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Hybrid Renewable Power Plant Sizing – Graphical Decision Tool, Sensitivity Analysis and Applications in Ajaccio and Tilos

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Abstract

When sizing a renewable energy power plant in a grid-connected scenario, the optimal solution depends on the energy exchange rates between the actors of the electrical network. This study presents an optimization method that can be adapted to various power plant configurations to obtain the best size for each component, depending on the weather and the consumption. The optimization problem is solved in two steps. A Multi-Objective Particle Swarm Optimizer gives the trade-off between the cost of the components and the amount of non-renewable energy used, then the post-treatment takes into account the energy exchange tariffs and presents the solutions that minimize the production cost for any import and export rates. Those results can be used to evaluate the feasibility of an installation or to define the exchange tariffs with the grid regulation entity. This study also showcases the effect of the economic assumptions and of the choice of the energy management strategy on the optimal solution. The results show that the variation of the optimal production cost is limited but the component size has to be adapted accordingly. In the same way, the Energy Management Strategy used influences the plant design without affecting significantly the production cost.

Keywords: Hybrid power plant ; Optimal sizing ; Techno-economic study ; Sensitivity analysis ; Energy Management Strategies

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Introduction

With the global warming threat and the new incentives to increase the renewable power integration, more and more green energy production facilities are being installed [1, 2]. Those power plants are spread out on the territory and inject power in the electrical grid in remote nodes, as opposed to the usual centralized production. Decentralized energy can also help non or poorly interconnected areas to increase their power quality with a better grid stability [3].

The most common production means from Renewable Energy Sources (RES) are Hydro-Electricity, PhotoVoltaic (PV) and Wind Turbines (WT). However wind and solar powers are not controllable and can be tough to predict [4, 5, 6]. Hybrid production systems using both PV and WT can improve the RES penetration [7] and can be coupled with Fuel Generators or with Energy Storage Systems (ESS) to provide energy when the RES are not available. Several ESS exist like Battery Storage (BS), Pumped Hydro storage (PH), Hydrogen storage (H₂), etc, but storing electrical energy is still a big challenge.

Developing and installing new production plants is expensive and can be an economic risk for the investors. As such, they should be thoughtfully sized so that they provide the best performances with the lowest cost. This is a complex optimization problem that is often encountered in the literature [8].

The algorithms are for the most part developed for a specific test case such as PV/WT/BS plants [9, 10], PV/H₂ [11] and many other configurations [12, 13]. The optimization methods usually try to minimize the energy production cost [14] while keeping a low Loss of Power Supply Probability (LPSP) [15]. When Renewable Energy Sources are coupled with another production mean (like Fuel Generators), the fuel price is also taken into account in the production cost [16]. The solving method can be straightforward for problems with few parameters [17, 18] or more complex like Genetic Algorithm [19], Grey Wolf Optimizer [20], Mixed Integer Linear Programming [21, 22] or Particle Swarm Optimizers [23, 24].

Hybrid production microgrids can be categorized as stand-alone or grid connected. For stand-alone applications, the energy market costs do not affect the optimal solution. Providing energy to consumers without relying on the grid requires a heavy infrastructure with an important storage reserve or controllable production means. It also implies that any exceeding energy is lost when the storage is full.

The methodology presented in [25] aims to optimize a PV, Wind, Diesel and Battery stand-alone power plant. The algorithm changes the size of the components within a loop until the constraints are satisfied. It also allows some low priority load to be switched off to save energy. This solution can be adapted to several configurations but, since it performs an exhaustive search, it would require too much computation time if the number of components to size increases.

In [26], the authors use a Genetic Algorithm to size a Photovoltaic array associated with a Pumped Hydro storage in stand-alone configuration. It is a bi-objective optimization that minimizes both the cost of the system and the LPSP. Since the plant is not grid connected, any exceeding energy that cannot be stored is lost. Performing the same study with a grid connection would need to consider the energy exchange rates and would result on different optima.

Grid-connected applications may be more profitable as they can trade energy

with other partners [27]. The exchange rates costs depend on the demand and on the energy wholesale markets and have to be considered in the optimal sizing problem [28].

The method presented in [29] uses a mono-objective Genetic Algorithm to minimize the Net Present Value of a Photovoltaic, Wind and Biomass power system. The plant is connected to the grid and can sell the energy it produces. It does not however include a storage system and cannot export energy at the most profitable time periods.

Another approach can be found in [30]. The authors use and improve a bat optimization algorithm in order to size the components of a microgrid with a Micro-Turbine, a Fuel Cell, a PV array, a Wind Turbine and a Battery storage. The objective is to minimize the total cost, including the exchanges with the main grid. In those studies, the exchange rates are defined prior to the optimization so any change in those tariffs would require new and time consuming computations.

In poorly or non-interconnected area, such as islands, the energy market is not always available. In this case, the tariffs are fixed by the grid management entity or can be negotiated during call for tenders. Moreover, producing energy in those areas is expensive (above 300€/MW.h produced [31]) and due to their access difficulty and their small size, those areas also suffer from bad distribution quality [32].

This paper presents a sizing optimization for a grid-connected hybrid power plant associated with a storage. The aim is to obtain the size of each component of the plant so that the energy production cost is the lowest for any energy import and export tariffs. The study also includes a sensitivity analysis of the solution to showcase the importance of the economic assumptions and the choice of an Energy Management Strategy.

The methodology presented in this paper is a two-step algorithm. To avoid the need of a new study if the exchange rates vary, a bi-objective optimization minimizes the system cost and the amount of non-renewable energy used, without the trading costs. The results form a Pareto front where each point represents a plant sizing. The importation and exportation tariffs are introduced in a second step and the energy production cost is computed for each solution of the Pareto front. The plant which has the lowest production cost is then selected as the optimal solution.

The Pareto front is obtained with the method described in [33, 34]. The model uses 12 parameters and can be adapted to various plant configurations by deactivating the components that are not used. The model simulates the behavior of a given plant according to an Energy Management Strategy (EMS) and returns the amount of non-renewable energy that has to be imported to fulfill the power demand. The optimization problem is solved by a Multi Objective Particle Swarm Optimizer (MOPSO) [35, 36]. The results are then post-treated to take into account the energy exchanges and return the plant with the lowest production cost. The solution is presented as four contour maps that represent the optimal plant sizings depending on the energy importation and exportation tariffs.

The optimal solution depends on several factors, including the economic assumptions and the way the power are exchanged in the microgrid. To quantify their effect, the optimization is run with different cost assumptions and Energy Management Strategies.

The first section of this paper presents the plant model and the algorithm used to solve the optimization problem. Section 2 describes the post-treatment where the optimization results are used to define the solution that minimizes the production cost for any importation and exportation tariffs. The methodology is then illustrated with two examples in Greece and in France. The third section details the economic sensitivity analysis and shows the effects of price variations on the Pareto front, the plant performances and the sizing of the optimal solutions. Finally the fourth section presents four energy management strategies and how they can affect the results.

1 Optimization problem

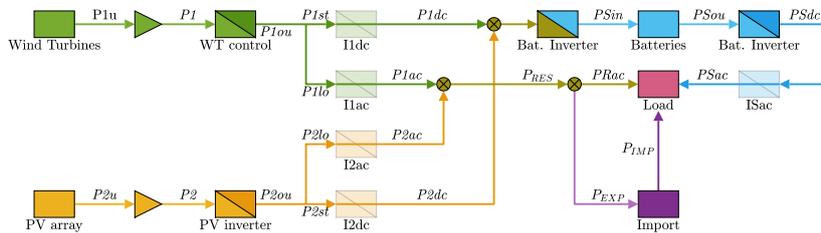


Figure 1: Algorithm configuration for a Wind Turbine, PV array, Battery storage microgrid.

A framework to optimize the size of each component for a given plant has been proposed in [33]. The method aims to reduce the amount of energy not produced by renewable sources –referred as imported energy– and the total cost of the equipments. The algorithm presented can easily be adapted to a wide array of plant configurations. As it is coded in Matlab, it is more flexible than the commercial simulation tools [37].

The plant components are modeled by their maximum power and their efficiency, that depends on the input power. The powers produced by the Renewable Energy Sources (RES) are obtained from meteorological data using numerical models. Those powers are then routed to the load or to the storage, taking into account the power limitations and the efficiencies of each component. If needed, energy can be imported to back up the RES. Those importations can come from an external grid or from controllable sources such as Fuel Generators.

If the production is above the consumption, the algorithm keeps track of the exceeding power and labels it as power available for export. In the post processing, this energy will be discarded or sold to the grid if exportation is possible. In the same way, energy can be exported if the production exceeds the consumption. More details on this algorithm can be found in [33].

The optimization is done using a Multi Objective Particle Swarm Optimizer (MOPSO) set to minimize the amount of energy imported and the Annualized Cost of System (ACS). Particle Swarm algorithms are derivative-free stochastic methods that can solve efficiently large scale optimization problems under constraints. Unlike some algorithms that use the derivative of the objective function, the MOPSO only need the simulation results to move the particles. This avoids the time consuming phase of computing the derivative of the objec-

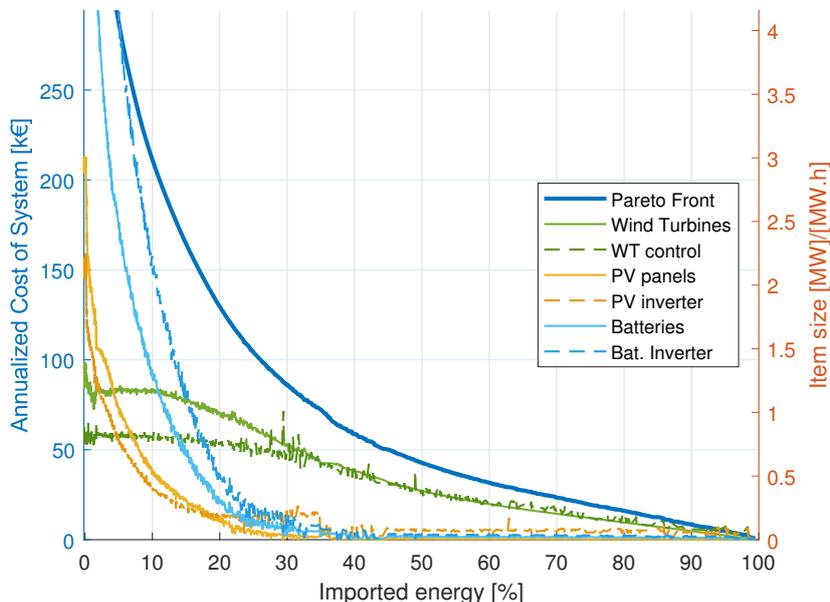


Figure 2: Pareto front result for Tilos Island. Annualized Cost of System in dark blue vs. energy importations. The green, yellow and blue lines show respectively the size of the Wind Turbine, the PV panels and the Battery bank.

tive function that must be done via finite differences in the case of the sizing optimization problem.

In the MOPSO, each particle is a vector containing the sizes of all the components in a plant configuration. A first swarm is randomly set up in the study domain and the plant behavior is computed with the plant model described above. The particles are then moved depending on the swarm best performances and on their own. This process is iterated until the swarm converges or a maximum iteration threshold is reached.

The optimization results form a Pareto front of the ACS versus the Energy Importations. The costs of the importation and eventual exportation are not taken into account in this part of the optimization but will be used in the post-processing described in the next section.

As a first example, we will use a hybrid power plant in Tilos Island, Greece [38]. Tilos is located in the Aegean Sea ($36^{\circ}26'0''N$, $27^{\circ}22'0''E$) that hosts around 500 inhabitants in winter and nearly 2000 during the summer. The average power consumption is 370 kW with spikes up to 1 MW for an annual consumption of 3.6 GW.h [31]. In the scope of this study, the consumption profile has been majored by 20% to factor in the expected growth in the future years [39]. Tilos is currently powered from an undersea cable connected to the Kos-Kalimnos islands. However, it is the last node in the network and is often subject to disconnections. In that case, a 1.45 MW Fuel Generator is used as a backup but, depending on the weather conditions, several days can be spent before firing up the generator.

With this in mind, a H2020 European project aims to develop a smart grid using solar and wind resources to reduce the energy imported and even make

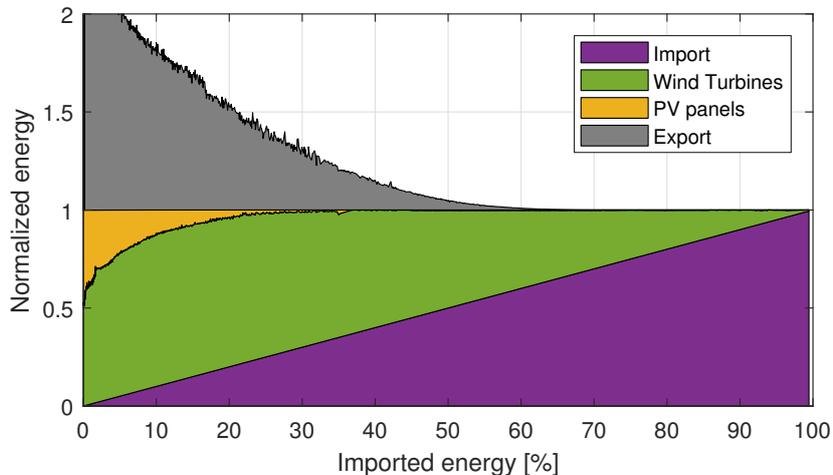


Figure 3: Energy repartition for each plant in the Pareto front for Tilos Island. The values are normalized with respect to the yearly load consumption $E_{CA} = 3.6$ GW.h.

the island partially autonomous [40, 41]. The renewable resources are indeed abundant with an average yearly solar irradiation of 1750 kW.h/m^2 and an average wind speed of 6 to 7 m/s.

The system is made up of a Wind Turbine, a Photovoltaic array and a Sodium-Nickel-Chloride battery bank (NaNiCl_2). The powers produced are converted to high voltage AC and routed either to the load or to the energy storage. Before reaching the batteries, the power is converted to DC and regulated by inverters. Those inverters convert the current back to AC when the batteries are discharged. Figure 1 presents the algorithm set up to model this configuration.

The weather data comes from measurement stations installed on purpose in Tilos. The PV production is estimated from the global irradiance and the temperature and the wind power from the wind speed. Although the data is recorded every minute, the simulations are run with one hour resolution to reduce the computation time needed. For one year simulation, the difference in the model outputs induced by the new timestep is not significant. Furthermore, the plant modeling has been tested during the H2020 project and has proven to be representative of the real plant behavior.

The cost of the system includes the investment cost of each equipment, its maintenance and replacement costs, taking into account the actualization rate. The cost data is taken from [42] for PV, from [43] for WT and from [44] for the storage. The total cost of system is then divided by the plant lifetime (25 years) to obtain the ACS.

The optimization results are presented in Figure 2. Above 35% of imported energy, the optimal solution is to install only the Wind Turbine and import energy when there is not enough wind. Between 15% and 35% the best solutions are obtained by pairing the Wind Turbine with PV panels, still without storage. The highest autonomy requirements (below 15% imported energy), are reached by adding the battery bank. However the Pareto slope is steep and gaining

autonomy results in an important additional cost.

As mentioned before, this optimization is done without taking into account the energy trading costs. Although more importation means a lesser cost of system, the energy has to be bought nonetheless and, depending on the import rate, it can result in a higher annual cost. More autonomy means an excess of energy produced, as presented in Figure 3. Selling this energy can help the plant financial balance if the exportation tariff is high enough.

The next section proposes a Graphical Decision Tool to quickly obtain the best plant configuration based on the energy exchanges costs.

2 Graphical Decision Tool

The optimization does not define an optimal plant size as it is. Instead, it proposes N_s solutions forming a Pareto front. Since the energy importation and exportation costs have not yet been taken into account, the total cost of energy production is unknown ; however, for each plant, the algorithm gives how much and when energy is imported or exported. By knowing the import and export tariffs, it is possible to compute the financial amount spent and earned during one year exploitation, even if those tariffs are time dependent. Producers in poorly interconnected areas do not have access to the Energy Spot market. The exchanges rates are fixed in the tender with the energy regulation entity. They can be fixed or depend on time (seasonal, peak/off-peak prices).

For the sake of simplicity, the tariffs are assumed constant in this paper. Let C_{in} being the importation and C_{out} the exportation prices (€/MW.h). The yearly load consumption is denoted E_{CA} (MW.h). The i^{th} plant in the front has an Annualized Cost of System $ACS(i)$, an amount of energy imported $E_{IA}(i)$ and exported $E_{EA}(i)$. Its energy production cost (in €/MW.h) can be written as follows:

$$C_{prod}(i) = \frac{ACS(i) + E_{IA}(i) \cdot C_{in} - E_{EA}(i) \cdot C_{out}}{E_{CA}} \quad (1)$$

In order to represent the cost for the local consumers, the total price is normalized with respect to the energy consumed by the load rather than with the total energy produced.

By assuming an importation and an exportation cost, the Figure 4 can be drawn to illustrate the effect of each element on the production cost. As expected, a plant relying on importations spends high amounts to buy energy. On the other hand, almost autonomous plants import only a little energy, have important costs for buying and maintaining the equipments but produce more energy than needed and can export it to reduce the final balance.

The solution i^* minimizing the production cost, for given importation and exportation tariffs, is chosen among the N_s solutions:

$$i^*(C_{in}, C_{out}) = \underset{i \in [0, N_s]}{\operatorname{argmin}} C_{prod}(i) \quad (2)$$

C_{in} and C_{out} are discretized and, for each couple, the best solution $i^*(C_{in}, C_{out})$ is obtained. It is a linear computation and is done instantaneously. It is then possible to draw the maps of the optimal cost of system (Fig. 5a), the percentage of imported energy (Fig. 5b), the amount of exceeding energy (Fig. 5c) and the

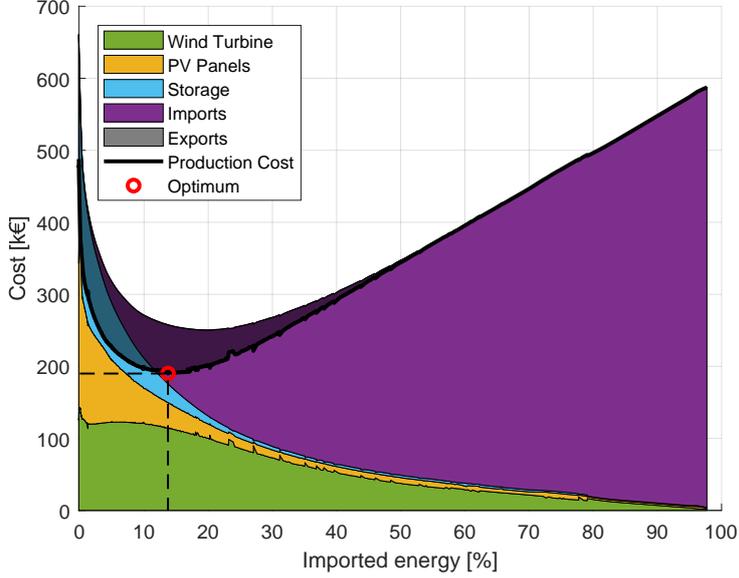


Figure 4: Cost repartition with $C_{in} = 200$ €/MW.h and $C_{out} = 30$ €/MW.h in Tilos Island.

energy production cost (Fig. 5d) depending on the importation and exportation rates.

With such figures, it becomes easy to quickly evaluate the plant feasibility and the reachable objectives. They may be used in the project pre-studies or during tariff negotiations with the grid regulation entity.

In the example of Tilos Island, if the import cost is 200 €/MW.h and the export cost is 30 €/MW.h, Figure 5a gives that the optimal solution has an ACS of 176 k€, 13.7% imported energy (Fig. 5b) and produces 2.3 GW.h more than it is consumed. Assuming that all this exceeding energy can be sold, (Fig. 5c), the production cost goes down to 63.6 €/MW.h (Fig. 5d). The size of each component can also be read on the right axis of Figure 2 for 13.7% imported energy and are summed up in Table 1.

The same study can be done for Ajaccio in Corsica ($41^{\circ}55'36''N$, $8^{\circ}44'13''E$). To keep the same size factor, only a community of around 500 inhabitants is considered. The objective is to power an eco-neighborhood with renewable energy sources and a grid connection as backup or for exporting the exceeding energy. The consumption profile is taken from EDF Open Data [45] scaled down to 500 inhabitants and the weather data come from measurements realized in our experimental platform. The results are presented in Figure 6. In Ajaccio, the energy production cost is higher than in Tilos and it is more expensive to reach the same autonomy. It can be explained by the lack of wind power and the increased need of storage capacity to supply energy at night. Assuming the same exchange rates as in Tilos, the optimal solution costs 304 k€ every year and offers only 74.5% autonomy. Even when accounting for the sell of exceeding energy, the production cost reaches up to 129 €/MW.h but stays below the actual production cost in Corsica [32].

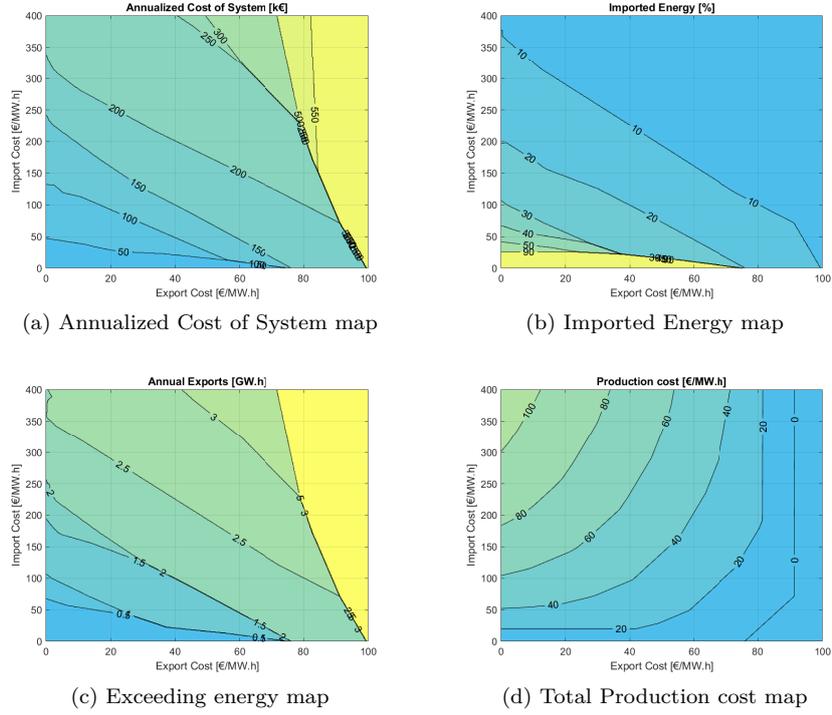


Figure 5: Graphical Decision Tool maps for Tilos test case.

	Wind Turbine	PV array	Batteries	ACS	Autonomy	Prod. cost
Tilos	1120 kW	341 kW	800 kW.h	176 k€	86.3 %	63.6 €/MW.h
Ajaccio	837 kW	1660 kW	2650 kW.h	304 k€	74.5 %	129 €/MW.h

Table 1: Comparison of optimal solutions for Tilos and Ajaccio under the same exchange rates assumptions.

The solutions for Tilos and Ajaccio are presented in Table 1. The plant in Ajaccio logically relies on a smaller Wind Turbine than in Tilos. To satisfy the power demand, it however needs five times the PV power installed and three times the battery capacity. This is the main cause to the cost increase between the two locations.

The results presented here are based on economic assumptions from [46]. These values vary with time and depend on the location for taxes and workforce salary. They can affect the optimal solution and make a plant less profitable. The next section focuses on the results sensitivity to the cost assumptions.

3 Sensitivity analysis

A change in the cost assumptions can affect the optimization results significantly, either by moving the Pareto front or by changing the optimal component sizes for an individual solution. The three next subsections show the effects of a price

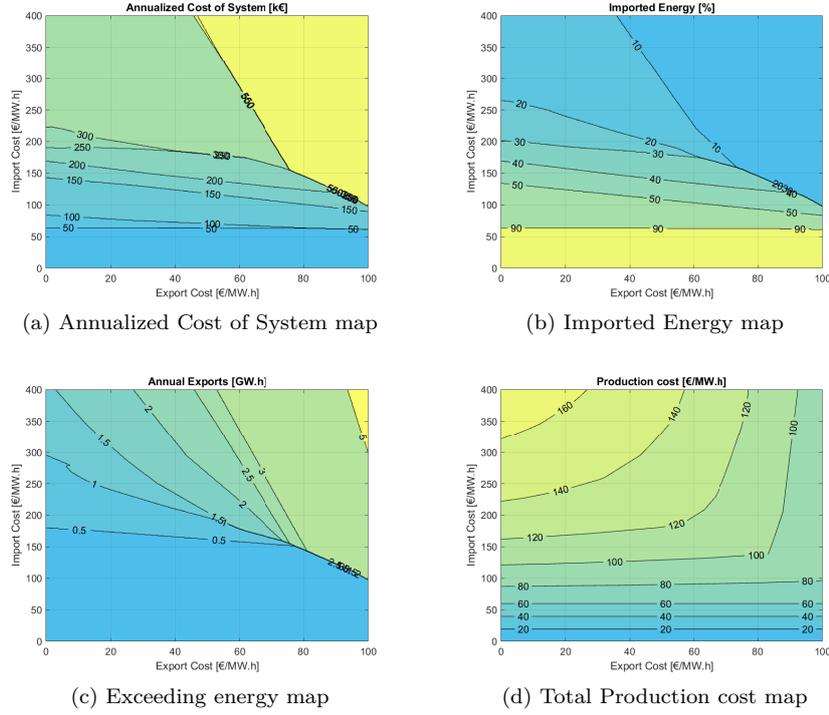


Figure 6: Graphical Decision Tool maps for Ajaccio test case.

variation on the Pareto front, on the optimal solution for a given exchange rate and on the size of the components of that solution. For the sake of concision, only the results for Tilos are presented in this paper. The optimizations are run using the Priority List as the Energy Management Strategy. The optimal sizing may also depend on the EMS used. As such, its influence will be studied in Section 4.

The solution presented in Section 2 will serve as reference. From the previous cost assumptions, five parameters will be increased by +10% one after the other. The values that will be altered are:

- The energy importation cost (Import tariff)
- The wind turbine buying cost (WT CapEx)
- The battery buying cost (Bat. CapEx)
- The wind turbine maintenance cost (WT OpEx)
- The PV panel buying cost (PV CapEx)

The optimization problem is written so that the energy exchanges costs do not affect the Pareto front so only four additional optimizations need to be done. The optimizer is run once again from the start with the same parameters so that the results can be compared with the reference solution.

3.1 Pareto Front sensitivity

The four fronts obtained are presented in Figure 7. Despite the change in the cost assumptions, the Pareto fronts stay similar to the reference. This means that, for a given autonomy, the optimal cost of system stays stable even if the

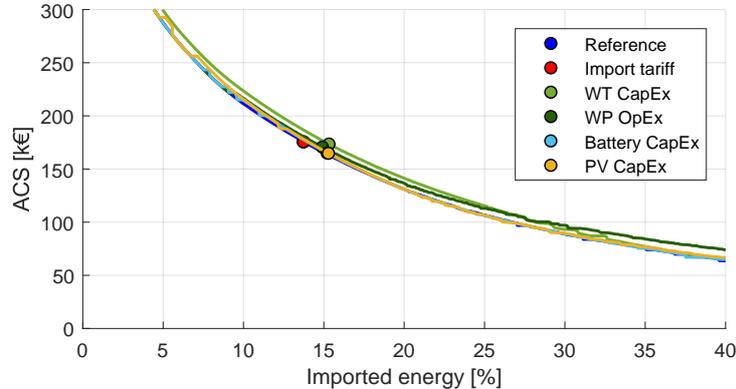


Figure 7: Optimization solutions obtained for the base assumptions and the sensitivity analysis.

Solution	ACS	Imports	Prod. cost
Reference	176 k€	13.7 %	63.6 €/MW.h
Import tariff	176 k€	13.7 %	66.4 €/MW.h
WT CapEx	173 k€	15.3 %	68.9 €/MW.h
WP OpEx	171 k€	14.9 %	65.9 €/MW.h
Battery CapEx	165 k€	15.2 %	64.5 €/MW.h
PV CapEx	165 k€	15.3 %	63.8 €/MW.h

Table 2: Plant performances for different economic assumptions.

equipment costs vary. The algorithm is able to balance one component cost increase with the other elements to keep the same amount of renewable energy used. It does not ensure however that the energy production cost is not affected. Its variation is assessed in the next section.

3.2 Optimal solution sensitivity

While the Pareto front changes only slightly, the optimal solution for given importation and exportation costs is affected. As an example, the importation rate is assumed to be 200 €/MW.h and the exportation rate to 30 €/MW.h. In this case the optimal solution for the base assumptions offers 86.3% autonomy for an ACS of 176 k€ and an Energy Production cost of 63.6 €/MW.h.

The optimal solutions for the test cases are identified as colored dots in Figure 7 and their performances are presented in Table 2. As expected, changing the economic assumptions affects the optimal solution: the ACS varies between 165 and 176 k€ and the imported energy fraction between 13.7 and 15.3%. The energy production cost is also altered and suffers a 8.2% increase in the worst case. The biggest variation is a 11.6% rise in the energy imported. Although the changes are significant, the algorithm gives a good estimation of the ACS and of the autonomy despite the uncertainties.

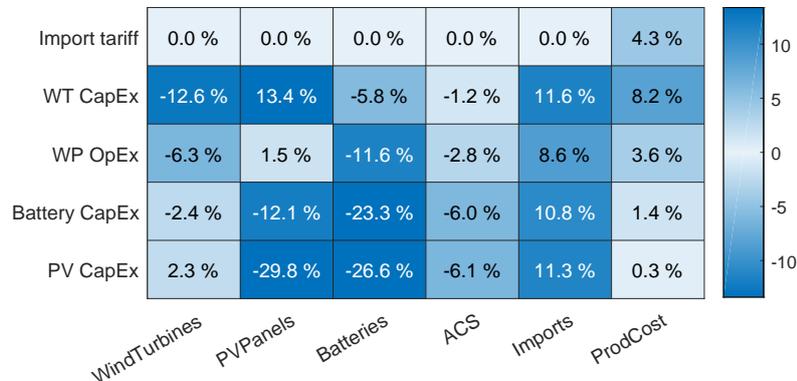


Figure 8: Relative deviation in percent from the base optimization with different cost assumptions for a 10% increase.

3.3 Components size sensitivity

Despite the optimal solutions having relatively similar performances, the size of the components is heavily affected by the different assumptions. The Figure 8 details the relative deviations from the reference solution. As seen before, the production cost stays stable but if the costs associated with a component increase, the optimizer logically reduces its size and compensates with other elements.

The sizing obtained with the increase of the import cost is the same than the reference. The difference is not significant enough to change the optimal configuration due to the finite number of optimal solutions computed. The energy production is however more expensive. An increase of the initial cost or the maintenance cost of any component logically results in a solution with a smaller component. For example, if the PV panel buying cost increases by 10%, the installed PV power is reduced by almost 30%. The storage capacity is also reduced while the Wind Turbine power is slightly increased. It leads to a cheaper plant but those savings are nullified as the plant relies more on the importations to mitigate the lack of PV power.

In conclusion, if the economic assumptions vary, the Pareto front and the optimal performances are stable but the size of each component may change significantly. The next section presents different Energy Management Strategies and their effects on the solution.

4 Energy Management Strategies

The plant ability to power the consumers with renewable energy depends on the storage management strategy. A real life implementation should include technical limitations (maximum power, ramp rate, start-up delays, battery cycling, ...), regulatory limitations (guaranteed power, profile limitation, ...) and weather and consumption forecast.

The development of smart Energy Management Strategies (EMS) is a complex task that is abundantly studied in the literature [47]. The EMS often

require an optimization (Linear Programming, Model Predictive Control) to obtain the best plant operation. Complex solutions are not suitable in our study. Since a lot of simulations have to be done, the EMS must run quickly otherwise the optimization would require too much computation time. The EMS used here are simple strategies that run without optimization and do not use forecasts for load or production.

4.1 Priority list

Priority list is the simplest strategy presented here and is the one that has been used for the previous simulations. In order to minimize the importations, the load is first powered from the renewable energy sources then from the battery bank. When it is not sufficient, the remaining energy is imported. If the RES production exceeds the consumption, the storage is charged and when it is full, the exceeding energy is exported.

This management strategy offers the best autonomy for a given plant. However, it stresses the storage with numerous charging cycles and gives imported and exported powers with important variations. To reduce the sudden change when the storage gets completely emptied, its power can be limited when the storage State of Charge reaches a given limit. It slightly degrades the performances while smoothing the grid power. However, it still may not be allowed by the grid provider.

4.2 Peak Shaving

In the Peak Shaving strategy, the storage is used to power the load when the consumption is maximum [48]. This helps reducing the size of the power components and the maximum imported power.

The load consumption peak and the RES production peak do not occur in the same time. The idea behind the Peak Shaving strategy is to store the energy excess during the peak production and use it during the peak consumption. To reduce the size of the storage needed, its State of Charge is brought back to 50% by means of a proportional controller when enough power is available. In poorly interconnected areas and small micro grids, this strategy is particularly useful as it allows to use smaller controllable sources (e.g. a Diesel Generator) and smaller power transmission lines to the main grid.

4.3 Grid power moving average

Another simple strategy is to force the grid power to be the average of the consumption minus the RES power. In this way, the power drawn or sent to the grid varies slowly and the variations are absorbed by the storage. This strategy stresses the storage as it is forced to compensate for every deviation from the average, even in case of small variations that would not have disturbed the grid. To achieve slow power variations, the average has to be done on a wide time window, resulting in long periods when the storage is used but it requires an important capacity.

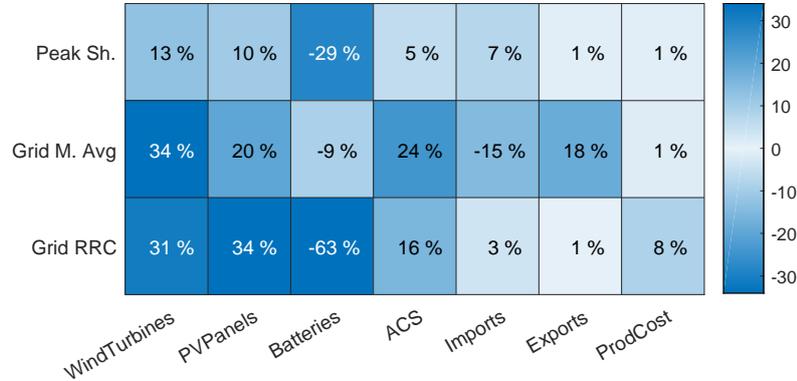


Figure 9: Relative deviation in percent from the Priority List for Peak Shaving strategy (Peak Sh.), Grid Moving Average (Grid M. Avg) and Grid Ramp Rate Control (Grid RRC).

4.4 Ramp Rate Control

The Ramp Rate Control aims to reduce the maximum power variation for a given component. Unlike moving average, it only triggers when the variation exceeds a threshold and avoids unnecessary charge-discharge cycles. According to [49], a Ramp Rate Control strategy can reliably limit the power variations from and to the grid. It can be applied to the grid power (the storage takes the difference and is stressed) or to the storage power (the grid takes the difference and the import/export vary).

The algorithm implemented is inspired from the work presented in [50, 51] and is described in details in [52]. It is configured so that the grid power ramp rate stays below 10% of the installed power per hour. The strategy also implement a State of Charge controller aiming to keep the storage half charged.

4.5 Effect on the optimal sizing

Three additional optimizations are run with the strategies presented above and their result is compared with the Priority list. As before, the comparison is done with an importation rate of 200 €/MW.h and an exportation rate of 30 €/MW.h. The deviations from the reference are presented in Figure 9.

The Peak Shaving strategy requires bigger energy sources. As the battery bank is only used during peak hours, its size can be reduced. It yields a more expensive system with the same autonomy. In the end, the production cost and the exported energy are the same as the results obtained with the Priority List.

The optimal solution with the Grid Moving Average Strategy also offers the same production cost than the reference. It needs bigger Wind Turbines and PV array, hence a higher cost of system. This cost is balanced by a reduction in energy importations and an increase on the exportations. However this strategy stresses heavily the storage system with numerous charge cycles and it can increase the replacement cost in the long run. To compensate, it may be possible to negotiate better exchange tariffs since the power exchanged is smoothed.

For the Ramp Rate Control strategy the storage capacity can be reduced

as the batteries only need to compensate the quick power variations. The autonomy stays the same so the requirement for PV and WT is increased to compensate for the lack of storage. The system is more expensive and results on a 8% increase of the production cost. On the other hand, this strategy guarantees that the exported power variations are limited so it may be sold at a better price.

The EMS affects the optimal solution and must be chosen in accordance with the local grid code and the performances wanted. The Priority List results in the lowest cost of system and production cost but has to rely on imported power. The Peak Shaving strategy would be better suited if the import power is limited but comes with a reduction in autonomy. The Grid Moving Average strategy generates smoother power exchanges but would need a storage able to tolerate quick and frequent variations. Finally the Ramp Rate Control strategy should be used in small networks where important power variations can disturb the distribution grid. For example, the Diesel Generators usually used to produce electricity on islands cannot accommodate for those variations. They are often paired with expensive combustion turbine generators that drastically increase the energy cost when they are fired [31, 32].

5 Conclusion

This paper presents an optimization for a grid-connected hybrid power plant associated with a storage. The optimization is done with a Multi Objective Particle Swarm Optimizer. The post-treatment then takes into account the energy importations and exportations to choose the plant offering the lowest energy production.

The algorithm is applied to the sizing of a Wind/Photovoltaic/Battery plant. Two locations are examined: Tilos in Greece and Ajaccio in France and the results are compared for 200 €/MW.h importation cost and 30 €/MW.h for the exports.

In Tilos, the algorithm finds a solution with an energy production cost of 63.6 €/MW.h and an autonomy of 86.3%. This plant can power the island with Renewable Energy Sources while being cost competitive with the undersea cable. In Ajaccio however, the lack of wind causes the optimal solution to have only 74.5% autonomy. The production cost reaches 129 €/MW.h but is still below the current production cost [32]. If the exchange rates are modified, the new optimum can immediately be found with the Graphical Decision Tool developed.

The solution can depend on the component costs and on the Energy Management Strategy. A sensitivity analysis has been done for the results in Tilos. Increasing the cost of components by 10% has little effect on the production cost but can change drastically the plant sizing. In the same way, the production cost remained relatively constant for the EMS tested but the component sizes have to be adapted to the chosen strategy. It may also be possible to negotiate better import and export tariffs since the power exchanges follow additional constraints.

This optimization method can reliably give the optimum production cost depending on the plant location, the load consumption, the EMS strategy and the grid trading costs. To obtain the optimal size for the plant elements with

confidence, it is mandatory to have trustworthy data on their buying cost, maintenance and life expectancy.

In future works, we will focus on implementing new management strategies that complies with the grid code so that the modeling can more accurately represent a real life power plant. We will also include peak and off-peak energy pricing in the strategy and in the decision tool. As the data collected from the Tilos installation supports our results, it is also envisaged to use our algorithm in order to size a small scale PV power plant associated with a storage to supply a smart-village in Corsica.

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References

- [1] European Commission (EurObserv'ER), Photovoltaic Barometer, Tech. Rep. April, European Commission (2018).
- [2] European Commission (EurObserv'ER), Wind Energy Barometer, Tech. rep., European Commission (2018).
- [3] S. Zurmühlen, G. Angenendt, M. Heinrich, H. Axelsen, D. U. Sauer, Grid-Relieving Effects of PV Battery Energy Storage Systems with Optimized Operation Strategies, in: 33rd European Photovoltaic Solar Energy Conference and Exhibition, WIP, 2017, pp. 2052–2056. doi:10.4229/EUPVSEC20172017-6CO.16.4.
- [4] C. Voyant, G. Notton, S. Kalogirou, M.-L. Nivet, C. Paoli, F. Motte, A. Fouilloy, Machine learning methods for solar radiation forecasting: A review, *Renewable Energy* 105 (2017) 569–582. doi:10.1016/j.renene.2016.12.095.
- [5] A. Heimo, Weather Intelligence for Renewable Energies - Current State Report 2012, Tech. Rep. August, COST (2012).
- [6] M. Q. Raza, M. Nadarajah, C. Ekanayake, On recent advances in PV output power forecast, *Solar Energy* 136 (2016) 125–144. doi:10.1016/j.solener.2016.06.073.
- [7] J. K. Kaldellis, Stand-Alone and Hybrid Wind Energy Systems: Technology, Energy Storage and Applications, Woodhead Pub., 2010.
- [8] A. H. Fathima, K. Palanisamy, Optimization in microgrids with hybrid energy systems - A review, *Renewable and Sustainable Energy Reviews* 45 (2015) 431–446. doi:10.1016/j.rser.2015.01.059.
- [9] L. Xu, X. Ruan, C. Mao, B. Zhang, Y. Luo, An improved optimal sizing method for wind-solar-battery hybrid power system, *IEEE Transactions on Sustainable Energy* 4 (3) (2013) 774–785. doi:10.1109/TSTE.2012.2228509.

- [10] Y. Oğuz, M. F. Özsoy, Sizing, design, and installation of an isolated wind-photovoltaic hybrid power system with battery storage for laboratory general illumination in Afyonkarahisar, Turkey, *Journal of Energy in Southern Africa* 26 (2015) 70–80.
- [11] C. Darras, G. Bastien, M. Muselli, P. Poggi, B. Champel, P. Serre-Combe, Techno-economic analysis of PV/H₂ systems, *International Journal of Hydrogen Energy* 40 (30) (2015) 9049–9060. doi:10.1016/j.ijhydene.2015.05.112.
- [12] Y. Zhao, H. Hong, H. Jin, Optimization of the solar field size for the solar-coal hybrid system, *Applied Energy* 185 (2017) 1162–1172. doi:10.1016/j.apenergy.2016.01.069.
- [13] W. Fang, Q. Huang, S. Huang, J. Yang, E. Meng, Y. Li, Optimal sizing of utility-scale photovoltaic power generation complementarily operating with hydropower: A case study of the world’s largest hydro-photovoltaic plant, *Energy Conversion and Management* 136 (2017) 161–172. doi:10.1016/j.enconman.2017.01.012.
- [14] A. Kaabeche, M. Belhamel, R. Ibtouen, Sizing optimization of grid-independent hybrid photovoltaic/wind power generation system, *Energy* 36 (2) (2011) 1214–1222. doi:10.1016/j.energy.2010.11.024.
- [15] M. Zebarjadi, A. Askarzadeh, Optimization of a reliable grid-connected PV-based power plant with/without energy storage system by a heuristic approach, *Solar Energy* 125 (2016) 12–21. doi:10.1016/j.solener.2015.11.045.
- [16] R. Belfkira, L. Zhang, G. Barakat, Optimal sizing study of hybrid wind/PV/diesel power generation unit, *Solar Energy* 85 (1) (2011) 100–110. doi:10.1016/j.solener.2010.10.018.
- [17] C. Darras, S. Sailler, C. Thibault, M. Muselli, P. Poggi, J. C. Hogue, S. Melscoet, E. Pinton, S. Grehant, F. Gailly, C. Turpin, S. Astier, G. Fontès, Sizing of photovoltaic system coupled with hydrogen/oxygen storage based on the ORIENTE model, *International Journal of Hydrogen Energy* 35 (8) (2010) 3322–3332. doi:10.1016/j.ijhydene.2010.01.060.
- [18] A. Zucker, T. Hinchliffe, Optimum sizing of PV-attached electricity storage according to power market signals - A case study for Germany and Italy, *Applied Energy* 127 (2014) 141–155. doi:10.1016/j.apenergy.2014.04.038.
- [19] J. Hirvonen, H. ur Rehman, K. Deb, K. Sirén, Neural network metamodelling in multi-objective optimization of a high latitude solar community, *Solar Energy* 155 (2017) 323–335. doi:10.1016/j.solener.2017.06.040.
- [20] A. Yahiaoui, F. Fodhil, K. Benmansour, M. Tadjine, N. Cheg-gaga, Grey wolf optimizer for optimal design of hybrid renewable energy system PV-Diesel Generator-Battery: Application to the case of Djanet city of Algeria, *Solar Energy* 158 (October) (2017) 941–951. doi:10.1016/j.solener.2017.10.040.

- [21] A. Malheiro, P. M. Castro, R. M. Lima, A. Estanqueiro, Integrated sizing and scheduling of wind/PV/diesel/battery isolated systems, *Renewable Energy* 83 (2015) 646–657. doi:10.1016/j.renene.2015.04.066.
- [22] J. Cervantes, F. Choobineh, Optimal sizing of a nonutility-scale solar power system and its battery storage, *Applied Energy* 216 (February) (2018) 105–115. doi:10.1016/j.apenergy.2018.02.013.
- [23] A. K. Bansal, R. A. Gupta, R. Kumar, Optimization of hybrid PV/wind energy system using Meta Particle Swarm Optimization (MPSO), in: *India International Conference on Power Electronics 2010*, IEEE, 2011, pp. 1–7. doi:10.1109/IICPE.2011.5728079.
- [24] N. Phuangpornpitak, W. Prommee, S. Tia, W. Phuangpornpitak, A study of particle swarm technique for renewable energy power systems, in: *Proceedings of the International Conference on Energy and Sustainable Development: Issues and Strategies (ESD 2010)*, IEEE, 2010, pp. 1–6. doi:10.1109/ESD.2010.5598791.
- [25] A. M. Eltamaly, M. A. Mohamed, A. I. Alolah, A novel smart grid theory for optimal sizing of hybrid renewable energy systems, *Solar Energy* 124 (2016) 26–38. doi:10.1016/j.solener.2015.11.016.
- [26] T. Ma, H. Yang, L. Lu, J. Peng, Pumped storage-based standalone photovoltaic power generation system: Modeling and techno-economic optimization, *Applied Energy* 137 (2015) 649–659. doi:10.1016/j.apenergy.2014.06.005.
- [27] J. Koskela, A. Rautiainen, P. Järventausta, Using electrical energy storage in residential buildings – Sizing of battery and photovoltaic panels based on electricity cost optimization, *Applied Energy* 239 (2019) 1175–1189. doi:10.1016/j.apenergy.2019.02.021.
- [28] R. Dufo-López, Optimisation of size and control of grid-connected storage under real time electricity pricing conditions, *Applied Energy* 140 (2015) 395–408. doi:10.1016/j.apenergy.2014.12.012.
- [29] A. González, J.-R. Riba, A. Rius, Optimal Sizing of a Hybrid Grid-Connected Photovoltaic-Wind-Biomass Power System, *Sustainability* 7 (9) (2015) 12787–12806. doi:10.3390/su70912787.
- [30] B. Bahmani-Firouzi, R. Azizipanah-Abarghooee, Optimal sizing of battery energy storage for micro-grid operation management using a new improved bat algorithm, *International Journal of Electrical Power & Energy Systems* 56 (2014) 42–54. doi:10.1016/j.ijepes.2013.10.019.
- [31] D. Zafirakis, G. Tzanes, J. K. Kaldellis, An advanced microgrid simulator for stand-alone and market-dependent energy strategies, in: *2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, IEEE, 2017, pp. 1–6. doi:10.1109/EEEIC.2017.7977623.

- [32] G. Notton, J.-L. Duchaud, M. Nivet, C. Voyant, K. Chalvatzis, A. Fouilloy, The electrical energy situation of French islands and focus on the Corsican situation, *Renewable Energy* 135 (2019) 1157–1165. doi:10.1016/j.renene.2018.12.090.
- [33] J.-L. Duchaud, G. Notton, C. Darras, C. Voyant, Multi-Objective Particle Swarm optimal sizing of a renewable hybrid power plant with storage, *Renewable Energy* 131 (2019) 1156–1167. doi:10.1016/j.renene.2018.08.058.
- [34] J.-L. Duchaud, G. Notton, A. Fouilloy, C. Voyant, Wind, solar and battery micro-grid optimal sizing in Tilos Island, *Energy Procedia* 159 (2019) 22–27. doi:10.1016/j.egypro.2018.12.012.
- [35] J. Kennedy, R. Eberhart, Particle swarm optimization, in: *Proceedings of ICNN'95 - International Conference on Neural Networks*, Vol. 4, IEEE, 1995, pp. 1942–1948. doi:10.1109/ICNN.1995.488968.
- [36] M. Reyes-Sierra, C. Coello, Multi-objective particle swarm optimizers: A survey of the state-of-the-art, *International Journal of Computational Intelligence Research* 2 (3) (2006) 287–307.
- [37] S. Sinha, S. S. Chandel, Review of software tools for hybrid renewable energy systems, *Renewable and Sustainable Energy Reviews* 32 (2014) 192–205. doi:10.1016/j.rser.2014.01.035.
- [38] K. Kaousias, G. Papoutsis, E. Stavropoulou, T. Patsaka, C. Kourelis, Z. Mantas, J. Kaldellis, C. Pronios, T. Delaplagne, G. Notton, M. Todeschini, D. H. Alamo, The European Research Project “TILOS”, in: *2018 CIGRE Session*, 2018, pp. 1–10.
- [39] Direction des Systèmes Energétiques Insulaires, Bilan Prévisionnel de l'Equilibre Offre/Demande d'Electricité - Corse, Tech. rep., EDF SA (2017).
- [40] TILOS - Technology Innovation for the Local Scale Optimum Integration of Battery Energy Storage, <https://www.tiloshorizon.eu/> (2019).
- [41] G. Notton, M. L. Nivet, D. Zafirakis, F. Motte, C. Voyant, A. Fouilloy, Tilos, the first autonomous renewable green island in Mediterranean: A Horizon 2020 project, in: *2017 15th International Conference on Electrical Machines, Drives and Power Systems, ELMA 2017 - Proceedings*, IEEE, 2017, pp. 102–105. doi:10.1109/ELMA.2017.7955410.
- [42] R. Fu, D. Feldman, R. Margolis, M. Woodhouse, K. Ardani, U.S. Solar Photovoltaic System Cost Benchmark: Q1 2017, Tech. Rep. August, U.S. Department of Energy (2017). doi:10.2172/1390776.
- [43] IRENA, TECHNOLOGY ROADMAP, in: *SpringerReference*, Springer-Verlag, Berlin/Heidelberg, 2018, p. 160.
- [44] IRENA, Electricity Storage and Renewables : Costs and Markets To 2030, Tech. rep., International Renewable Energy Agency, Abu Dhabi (2017).
- [45] Open Data EDF Corse, <http://opendata-corse.edf.fr> (2019).

- [46] Open Energy Information - Transparent Cost Database, <https://openei.org/apps/TCDB/> (2019).
- [47] H. Abdi, S. D. Beigvand, M. L. Scala, A review of optimal power flow studies applied to smart grids and microgrids, *Renewable and Sustainable Energy Reviews* 71 (May 2015) (2016) 742–766. doi:10.1016/j.rser.2016.12.102.
- [48] Y. Yang, Y. Zhang, P. E. Campana, J. Yan, Peak-shaving and profit-sharing model by Aggregators in residential buildings with PV– a case study in Eskilstuna, Sweden, *Energy Procedia* 142 (2017) 3182–3193. doi:10.1016/j.egypro.2017.12.488.
- [49] M. J. E. Alam, K. M. Muttaqi, D. Sutanto, A Novel Approach for Ramp-Rate Control of Solar PV Using Energy Storage to Mitigate Output Fluctuations Caused by Cloud Passing, *IEEE Transactions on Energy Conversion* 29 (2) (2014) 507–518. doi:10.1109/TEC.2014.2304951.
- [50] I. de la Parra, J. Marcos, M. García, L. Marroyo, Control strategies to use the minimum energy storage requirement for PV power ramp-rate control, *Solar Energy* 111 (2015) 332–343. doi:10.1016/j.solener.2014.10.038.
- [51] I. de la Parra, J. Marcos, M. García, L. Marroyo, Improvement of a control strategy for PV power ramp-rate limitation using the inverters: Reduction of the associated energy losses, *Solar Energy* 127 (2016) 262–268. doi:10.1016/j.solener.2016.01.032.
- [52] J.-L. Duchaud, G. Notton, C. Darras, C. Voyant, Power ramp-rate control algorithm with optimal State of Charge reference via Dynamic Programming, *Energy* 149 (2018) 709–717. doi:10.1016/j.energy.2018.02.064.