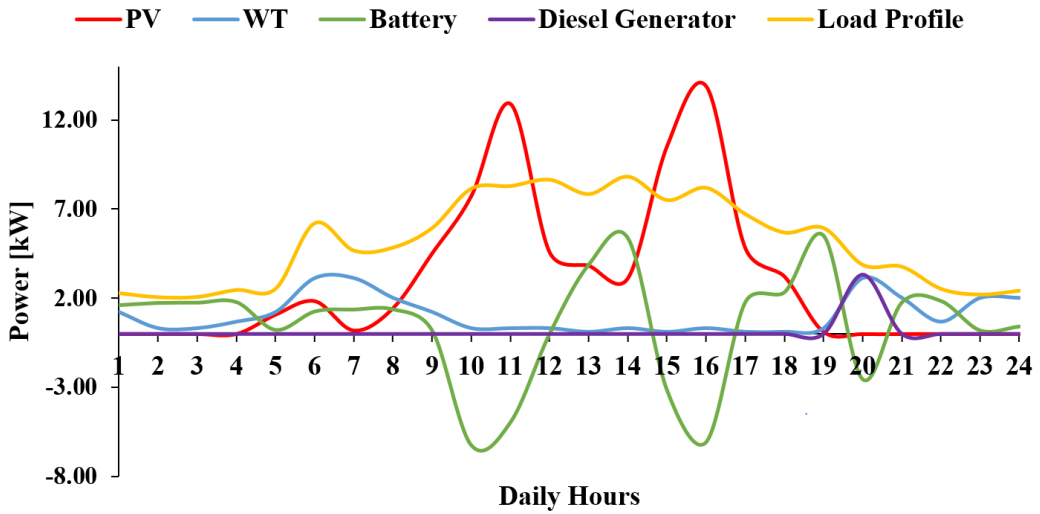


Figure 11: Simulation results of the 17th June 2018

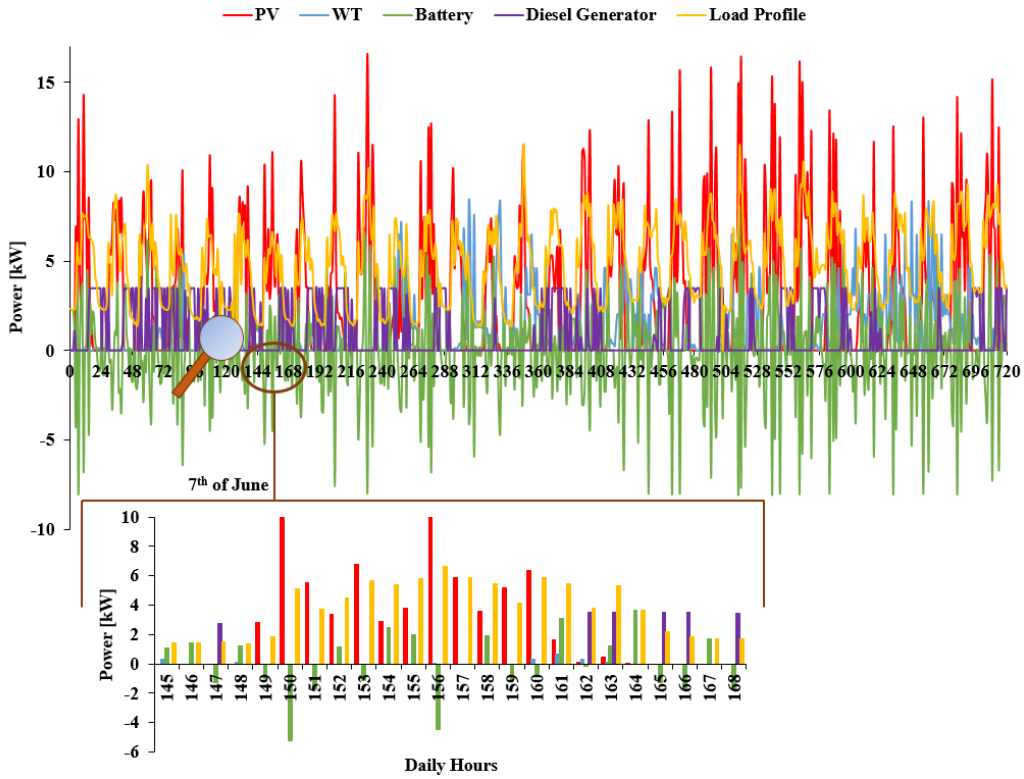


Figure 12: Load profile and contribution of the HRES over a month

469 Table 5 shows the GHGs emissions in terms of CO₂ and NO_x due to the elec-
 470 trical energy provided by the diesel generator. It also provides a comparison
 471 between the total GHGs emissions if the load would be entirely satisfied by the
 472 diesel generator. It is worth noticing the remarkable reduction due to the intro-
 473 duction of the renewable energy technologies in the energy system.

Table 5: GHGs emissions savings

Day	El. Energy Delivered [kWh]	CO ₂ [kg]	NO _x [kg]	CO ₂ diesel only [kg]	NO _x diesel only [kg]	CO ₂ savings %	NO _x savings %
1 st June	31.3	71	0.38	33	1.74	79	79
2 nd June	12.9	32.2	0.17	330	1.72	90	90
3 rd June	19.8	48	0.25	332	1.73	86	85
4 th June	2.8	8.3	0.04	307	1.59	97	97
5 th June	5.4	16.4	0.09	296	1.53	94	94
6 th June	2.5	8.5	0.04	284	1.48	97	97
7 th June	24.5	55.2	0.29	297	1.53	81	81
8 th June	24.4	55.2	0.29	293	1.52	81	81
9 th June	17.5	39.4	0.21	324	1.68	88	88
10 th June	13.1	32.1	0.17	369	1.91	91	91
11 th June	28	63.1	0.34	301	1.56	79	79
12 th June	24.1	55.4	0.29	319	1.65	83	82
13 th June	6.8	15.8	0.08	310	1.61	95	95
14 th June	28	63.1	0.34	294	1.53	79	78
15 th June	6.9	15.8	0.08	336	1.75	95	95
16 th June	2.6	8.4	0.04	340	1.77	98	98
17 th June	3.3	8	0.04	364	1.89	98	98
18 th June	2.6	8.4	0.04	364	1.90	98	98
19 th June	2.2	8.6	0.04	337	1.76	97	98
20 th June	19.2	48.3	0.25	345	1.80	86	86
21 st June	3.2	8	0.04	343	1.79	98	98
22 nd June	9.8	24.1	0.13	367	1.91	93	98
23 rd June	13.4	31.9	0.17	364	1.90	91	91
24 th June	13.8	31.6	0.17	398	2.08	92	92
25 th June	0	0	0	386	2.02	100	100
26 th June	9.6	24.2	0.13	340	1.77	93	93
27 th June	0	0	0	356	1.86	100	100
28 th June	10.1	23.9	0.13	350	1.83	93	93
29 th June	2.1	8.6	0.04	376	1.96	98	98
30 th June	0	0	0	385	2.01	100	100
Month	678	1,710	25	10,138	52.8	83	52

474 3.2. Case 3

475 Table 6 refers to Case 3 and provides the values of the minimum and the
 476 maximum NPC, as well as the difference between them whether a hourly en-
 477 ergy deficit is accepted. It is worth noticing that, reducing the percentage of the
 478 total hourly load, the difference between the maximum and the minimum NPC
 479 decreases down to 57%.

Table 6: Minimum and maximum NPCs from different configurations with demand management

% of load demand to satisfy	Min NPC [€]	Max NPC [€]	Max - Min NPC [€]	% of the decrease
100%	47,688	182,475	134,787	—
90%	44,662	165,088	120,426	11 %
80%	42,501	147,645	105,144	22 %
70%	40,339	130,639	90,300	33 %
60%	38,178	113,005	74,827	44 %
50%	37,252	95,863	58,611	57 %

480 Table 7 lists the results obtained in a time span of 24 hours, considering a
 481 decreasing battery price with steps of 5% until a drop of 50% is achieved, corre-
 482 sponding to a battery price of 581 €/kWh. Table 7 highlights how a reduction
 483 of the battery price affects the number of PV panels, wind turbines, battery units
 484 and the NPCs of both HRES and diesel generator. It can be noticed how a reduc-
 485 tion of the battery price leads to an increase of the battery units until their price
 486 drops to 50%. Precisely, the most expensive solution occurs for the simulation
 487 of the 16th of June, while the cheapest is obtained for the 9th of June. The need to
 488 exploit the sun source, coupled with a consistent reduction of the battery price,
 489 leads to an increase of the PV units so that the battery cost becomes competi-
 490 tive with respect to the PV one. Considering the diesel generator, its total NPC
 491 slightly increases when the battery price decreases of 10%, which corresponds
 492 to 1,040 €/kWh, since the generator is preferred than the PV panels: for this
 493 reason, the cost of the diesel generator decreases until to 7,860 € since it is only
 494 used as a backup.

Table 7: Results obtained considering a decreasing battery price

Battery Price [€/kWh]	PV panels		Wind turbines		Battery units		NPC Generator [€]		NPC HRES [€]	
	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min
1,223	182	35	0	1	17	0	53,409	7,860	182,475	47,688
1,162	182	35	0	1	17	0	53,409	7,860	179,962	47,688
1,101	151	35	0	1	22	0	53,432	7,860	177,415	47,688
1,040	145	29	0	1	23	1	53,389	7,860	174,045	47,615
978	145	29	0	1	23	1	53,389	7,860	170,589	47,465
917	141	29	0	1	24	1	52,862	7,860	167,155	47,317
856	142	29	0	1	41	1	16,800	7,860	163,329	47,169
755	144	29	0	1	45	1	7,860	7,860	142,457	46,924
697	144	25	0	1	45	2	7,860	7,860	146,130	46,744
639	144	25	0	1	45	2	7,860	7,860	139,804	46,463
581	205	25	0	1	29	2	7,860	7,860	137,314	46,182

495 Table 8 shows the results obtained after a sensitivity analysis performed on
 496 the diesel price, considering the most expensive and the cheapest system config-
 497 uration. An increasing diesel price with steps of 0.2 €/l has been considered,
 498 starting from a value of 1.4 €/l to a value of 3.8 €/l. When dealing with the
 499 most expensive solution, an increase of the diesel price from 1.4 to 1.6 €/l leads
 500 to a consistent increase of the number of PV panels and battery units. Then, their
 501 number remains stable until a value of 2.4 €/l is reached. This occurs in the day
 502 characterized by the most expensive configuration changes from the 9th to the
 503 14th of June during which the HRES configuration is the same also with a diesel
 504 price of 2.8 €/l. This is due to the fact that, considering a diesel price that varies
 505 from 1.6 €/l to 2.8 €/l, the increase does not affect the competitiveness of the
 506 diesel generator with respect to the other generators. This is also demonstrated
 507 by the fact that the total NPC of the system grows progressively. Moving from
 508 2.8 €/l to 3 €/l, the algorithm favors a solution constituted by a higher number
 509 of battery units and the diesel generator, where the former does not contribute
 510 to the load energy needs. This is demonstrated by the fact that the total NPC of
 511 the system remains constant.

Table 8: Simulation results with a decreasing fuel price

Fuel Price [€/l]	PV panels		Wind turbines		Battery units		NPC HRES [€]		Day of June	
	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min
1.4	169	35	0	1	6	0	167,261	47,688	9 th	27 th
1.6	182	35	0	1	17	0	173,365	47,688	9 th	27 th
1.8	182	35	0	1	17	0	177,920	47,688	9 th	27 th
2.0	182	35	0	1	17	0	182,475	47,688	9 th	27 th
2.2	182	35	0	1	17	0	187,030	47,688	9 th	27 th
2.4	182	35	0	1	17	0	191,585	47,688	9 th	27 th
2.6	105	35	0	1	17	0	198,445	47,688	14 th	27 th
2.8	105	35	0	1	17	0	205,738	47,688	14 th	27 th
3.0	105	35	0	1	52	0	207,396	47,688	14 th	27 th
3.2	105	35	0	1	52	0	207,396	47,688	14 th	27 th
3.4	105	35	0	1	52	0	207,396	47,688	14 th	27 th
3.6	105	35	0	1	52	0	207,396	47,688	14 th	27 th
3.8	205	35	0	1	52	0	207,396	47,688	14 th	27 th

512 4. Conclusions

513 A MILP algorithm has been developed with the aim of analysing how the
514 choice of the reference dataset for designing a HRES can strongly affect the opti-
515 mal configuration due to the strong variability of the renewable energy sources.
516 The algorithm was used considering a case study of a mountain hut located in
517 South-Tyrol (Italy) at an altitude of 2,200 m a.s.l. where the national power grid
518 is not present. The applied methodology considers a hybrid system composed by
519 PV panels, wind turbines, a diesel generator and lead-acid batteries as storage
520 solution.

521 The algorithm computes the optimal number of PV panels, wind turbines,
522 battery units and the energy provided by the diesel generator, constituting the
523 optimization variables of the problem, with the aim of minimizing the total Net
524 Present Cost (NPC) of the system over its entire lifetime. As input, a dataset based
525 on a measurement campaign performed in the month of June 2018 related to the
526 wind speed on site and the power consumption of the hut was used. These data
527 were collected each minute per each day and their hourly average values were
528 computed and used. The data related to the sun radiation were downloaded by
529 the PVGIS database. Two sizing approaches were evaluated: in one case, the
530 sizing of the components is based on the dataset of single days operation; alter-
531 natively, the sizing is based on the whole dataset covering one month operation.

532 Based on these two approaches, the algorithm simulates the behavior of the op-
533 timal system over one month.

534 Results showed a strong variability related to the optimal sizing of power
535 generators and batteries in the HRES, which strongly depends on the variability
536 of the renewable sources as well as on the load profile. This demonstrates that
537 the proper selection and analysis of the dataset for sizing a HRES is fundamental
538 to obtain adequate performance. Considering only a daily load profile and a daily
539 pattern of both sun and wind sources, the HRES sizing could not meet the needs
540 of the load in all the days if a proper representative day of the entire month is not
541 defined. However, a lower capital cost would be required in most of the cases. On
542 the other hand, its sizing leads to an oversizing of the components when dealing
543 with the whole dataset. Therefore, a demand management could help to reduce
544 the size of the components and, at the same time, grate the energy supply when
545 the most demanding conditions occur. Results showed that: 1. the optimal siz-
546 ing of a HRES strongly depends on the renewable sources and their variability,
547 2. the storage systems, coupled with conventional generators, are still necessary
548 to avoid the oversizing of the entire system, as well as of the batteries bank, 3. the
549 modulation of PV power, wind power and an eventual demand side management
550 strategy is crucial to avoid the oversizing due to the variable percentage of the
551 load to be satisfied each hour of the day, which decreases the difference between
552 the maximum and the minimum costs of the HRES . Results also demonstrate a
553 significant reduction of the GHGs emissions due to the use of renewable energy
554 technologies. Furthermore, a sensitivity analysis has been performed on both
555 the fuel and battery costs, showing how these parameters can influence the op-
556 timal sizing of the system. In particular, considering a possible future scenario
557 characterized by a significant battery price reduction, HRESs would significantly
558 reduce their dependency on fossil-fuel conventional generators.

559 This algorithm constitutes a tool capable of providing a detailed description
560 of different possible scenarios, thus helping engineers to design the system prop-
561 erly. Further developments of this investigation may include the use of a PHES
562 equipped with Pumps-as-Turbines (PaTs) instead of conventional hydraulic tur-
563 bines or conventional batteries storage systems. Indeed, the lower cost of PaTs
564 compared to conventional hydraulic turbines and battery storage systems can
565 reduce the total cost of an HRES, thus pushing further their future deployment.

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