Efficient energy system modelling for multi-objective optimisation

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ABSTRACT: Energy systems, on which our modern society rely, are in constant transformation. Technological evolution, climate change or the finitude of fossil fuels are some reasons to rethink the centralized, carbon-based energy networks. This way, the design of future energy systems have to take into account multiple concerns, such as local resilience, in addition to technical and economic ones.

This paper presents a decision-support tool for the conception of energy systems focusing on the electric vector. The tool was designed using an energy system model implemented in an optimisation algorithm. It takes into account several constraints simultaneously – equilibrium between production and consumption as well as resources availability – and assess the influence of technical parameters on the global performances of the system. An energy system is considered as a combination of production, storage and transport technologies with their operating strategies. The tool's modularity allows to choose the models adapted to a quick optimisation of energy systems or to an analysis of technical parameters.
The second part of the paper presents the optimisation of a local energy system. Search space is composed of production and storage technologies' number and their operating strategies. Main goals are to find trade-offs between different economic and technical objective-functions – such as levelized cost of energy or local autonomy. Therefore, a genetic algorithm method was used to perform a multi-objective optimisation based on the model. The impact of the operating strategy adopted is underlined.

KEYWORDS: decision support, energy systems modelling, multi-objectives optimisation

INTRODUCTION

Energy consumption has increased for more than a century to sustain our changing way of life. Among energy vectors, electricity presents the biggest development of the past fifty years and may highlights advantages in terms of environmental concerns. Huge networks were built around main power plants, nuclear and hydroelectric ones in France. Economic challenges of the twentieth century have evolved and society's concerns are more related to social and environmental impacts. Same set of technologies cannot be designed to balance the increase in consumption and the end-of-life of current power plants. Therefore, new energy systems (ES) – i.e. sets of production, storage and transport technologies – need to be created. The development of distributed energy sources may represent an alternative to the current technologies. However, as they are dependent on intermittent resources, they can be supplemented by storage technologies. These configurations allow a local design for energy systems, microgrids, partially autonomous from the main grid if necessary. Economic, technical and environmental indicators have to be taken into account to assess the relevance of these new systems.

This paper focuses on the conception of ES. The purpose of the work described below is to create a decision-support tool able to find, for a local context, various optimal energy systems that are compromises between economic and technical objectives. The tool uses a physical modelling that simulates the operation of an energy system. Then it runs this model into an optimisation algorithm to find optimal energy systems.

Energy system modelling can be performed following two main methods according to the purpose. Prospective studies that assess huge networks and determine the best choice to make between a range of technologies will use a simplified modelling. Some of them use bottom-up "technological" methods [1] with some physical background but others prefer top-down "economical" modelling with aggregated variables [2]. The time step of their simulation can range from hours to years [1]. On the other hand, studies analyse precisely the operation of one specific energy system [3]. Their models are very detailed according to the technical parameters they want to assess and the time step used is small enough to capture the physical phenomena analysed, influence of temperature on the production of PV panels [4]. Whereas prospective studies consider often only a few variables like the technologies' number and use a long time step, detailed studies take also into account management parameters and short time steps. The study of local technological parameters requires detailed models. On the other hand, a model designed to minimise the computation-time (CPU-time) of the optimisation needs to be simplified. This conflict can be solved by finding compromises between accuracy and CPU-time. The present work tries to solve the conflict by using a systemic approach, i.e. several models with different levels of detail.

Once the energy system modelled and its operation simulated, an optimisation process can be performed to find the best solutions. Although systems need to be compared following many various indicators, optimums are often found using single-objective (SO) optimisation with an economic indicator [5]. Optimisation is sometimes performed with both economic and environmental objectives but using a prior weighting to be adapted to SO algorithm [6]. More rarely, multi-objectives (MO) optimisations without prior weighting are performed [7]. To tackle such complex problems in the most exhaustive manner, it seems important to take into account several impacts of energy systems, especially as they can be antagonists. Moreover, finding compromises does not overly restrict the tool user's choice and allows the analysis of interesting systems that would not have been considered initially. The latter can apply further discrimininating criteria to selected the best solution for its situation.

In the case of energy systems modelling and sequential simulation, indicators cannot be formulated explicitely, hence classical Lagrangian optimisation methods cannot be used. The use of metaheuristic optimisation algorithms allowing studying non-explicit and non-weighted objective-functions is required. Numerous methods exist such as gradient-method, Particle Swarm Optimization or MO Evolutionary Algorithms (MOEA). The advantage of evolutionary, also called genetic, algorithms is their ability to deal with 0-order objective functions and to explore the entire design space. In the literature, several methods have been used like Strength Pareto Evolutionary Algorithms (SPEA [8] and SPEA-II [9]), Non-dominated Sorting Genetic Algorithms (NSGA and NSGA-II [10]), Pareto Archived Evolution Strategy (PAES [11]) or Adaptive Pareto Algorithm (APA [12]). They allow finding Pareto-optimal solutions between the different objectives, i.e. ES that dominate the others on at least one objective, but they are time-consuming due to the repetition of the criteria's evaluation for each individual. The ES modeling choices and performance-to-CPU-time ratio of the simulation is all the more important.

The paper is structured as follow. Section 1 describes the modelling and the simulation of energy systems. Optimisation method, objectives and parameters are detailed in Section 2. Section 3 presents and discusses the results of the casy study. Eventually a conclusion underlines the main results and presents some perspectives.

1. MODELLING AND SIMULATION

The challenge of energy system modelling is to represent accurately the behaviour of the system with a computation-time (CPU-time) adapted to the use of a genetic optimisation algorithm.

1.1 Models

In order to find efficient and innovative energy mixes, this work aims at analyzing the influence of local technological parameters on the global performances of the system. Therefore, detailed models need to be developped. However, to remain compatible with the optimisation needs, several layers of modelisation have been implemented, from global pattern to very detailed models, all represented by interconnected blocs. Simulation and optimisation may then be able to use a layer or another according to the precision-to-CPU-time ratio. The advantage of this approach is its modularity and its ability to analyse both the global behaviour and the physical and technological frontiers of energy systems.

So far, only low level models have been implemented, allowing access to the main parameters of each technology, surface and efficiency of photovoltaic (PV) panel or power curve of the wind turbine for example. Uncontrollable renewable energy sources are modeled thanks to basic proven models [13]. For storage technologies, a common model is used with different parameters according to the technology [14]. All technologies are defined by their capacity, their charging and discharging rates, their loss coefficient during charge and discharge and their coefficient and reference period for auto-discharge. The evolution of their energy level is measured with a common criterion, the State of Energy defined as the ratio between the contained energy in the storage at a time over the installed capacity [14]. Controllable technologies, such as gas power plants, are characterised by their installed power and the ramp to increase the output electrical power.

1.2. Management parameters

Models briefly presented above concern the design of technologies, not the way they work together. The set of rules describing the operation of an energy sub-system is called here a management strategy. Studies on microgrids focusing on conception choices usually consider fixed strategies [15]. When consumption needs to be balanced, the developed behaviour model considers that technologies have to deliver the correct amount of electricity in a sequential manner, one after the other. It relies on the production priority order defined between technologies, usually considered fixed in prospective models [1].

Many performances indicators used in this study are based on the actual production of each technology, like the greenhouse gases emissions or economic indicators. The energy production depends on the management parameters described above, strategy and production priority order. Thus, it seems important to take into account these parameters among other technological ones. Depending on the technology's categories (controllable / uncontrollable / storage technologies), strategies may be applicable or not (see Table 1).

Table 1: *Description of the management strategies and their potential application to production controllable (CTRL), uncontrollable (UNCTRL) and storage technologies (STOR)*

Strategy number	Strategy description	CTRL	UNCTRL	STOR
1	Only balance consumption in the limit of P_{nom}*	X		X
2	Balance consumption and store in the limit of P_{nom}	X	X	
3	Balance consumption in the limit of the P_{nom} and store in the limit of P_{opti}*	X		
4	Only balance consumption in the limit of P_{opti}	X		X
5	Balance consumption and store in the limit of P_{opti}	X		
6	Produce at P_{opti} in the limit of the consumption and storage capacities	X		
7	Store only in the limit of P_{opti}	X		

*P_{nom} is the nominal power of the technology and P_{opti} its optimal power, for which efficiency is the best

1.3. Simulation

A sequential simulation is performed using the two management parameters: strategy for each technology and a general priority order. The time step may be chosen in a range from minutes up to hours, depending on the phenomena we want to take into account (management, wind speed, river water flow), the accuracy needed and the computation-time requirements. According to the management strategy and the power balance at each time step, energy system model allocates sequentially the power of each power plant to balance consumption and even store electricity in some cases. Simulation's output are the powers produced, stored or lost by each technology for each time step, along with the state of energy of the storage devices and various performance indicators detailed below. An example of output power and state of energy is shown on Figure 1.

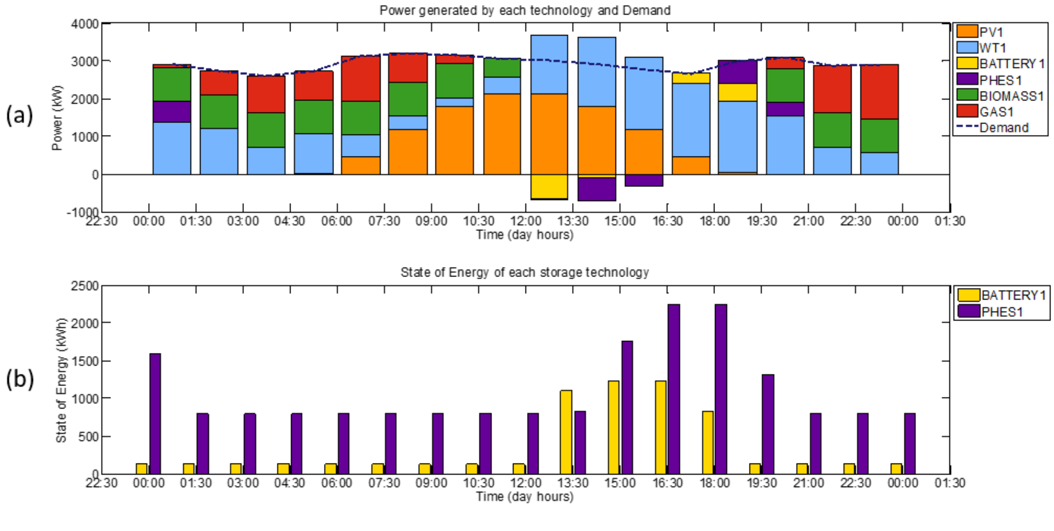

Figure 1: *One day sequential simulation of an energy system – **(a)** Cumulated power (kW) produced/stored along with the power demand of 6000 typical homes ; **(b)** State of energy (kWh) of the storage devices for each time step*

2. OPTIMISATION

2.1. Multi-objectives optimisation method

Among the possible metaheuristic optimisation methods able to consider non-explicit and non-weighted objective-functions evolutionary algorithms have been chosen for their ability to explore the entire design space. Among the different evolutionary algorithms, choice has been made to implement the developed model in the NSGA-II algorithm which is efficient, freely available and already mastered in the laboratory [10].

Genetic algorithms work like the evolution of species: an initial population with individuals characterized by their genes evolves over generations and the most adapted ones are more likely to survive. Here, the initial population is composed of energy systems characterized by the decision variables of the optimisation (number of each technology). Adaptation to the environment is measured through objective-functions and a generation is an iteration of the systems' selection and evolution processes. The final population presents different combinations of genes than the original one due to the need to adapt to its environment. The process followed by such an algorithm is detailed in Figure 2.

The evolution of genes – combinations of technologies with their management strategies – over generation happens thanks to two processes, crossover and mutations. The first method consists in the random combination of two individuals' genes to create a new individual, i.e. the number of wind turbines of a system applied to another. Mutation is the random mutation of an individual's genes. It allows exploring the entire conception space and avoiding local optimums. NSGA-II algorithm is usually used in the literature performing one of the two processes with a crossover probability of 90% and thus a mutation probability of 10%. Same configuration was used in this study. The best energy systems, i.e. the best compromises between the different optimisation's objectives, between the initial generation and the new systems created are selected to form a new generation the same size as the initial one. The last generation is composed of Pareto-optimal solutions.

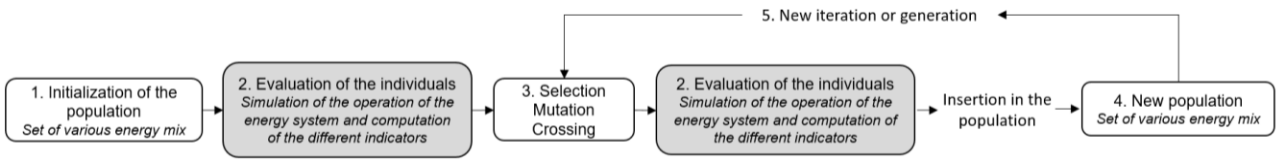

Figure 2: *Process to create a new generation with the genetic algorithm NSGA-II*

2.2. Objective-functions

The purpose of the multi-objectives optimisation is to find energy systems that are trade-offs between various objectives. According to the situation comparison criteria can change but the three main categories of criteria taken into account in this work are economic and technical ones. In order to underline the interest of the multi-objectives approach without prior weighting, one objective of each category has been chosen for this study.

2.2.1. Economic objective

The main objective used to compare energy systems is the cost of the system. It can be the investment cost, the operation and maintenance (O&M) cost, the lifecycle cost or the payback period for example. An indicator often used in the energy industry is the levelized cost of energy (LCOE, in €/kWh produced) which represents the total amount of money spent over the lifetime of a power plant divided by the energy produced during the same period, as described by Equation 1 [16]. Its popularity can be explained by the ease to understand it and the fact that it covers the overall lifetime costs and takes into account currency discount over time. LCOE can only compare technologies for a same situation (location and time). Unfortunately, its does not take into account the provided services like the frequency regulation or the reliability of the production. In a multi-objectives approach, other technical indicators can balance this lack.

Another major issue with LCOE is that elements considered to compute the lifecycle cost – land lease, insurance costs, taxes or carbon emissions for example – vary according to the source. Therefore, it is important to ensure a consistency between data for all technologies. In this work, LCOE formulas were taken from the Fifth report of the IPCC [17, p. 1333]. Nevertheless, storage technologies are not evaluated in this report and their LCOE values were taken from another study [18]. In a future work, a unique methodology to compute LCOE could increase the accuracy.

$$LCOE = \frac{sum\ of\ discounted\ costs\ over\ lifetime}{sum\ of\ electrical\ energy\ produced\ over\ lifetime} = \frac{\sum_{n=0}^{N} \frac{(I_n+O_n+M_n+D_n)}{(1+d)^n}}{\sum_{n=0}^{N} \frac{E_n}{(1+d)^n}} \quad (1)$$

With n the year, N the expected lifetime, I_n the investment costs during year n, O_n the operation costs during year n, M_n the maintenance costs during year n, D_n the residual value and d the discount rate.

In order to discriminate more efficiently energy systems, the economic objective used is the ratio of the lifecycle cost (LCCost, in €) of the system correspondig to the simulated period, deduced from Equation 2.

$$LCCost_{system} = \sum_{techno} LCOE_{techno} * Production_{techno} \quad (2)$$

2.2.2. Technical objective

The main purpose of an energy system is to provide enough electricity to the consumers at the right time. Technical indicators measure the reliability of power supply. Among existing indicators in the literature, we can encounter the energy not supplied [19], loss of load expectation (LOLE) [19], loss of load probability (LOLP) [20], wasted renewable energy [21] or autonomy level [22]. This work focuses on local energy systems, so the designed system can still rely on the main grid if needed and does not require a full autonomy. Therefore, the autonomy level (LA) for the main grid seems to be adapted to measure the reliability of local supply.

Two kind of autonomies can be analysed. Autonomy in terms of time measures the percentage of time when the energy demand is balanced by enough production. Energy autonomy, as defined here, measures the total energy produced to balance consumption and losses but also to store additional energy in the storage devices. Energy indicator ranges from zero, when there is no production, to the sum of the energy demand plus the additional energy that can be stored over the energy demand. When the energy autonomy is above one, it means that the total energy added to the system during the operation period represent more than the consumption and could have been used some other time before.

$$LA_{energy} = \frac{E_{produced}}{E_{demand} + E_{losses}} \quad (3)$$

With $E_{produced}$ the total energy produced during the period, E_{demand} the cumulated energy consumed during the period and E_{losses} the total losses during the period (transport and storage losses).

3. CASE STUDY

The following case study aims at underlining the ability of the designed tool to find optimal energy systems and the interest of the multi-objectives optimisation without prior weighting to explore the entire conception space in the case of energy systems.

3.1. Parameters

A local electric consumption curve for 6000 typical homes over 24h along with meteorological data (wind speed and solar irradiation) are considered as inputs with a 90 minutes time-step. Decision variables of the optimisation are detailed in Table 2. Maximum value and tolerance of each variable has been defined according to the maximum power consumed during the period, which is 3.2 MW.

Initial energy systems population’s size has been set to 1000 inidividuals in order to represent sufficient variety and ensure that the algorithm will converge toward global optimums and not local ones. Following convergence considerations, a maximum of 300 generations was taken into account.

As described before, the two objectives considered are LCOE and energy autonomy from the main grid in order to represent the different, antagonist, categories of impact of energy systems.

Table 2: *List of the decision variables with the range of their values and the tolerance associated*

Decision variables	Range	Tolerance
Number of wind turbines (Vestas V90 – 2MW)	0 – 3	1 turbine
Surface of PV panels	0 – 64,000 m²	3000 m²
Installed power of biomass power plant	0 – 3.2 MW	160 kW
Installed power of gas power plant	0 – 3.2 MW	160 kW
Battery capacity	0 – 35 MWh	1.7 MWh
Pumped hydroelectric energy storage (PHES) capacity	0 – 35 MWh	1.7 MWh
Management strategy	14 combinations	1
Priority order	6 combinations	1

3.2. Results

First, an optimisation with two objectives is performed. Figure 3 shows the values of the energy autonomy and the lifecycle costs of several energy sysems. The blue dots represent the Pareto front of the multi-objective optimisation. These results are compared to solutions of multi-objectives optimisations with prior weighting.

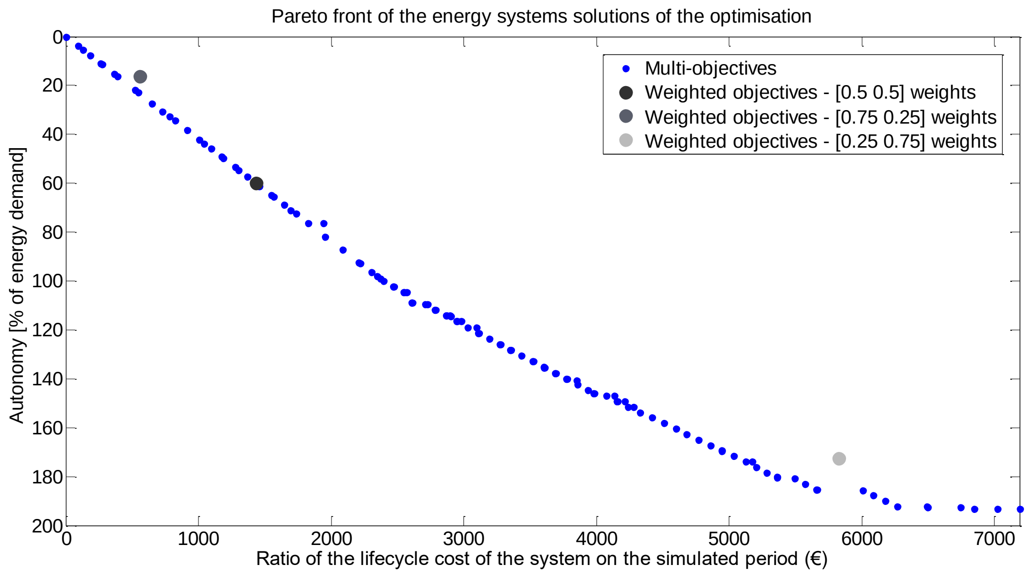

Figure 3: *Pareto front of the optimisation's solutions*

Single-objective optimisations present as expected a very good performance following their optimised objective but a bad one following the others, as underlined by the result of the energy autonomy optimisation. Lifecycle cost optimisation' autonomy is not too bad due to the added constraint. Weighted objectives show relatively good performances compared to the multi-objective Pareto front, with the solution of the equally weighted objectives on the front. However, it gives only one set of performances and parameters and the weights have to be chosen carefully a priori otherwise the performances of the solution varies a lot. The issue having only one solution is the risk to miss another energy system with potentially close performances but different parameters.

Some interesting energy systems were selected whose variables' values are represented on Figure 4. In the first graph, the installed power of each technology is represented, on the second the storage capacities and on the third the chosen priority order and control strategy. Two solutions of the multi-objectives optimisation, here "Multi-obj 1" and "Multi-obj 2", have been represented because they have the same performances has the weighted solution with equal priority between objectives, here 'Weighted 1'. Although they have the same power of gas installed, the capacity of the storage technologies differs along with the priority order and control strategy. Whereas the weighted solution's priority order puts first the storage devices, then the renewable energies and finally the controllable technologies, the other solutions place the controllable producers first in the priority order. Analysing technical parameters like control strategies and priority order inside a multi-objectives optimisation allows to distinguish energy systems with very close performances and thus to explore the conception space, what is impossible with a single-objective optimisation.

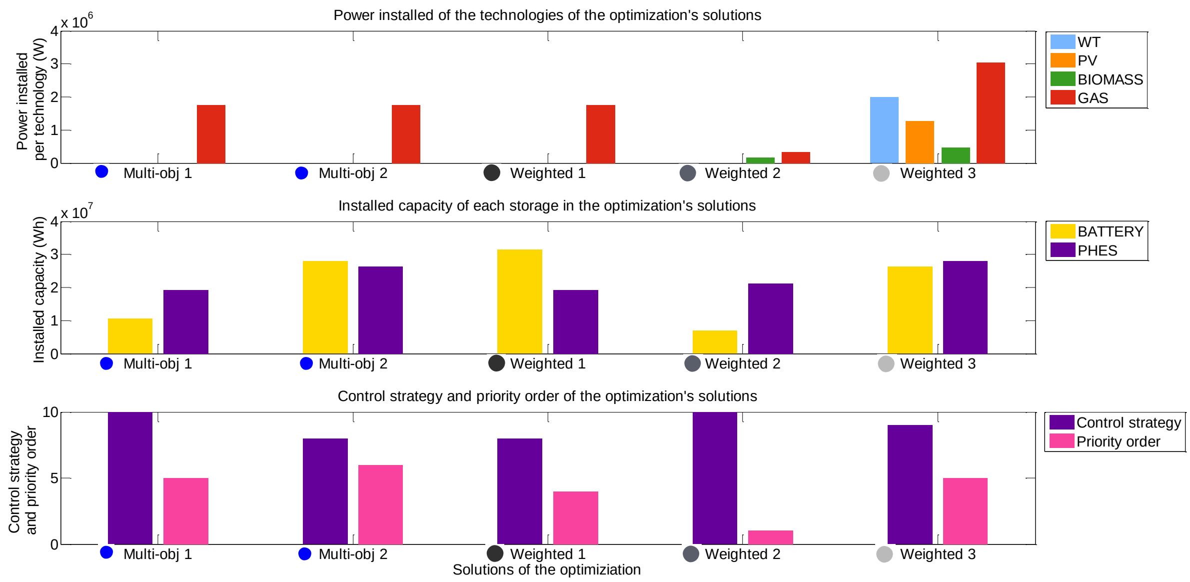

Figure 4: *Content of selected energy systems solutions of various optimisations*

The difference between the three weighted solutions underlines the influence of the weigthing choice. The solution giving more importance to the autonomy objective shows a greater variety of sources whereas the one with a bigger weight for the cost minimize the power installed, leading to a very low autonomy (selection has been made to avoid 0% autonomy). Nature of the optimal energy system depends on the weights chosen a priori. The multi-objectives optimisation applied here allows finding more diverse energy systems.

CONCLUSION

Power plants aging and new society's concerns are pushing for a rethink of the energy systems design. Distributed technologies with additional storage to balance their intermittency allow building local strategies in order to increase the autonomy from the main grid. However, these new options have to be compared to the existing network with economic, technical and environmental indicators. The work presented above aims at creating a decision-support tool to model, simulate and optimise energy systems. It focuses on technological parameters to model accurately power exchanges and to suggest innovative systems. In particular, management strategy is taken into account as a decision variable. To represent the complexity of energy systems design and the antagonism between some objectives, a multi-objectives optimisation algorithm without prior weighting, NSGA-II, has been performed to find different energy systems providing partial autonomy.

Non weighted multi-objectives optimisation allows finding more interesting energy systems than with a prior weighting. The exploration of the entire conception space leads to more diverse solutions. By exploring the design space without prior weighting, the developed tool offers a greater choice to the user and reveals energy systems compromises which the user would not have thought of. Especially, energy systems with very close performances but different characteristics have been found. Discriminating criteria can be applied afterward.

Robustness of the proposed mix to the variation of meteorological conditions or production capacities will be investigated in a future work to ensure a bigger reliability and more detailed models will be implemented in the tool in order to analyse the influence of local parameters.

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