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Advancements in Multi-Objective Optimization for Planning and Management of Multi-Energy Systems

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ABSTRACT

Traditionally, modelling tools for Multi-energy systems planning and management focus on the minimization of a single monetary objective. Multiple objectives are usually merged via monetization rates. The work presented herein aims to develop modelling frameworks to explore of configurations of Multi-energy systems according to non-comparable objectives and extract trade-off solutions through optimization algorithms. Three different methodologies are presented, integrating the single-objective configuration model CALLIOPE with multi-objective algorithms for exploring the decision space. These are tested on a synthetic case study and evaluated for their input data requirements, computational demands and ability to thoroughly map the solution space. Results show each approach returns optimal system configurations, with considerably different technology mixes depending on objective priorities. The methodologies highlighted here represent a significant step forward in the search for multi-objective models for Multi-energy systems planning and management, to support the search for truly integrated, efficient, and sustainable solutions.

KEYWORDS

Multi-objective optimization, Multi-energy systems, Energy system modelling, Energy models, Evolutionary algorithms, Energy transition, Energy system decarbonization.

INTRODUCTION

Nowadays, energy systems worldwide face numerous challenges [1], which often require a partial or total re-evaluation of the system's operation and the paradigm employed for its planning and management [2].

The imperative of reducing greenhouse gases (GHGs) emissions to contrast rapid global warming means relying more significantly on non-programmable energy sources, like wind and solar energy, whose production cannot be regulated to respond to the fluctuations of the demand, unlike traditional fossil fuel-based energy sources [3], [4]. Energy storage solutions are increasingly sought after to alleviate this issue, but they come with their own sets of limitations, like elevated costs, low storage potential and limitations on their applicability.

Energy and heat production and delivery, which have traditionally been considered as two separated entities, are now progressively merging due to the phase-out of old heat generation technologies based on fossil fuels and the wider adoption of installations such as heat pumps and co-generations power plants [5]. Other systems, like transportation, are also expected to become more electrified [6]. This shift, in turn, increase the cumulative load on energy grids and alters energy demand patters.

Moreover, recent geo-political instabilities [7] and extreme weather patterns [8] have highlighted the fragility of many energy systems to fluctuations in the supply and demand, emphasizing the need to improve resilience by increasing independence from external sources and implementing measures to mitigate the impact of such instabilities [9].

Finally, energy systems are shifting from a more centralized configuration, with few energy production units such as large power plants, to a more distributed structure, with many privately-owned and low production installations all interacting and contributing to the balance of the system [10].

Multi-energy systems (MESs) have emerged as interesting and viable solutions to these new challenges, while also being able to increase the overall efficiency, sustainability, and resilience of the energy system [11]. In MESs, different energy vectors are integrated at various levels via a combination of generation, storage and conversion technologies, in order to balance the energy sources of the system and optimize the allocation of resources. The high degree of flexibility that characterize MESs helps managing the increase uncertainty caused, for example, by a significant increase of non-programmable energy sources or the volatility of the prices of importing or exporting energy via different vectors.

The planning and management of MESs poses significant challenges, due to the involvement of numerous technologies and the requirement for a high temporal resolution to effectively operate systems designed for swift responsiveness to external variations. The design of such systems is often supported by modeling tools (see [5] for a review), which enable the definition of their configuration and operating strategy through optimization. This optimization has traditionally been done using a single evaluation metric, focused on the minimization of the overall costs, for example to investigate optimal operation regarding energy consumption for residential building [12] or small, solar-powered energy communities [13] . This single-objective perspective reduces the computational complexity of the optimization [14], and the uncertainty correlated to the collection of data related to more difficult-to-quantify objectives. In case multiple objectives are included, they are often aggregated via user-defined weights to return to the single evaluation metric [15]. In the context of multi-energy planning, where the economic objective is ubiquitous and often predominant, this corresponds to the definition of the monetization rate of the other metrics.

This type of reduction, from often highly diversified objectives to a single economic indicator, is frequently a source of debates and controversies, due to the intrinsic difficulties related to estimating economic impacts, and the different degree of importance given to the considered objectives from different stakeholders.

In this context, the need for an integrated approach emerges to address the complexity of energy systems in all their facets. The integration of multi-energy models and advanced multi-objective optimization methodologies [16] represents an opportunity to tackle the intricate challenges of energy planning. These models go beyond traditional compartmentalization, allowing for a more holistic understanding of energy dynamics [17]. Moreover, by considering multiple non-comparable objectives, the result is not a single configuration but a range of different optimized system designs, each favoring a different set of objectives. [18], which can then be explored to highlight conflicts and synergies between objective and identify viable trade-offs solutions.

There are limited studies in literature that analyze multi-energy planning and management with a multi-objective perspective. For example, [19] examines a case study in residential contexts, demonstrating how multi-objective algorithms can effectively explore compromise solutions between planning costs, fuel consumption, and environmental impacts; in [20] both costs (to be minimized) and generation (to be maximized) are effectively optimized, while [21] explores cost and emission dynamics in a system comprising fifty buildings and including electric vehicles charging stations. Multi-objective optimization problems are sometimes solved using hierarchical optimization or pairwise comparison to identify a set of weights representing different stakeholder priorities, as in [22]

In recent works, multi-objective evolutionary algorithms (MOEAs) have been used for MES planning in multi-objective contexts In [23] and [24], two-objective modeling frameworks have been developed to design optimal investment plans that minimize both costs and emissions. These studies focus on the energy and heat supply of a medium-sized town and the energy and water supply of a small island, respectively..Finally, [25] utilizes a customized version of the EnergyPLAN model, called EPLANopt, which applies a multi-objective evolutionary algorithm (MOEA) to derive trade-off solutions between costs and emissions for the energy system of the South Tyrol region in Italy. While these works contribute valuable insights, they rely on specialized frameworks tailored to specific case studies. As a result, adapting them to different contexts requires significant effort compared to widely used single-objective MES models such as CALLIOPE [15], PyPSA [26], H2RES [27] or MUSEPLAN [28].

The above-mentioned literature highlights how the integration of multi-energy models and multi-objective algorithms allows for the consideration of multidimensional challenges beyond cost alone.

The central objective of this work is to develop a methodology that integrate multi-energy models and multi-objective optimization algorithms to increase not only applicative flexibility in multi-stakeholder contexts but also to reduce subjectivity in predefined trade-off balances. To do so, the explore and evaluate three different methos for developing multi-energy models with multiple objectives, aiming to extract the best paradigm in this regard. In particular, the three methods are: 1) coupling the single-objective multi-energy model CALLIOPE [15] with an exhaustive sampling procedure considering the relative weights of each optimization objective (method a); 2) the integration of CALLIOPE with evolutionary optimization algorithms for the optimal search of the weights defining the relative importance of the optimization objectives (method b); and 3) the use of evolutionary algorithms for solving the energy planning problem (method c).

Both the first and second methodology, by exploring conflicts and synergies between interests and indicators, allow the application of CALLIOPE in multi-objective contexts, while the intrinsic structure of the model remains single objective. The advantage offered by these techniques lies in eliminating subjectivity in trade-off variables (or weights) through either exhaustive sampling (method a) or advanced optimization techniques (method b). Finally, method c transforms CALLIOPE into a fully-fledged multi-objective planning and management tool.

These methodologies are tested on a synthetic case study based on the Sulcis-Iglesiente region in Sardinia, Italy. In this study, different MESs configurations are explored, which include additional renewable energy sources in the local energy system, change the current heat generation technologies and add energy storage options. These configurations are evaluated under four different objectives: economic costs, CO_2 emissions, PMx emissions, and energy self-sufficiency.

This paper presents modeling alternatives for MES planning and management that are truly multi-objective, allowing the identification of trade-off between different system configurations under multiple, non-comparable objectives. The methodologies described here also ensure a simple and easy integration with more widespread, single objective MES models, with minimal to no modifications to their code.

METHODS

The methods presented in this paper aim to overcome the need to define a-priori monetization rates (or any kind of aggregation weights or trade-offs variables) in single-objective multi-energy system optimization models, to allow for multi-objective analysis for non-comparable objectives.

To achieve this, the methodological workflow shown in Figure 1 was developed.. First, a schematization of the case study is defined on the single-target multi-energy systems modelling tool CALLIOPE. It includes both the technologies already installed in the analyzed area, and the pool of potential installations identified according to the territory's resources, from which the algorithm can choose to plan the system configuration. For each technology, the system defines its costs according to each objective. The configuration of the CALLIOPE model, required inputs, and returned outputs are described in Section 3.

The three methods employed to extract the set of Pareto-efficient decisions in the decision space of the problem differ in terms of modeling tools used, the number of inputs, and computational requirements. This section describes the structure and requirements of each methodology, while Section 5 discusses their advantages and limitations, including considerations based on the results obtained from the case study..

The analyzed methodologies are:

1. Exhaustive method (method a)
2. Evolutionary multi-objective optimization on weights (method b)
3. Evolutionary multi-objective optimization on system configuration (method c)

All algorithms analyzed here aim to solve the following optimization problem:

$$u_p^*, u_T^*, m^* = \underset{u_P, u_T, m}{arg\ \min} J(u_P, u_T, m) \quad (1)$$

u_p^* represents the optimal planning configuration, u_T^* is the optimal set of trade-off variables (or weights) that allows for a comprehensive exploration of the objective space, m^* identifies the operational management decisions, and J is the multidimensional objective function, comprised by all functions employed to derive the performances of the multiple objective considered in the analysis. The single-target multi-objective model CALLIOPE fully defines and optimizes m^* through a model predictive control (MPC) algorithm; thus, the identification of m^* will not be further discussed. On the contrary, the definition of u_p^* and u_T^* varies depending on the proposed methodology and will be subject of the analysis presented hereby. To evaluate the performance of the three methodologies in quantifiable manner, the consistency and diversity of the Pareto sets obtained from the algorithms is evaluated using two distinct and widely used performance metrics: the additive epsilon indicator and hypervolume.

The CALLIOPE model

CALLIOPE is an open-source software that enables the digitalization study, and optimization of complex multi-energy system. The model structure allows for the inclusion of generation, transmission, conversion, storage, and consumption technologies. These interact with each other in terms of energy flows attributed to different energy vectors, which can be produced, transported, converted, or consumed. Each system is bounded to satisfy some specific demands, also associated with an energy vector (e.g., demand for electricity or heat).

The specified energy system can also be connected to external entities, such as the national energy grid. The connection of the system to the electrical grid for energy import is modeled as a new technology for energy generation that allows the purchase of electricity at a variable, user-defined and time-varying price. The possibility of exporting excess energy to the grid, on the other hand, must be specified for each installed technology by specifying the selling price. The fulfillment of the local energy demands, however, takes priority over the energy export. The first panel in Figure 1 shows a schematization of the input necessary to create a model of a multi-energy system in CALLIOPE.

Once the system has been initialized with its installed or potential technologies and the different energy demands that characterize it, CALLIOPE searches for an optimal system configuration from both planning and management perspectives, i.e., which and in what quantities the available technologies should be installed, and how these technologies should be operated, on an hourly time resolution. To do this, CALLIOPE uses a MPC algorithm to optimize management, embedded within a Mixed-Integer Linear Programming (MILP) algorithm for extracting planning variables. In this way, for each system configuration found by the MILP algorithm, the software optimizes its management through MPC.

Both algorithms seek optimal solutions by minimizing a single performance indicator, which in CALLIOPE corresponds to cumulative costs. CALLIOPE allows the definition of different cost categories, whether economic costs or, for example, related to CO_2 emissions or particulate matter. These costs can arise from the installation, maintenance, and management of installed technologies or from the purchase of energy from external sources (whether imported electricity or fuels). It is also possible to include negative costs if there is a goal to maximize, for example, job creation. However, optimization is always performed by minimizing a single indicator, and thus the software requires the user to specify conversion weights for each objective to extract a single cumulative system performance value.

The optimized system returned by CALLIOPE includes the installed capacity for each technology and the operation strategy for each hourly timestep. Additionally, it also returns the fixed and variable costs associated with technologies and the cumulative total costs for each initialized cost category.

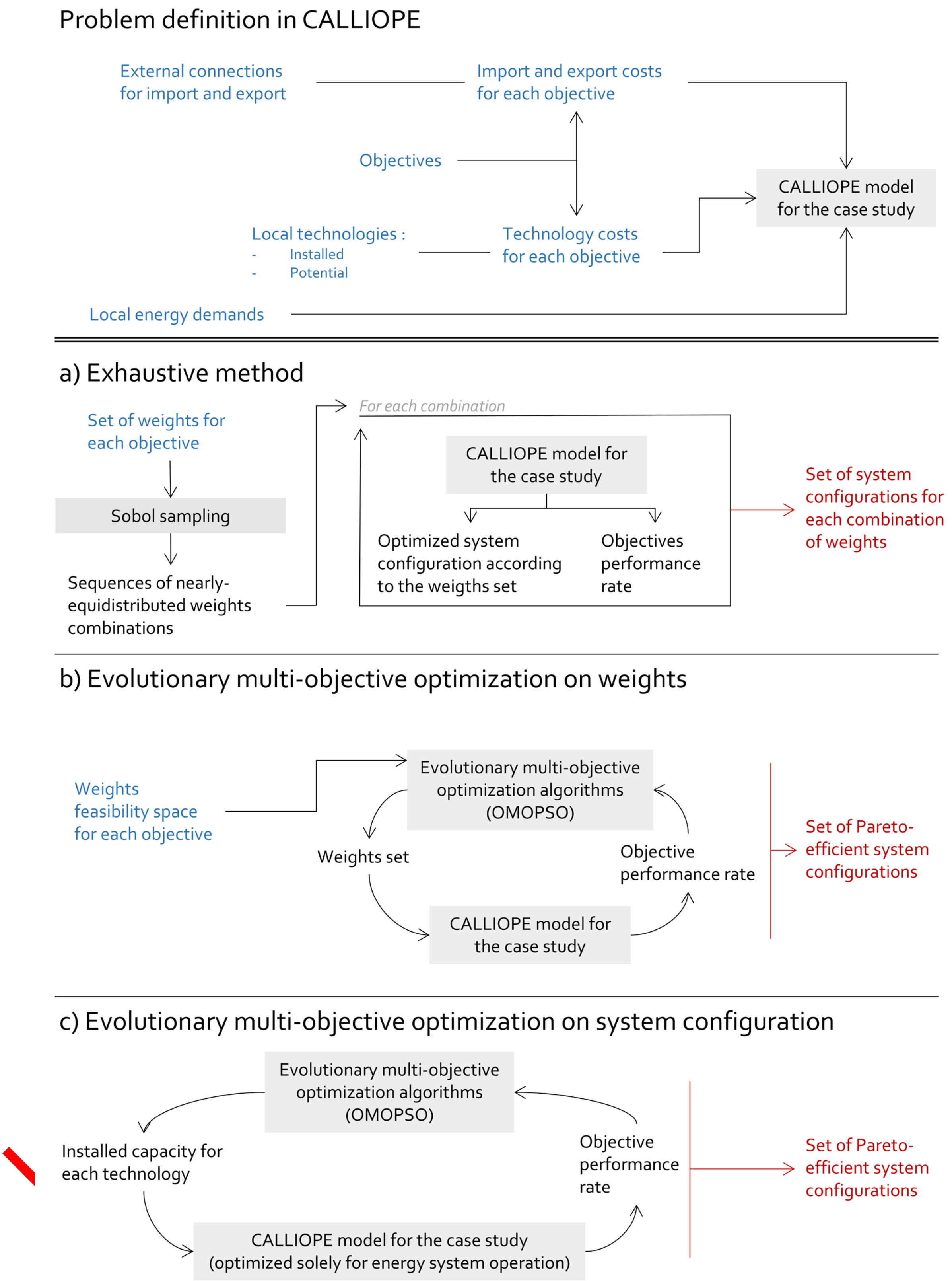

Figure 1. Paper workflow. The figure depicts a schematization of the procedures described in this paper. Blue text indicates user-defined inputs, while red text represents outputs. Mathematical and modeling tools used are shown in grey boxes.

Multi-objective optimization

The single-objective optimization structure of CALLIOPE does not allow for the exploration of trade-offs between different non-comparable objectives. Here, various multi-objective analysis methods integrating CALLIOPE are applied and compared.

All the methodologies used return a set of Pareto-optimal system configurations. When visualized in the objective space, these solutions form an approximation of the Pareto front, which contains all possible non-dominated system configurations for the objectives considered.

<u>Exhaustive method</u>. A simple and intuitive method to extract optimal system configurations showing the trade-offs between objectives, while remaining within the single-objective constrain of CALLIOPE, is to iteratively run the model for different combination of weights. The optimized system configurations obtained will reflect the relative importance of the objectives, depending on the assigned weights.

As described in Figure 1a, the exhaustive method (method A) requires the user to define, for each objective, a set of weight values. To find compromise solutions, the weights assigned to the objectives must ensure that their performances, once weighted, are comparable and have a similar impact on the cumulative indicator used for system optimization. This would typically require a basic prior knowledge on how the costs metrics for each objective compare to each other, so that the cost associated to each objective meaningfully influences the aggregated value used for the optimization, or the adoption of a very large set of weights.

Once defined, the elements in these sets are combined by computing their n-dimensional cartesian product (where n is the number of objectives) to extract the set of all the possible weight combinations **K**. Each subset $k \in \mathbf{K}$ is a vector containing a single weight value for each objective. The CALLIOPE software is then initialized and run for each k, and returns different configurations of the energy system, optimized based on the relative importance of the objectives. Considering the exhaustive nature of the approach, it follows that the cardinality of **K** must be high enough to encompass the analysis all the possible tradeoff between objectives. This iterative process yields a collection of optimal system configurations, each linked to distinct objective performances, collectively shaping the Pareto front associated with this method.

Clearly, it is challenging to predict the probability distribution of weights that would lead to the optimal approximation of the Pareto front. Consequently, this paper employs the Sobol sampling algorithm to extract weight combinations. The algorithm systematically samples the multidimensional space encompassing possible weight combinations for each objective, producing a quasi-equidistributed subset. While effectively enabling the multi-objective exploration of trade-offs, the mentioned method is constrained by the need to predefine the cardinality of . **K**. If set too small, it may result in an inadequate exploration of the Pareto front; if set too high, it may lead to excessive computational complexity.

Referring to the optimization problem expressed in equation 1, the method A therefore defines the set u_i^* of weights a priori, and for each combination, optimizes the energy planning u_p^* using the MILP algorithm.

<u>Evolutionary multi-objective optimization on weights.</u> An exhaustive exploration of the feasibility space of relative weights associated with each objective presents strong limitations both computationally and in terms of efficiently exploring trade-offs. A possible solution in this regard could be the use of Multi-Objective Evolutionary Algorithms (MOEAs) that, instead of determining the entire set of weight values to explore in advance, adapt the parameterization of their search through an optimization process.

Despite various types being proposed in the literature (see, for example,[29]), most MOEAs are characterized by a methodological process articulated in five main steps:

1. Initialization: randomly generate initial parameter values for optimization within a predefined feasibility interval.

2. Simulation: perform simulations using the generated parameter values.
3. Objective Evaluation: calculate the values of the optimization objectives based on the simulation results,
4. Pareto Selection: identify and store solutions that are Pareto-optimal.
5. Evolutionary Step: Generate a new set of parameter values for the next iteration through combinations of the archived Pareto-optimal solutions.

The steps two to five described in the list above are repeated until either some convergence criterion is met (no significant improvement between two consecutive iterations), or a certain amount of pre-defined function evaluations are reached.

In this work, the objective weights constitute the decision variables of the MOEA. In each iteration, the algorithm identifies a combination of weights which are then fed to CALLIOPE to obtain a system configuration, associated with a specific performance rate for each objective, as shown in Figure 1b.

It is noteworthy that, in contrast to method a, method b eliminates the necessity to predefine either **K** or its cardinality. Furthermore, in method b, the search process is optimized by the evolutionary algorithm itself, eliminating the need to assume the probability distribution of the parameters (or weight). These two factors offer significant advantages in terms of both computational efficiency and exploration effectiveness, since the only requirement is the definition of feasibility space for the weights.

In this work, the MOEA algorithm OMOPSO was selected (Optimized Multi-objective Particle Swarm Optimization, [30]). This algorithm employs a user-defined parameter ϵ as a threshold value below which the variation of an objective can be considered negligible, and therefore the solution found can be excluded.

Returning to equation 1, method B uses the OMOPSO algorithm described above to define sets u_t^* of weights that ensure the best possible exploration of the objectives space. As with the exhaustive method, energy planning and management (u_P, m) is optimized in CALLIOPE using MILP and MPC.

<u>Evolutionary multi-objective optimization on system configuration. </u> The third methodology involves the direct optimization of the energy system configuration by OMOPSO (method C). As shown in the diagram in Figure 1c, the methodology involves, as in the previous case, a coupling between CALLIOPE and a multi-objective evolutionary optimization algorithm. In this case, however, the decision variables optimized by the algorithm are not the weights assigned to the objectives, but the installed capacity for each available technology, defined as a percentage of the maximum capacity. Therefore, the planning of the energy system, which in the two methods previously described is carried out internally by CALLIOPE via the MILP algorithm, is entrusted to the MOEA, moving away from the single-objective optimization of the MILP to a fully multi-objective one. The optimization of energy system management, on the other hand, is still performed by CALLIOPE, considering only the economic objective.

Thanks to the separation of the optimization operations of planning and system management between two different algorithms, this methodology stands out from the previous ones for lacking the need to define sets or assign feasibility spaces to weights, like in the previous two methods. However, while all solutions found by the previous two methodologies were always optimally configurated by the MILP algorithm, here, most of the configurations found by the MOEA across its iterations will result sub-optimal. MOEAs typically require multiple iterations before returning optimized solutions to the problem. At the start of the algorithm and for the first generations, the analyzed system solutions are configured randomly or are extremely unoptimized. This is necessary to allow the evolutionary algorithm to learn which configurations are more efficient and converge towards Pareto-optimal solutions but may require a high number of iterations.

In reference to the optimization problem expressed in equation 1, method C foregoes the search for u_t^* in favor of only optimizing the system configuration u_P directly with OMOPSO, while the identification of m^* is still left to CALLIOPE via MPC.

Metrics of performance

The performance metrics employed in this investigation encompass the additive epsilon indicator and hypervolume. These metrics offering a quantifiable measure of the consistency and diversity of the Pareto sets approximation, respectively. Calculations for these metrics were performed in relation to the reference set, i.e.: the best-known Pareto approximation obtained by combining those of the three algorithms.

The additive epsilon-indicator [31] quantifies the largest distance that an approximation set must be translated to dominate the reference set. Consequently, it exhibits heightened sensitivity to gaps in trade-offs. If a Pareto approximate set contains gaps, solutions necessitate translation over a more considerable distance, resulting in a notably increased additive epsilon-indicator metric value. The lower the metric value, the lower the minimal worst-case distance from the reference set.

Hypervolume [29] measures the volume of the objective space dominated by an approximation set. Thus, the goal is to maximize this metric. In this study, hypervolume was normalized concerning the reference set hypervolume. Consequently, a value of 1 signifies that the approximation set dominates an equivalent volume as the reference set. Hypervolume stands out as a challenging and comprehensive metric, providing insights into an algorithm's convergence and the diversity of its representation of trade-offs.

EXPERIMENTAL CONFIGURATION

This section reports the steps taken to apply the methodologies described above to a synthetic case studied molded after the Sulcis-Iglesiente (SI) province in Sardinia, Italy, with the aim of showing which method can identify suitable alternatives and tradeoffs for the energy development of the examined territory.

Case study modelization and data availability

Modeling the case study in CALLIOPE requires hourly data on electricity and heat demand, the availability of solar and wind resources, and information on the characteristics and maximum theoretical capacity of potential future installations, considering the territory's availability. Though a collaboration with the University of Cagliari and the use of previous datasets of RSE, electricity and heat demand data were obtained via from the dataset of the Italian ministry of Economic Development and downscaled. The potential renewable energy production in the territory is estimated via the grid-based TOTEM [32] tool. All data are referred to the sample year 2015.

The technical and economic parameters of the currently installed technologies used in the simulations are derived from previous studies by RSE while the emission factor values come from estimates made by ISPRA (Italian Institute for Environmental Protection and Research, https://www.isprambiente.gov.it/it). It is specified that a capital cost of zero has been considered for all currently installed technologies.

The possible planning alternatives u_p involve the expansion of the electric and thermal, as well as the introduction of storage technologies, as shown in Figure 2. The technical and economic parameters of potentially installable technologies are derived from previous works by RSE [33], while emission factor values are not provided as they are considered null for all technologies. The values of the maximum installable capacity serve as constraints related to the territory's capacity to accommodate new technologies. It is important to note that this parameter serves only as a constraint in the planning problem, and the solution will define the optimal capacity based on the optimization objectives.

For photovoltaics, this value was calculated using the TOTEM tool, estimating the total suitable area for installation, and dividing it by an occupancy coefficient set at 11 m2/kW for ground installations and 5 m2/kW for rooftop installations, resulting in about 49 MW and 185

MW, respectively. For wind power, the possibility of doubling the currently installed capacity (about 100 MW) onshore and installing the same capacity offshore has been assumed, selecting the type of installation plant most suited given the wind energy data available.

Further planning alternatives include the installation of new heat pumps, with the potential capacity to fully cover the total heat demand (178 MW). These heat pumps present a higher efficiency then the one already installed (COP of 4 compared to 3.2). Finally, an electrochemical storage technology is introduced to add flexibility to the system. A maximum installable capacity has not been defined precisely given the uncertainties related to this technology and has been set to a sufficiently high value so to not result as an upper boundary to the optimization.

Finally, energy import from the grid is associated with both a time-varying economic cost, extracted by for the year 2015 from the website of the GME, the company responsible for organizing and managing energy markets in Italy [34], and a fixed CO_2 emission factor. For this study, it is assumed that no CO_2tax or other forms of carbon compensation are already included in the price of imported energy. For this study, it is assumed that no CO_2 tax or other forms of carbon compensation are included in the price of imported energy. This ensures that the emissions associated with imported energy are fully accounted for when quantifying total carbon emissions. On the other hand, energy export is also associated with revenues according to the varying energy prices reported by the GME

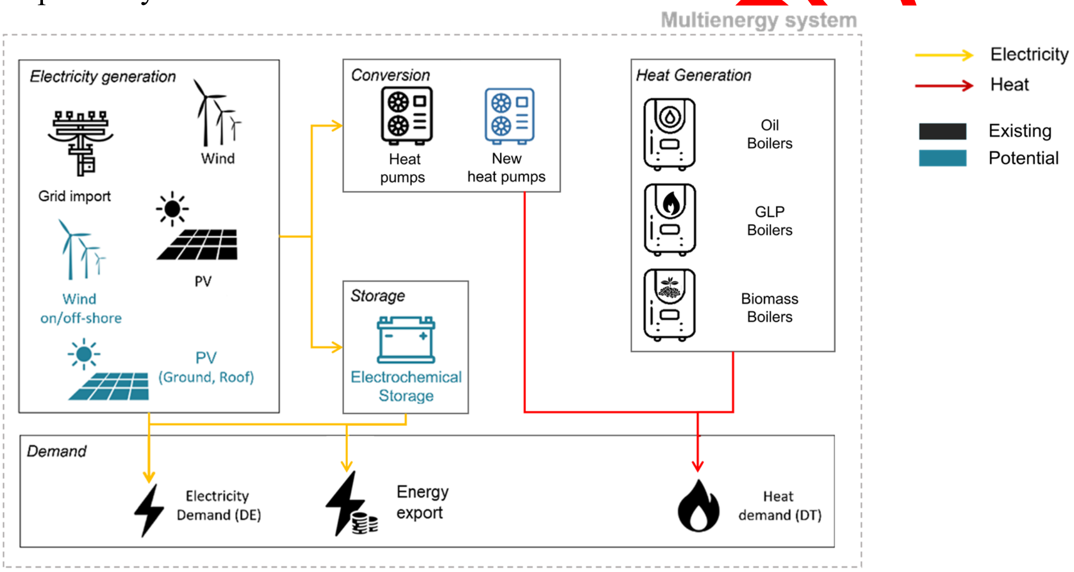

Figure 2. Conceptual framework of possible technological planning decisions in the synthetic case study.

Optimization objectives

Four distinct objectives have been identified for the Sulcis Iglesiente case study: the minimization of the total current net cost, the CO_2 emissions and the particulate emissions, and the maximization of the energy independence of the system. Each objective performance is monitored through the following utility functions.

The total current net cost J^C[€] is defined as the sum of investment costs C^{inv}, operational costs C^{oper} for each installed technology, plus the costs of importing from the grid C^{import}, and subtracting revenue from energy export C^{export}. Cash flows (operational costs, export revenue, and import costs) are discounted annually based on a specific discount factor J^C is mathematically defined as:

$$J^{C} = \sum_{j=1}^{n_{te}} \left(C_j^{inv} + \sum_{i=1}^{H} d_i C_{i,j}^{oper} \right) + d_i \sum_{i=1}^{H} C_i^{import} - d_i \sum_{i=1}^{H} C_i^{export} \tag{2}$$

Where n_{te} represents the number of installed technologies, and H is the time horizon. The discount factor d_i is expressed in terms of the applied discount rate ts as:

$$d_i = \frac{1}{(1+ts)^i} \tag{3}$$

CO_2 emissions $J^{CO_2}[kg]$ depends on all the energy produced by the installed technologies, both for the purpose of satisfying the local demand and exporting the energy to the grid, and are calculated as:

$$J^{CO_2} = \sum_{j=1}^{n_{te}} \left(\sum_{i=1}^{H} k_j^{CO_2} E_{i,j} \right) \tag{4}$$

Where $E_{i,j}[kWh]$ represents the energy produced at time step i by technology j, and $k_j^{CO_2}$ $\left[\frac{kg}{kWh}\right]$ is a specific emission coefficient for each technology. Locally, LPG and oil heat pumps emit CO_2. Moreover, the energy imported from the grid is attributed an emission rate equal to the national average for 2015 (0.26 $kgCO_2/kWh$, data from ISPRA [35]).

Particulate emissions $J^{PM_x}[kg]$ are expressed similarly to CO_2 emissions, i.e., as the product of the energy produced by a specific technology and an emission factor $k_j^{PM_x}$ $\left[\frac{kg}{kWh}\right]$. Mathematically:

$$J^{PM_x} = \sum_{j=1}^{n_{te}} \left(\sum_{i=1}^{H} k_j^{PM_x} E_{i,j} \right) \tag{5}$$

The analysis focuses only on local emission sources, thus only biomass boilers (emission factor: 0.66 $kgPM_x/kWh$), or LPG or fuel oil boilers (0.12 $kgPM_x/kWh$).

The independence from the energy grid J^{IN}[€], defined as the product of energy imported from the grid $E_{i,Rete}$ $[kWh]$ and the import price c_i^{import}, is mathematically expressed as:

$$J^{IN} = \sum_{i=1}^{H} c_i^{import} E_{i,Rete} \tag{6}$$

Experiment Parameterization

All three methodologies aim to identify multiple optimal alternatives for sustainable multi-energy territory planning and management. For each of them, an experiment is conducted on the case study presented in the previous section. The configurations of the three methods are as follows:

- Method a: Planning variables u_P are obtained for a single configuration of weights (or trade-off variables) through MILP. The value of weights u_T is exhaustively explored through a sampling of the feasibility space ([0-1], [0-10], [0-1]) using Sobol Sampling with a size of 1024. This implies that the planning problem is solved through MILP for 1024 function evaluations (FE), with weight values decided a priori through random sampling.

- Method b: Similar to the previous case, u_P values are obtained through MILP. The value of weights u_T is determined through evolutionary algorithms, with feasibility space [0-3], [0-30], [0-3]. The evolutionary nature of the algorithm enables an expansion (tripling) of the feasibility space compared to method a, requiring fewer assumptions about the system while avoiding an increasing in the computational burden. Each evolutionary algorithm performs 1000 FEs, starting from an initial population of 100. To ensure that the found solutions are not constrained to the 100 initial values, the algorithm is run with six seeds (i.e., initializations).
- Method c: In this case, the planning variables u_P are no longer optimized through MILP but through MOEA The algorithm's parameterization, as in the previous case, requires specifying a maximum number of FEs, an initial population, and the number of seeds. These values are set respectively to 10,000 FEs (the number of variables to be optimized is more than double compared to the previous case), 100, and six.

RESULTS

The methodologies described in the Method section have been applied to the Sulcis-Iglesiente case study, to assess and compare their effectiveness in extracting interesting and heterogeneous trade-off solutions for the planning and management of the multi-energy system.

Pareto front identification

Figure 3 displays the results obtained by the three methods in the considered case study. Each Pareto front shows a four-dimensional objective space, with the costs on the x axis and CO_2 emissions on the y-axis. Marker color indicates the energy independence (defined as the sum of the import costs), while the marker size represents PMx emissions. The frontiers exhibit an elbow-shaped structure which illustrating the trade-off between costs and CO_2 emissions. The color gradient, transitioning from yellow to blue as one moves to the right, signifies required investments for achieving grid independence. While the marker size experiences marginal variations along most of the frontier, the bottom-right region features larger dark blue circles, indicating the necessity of employing high PMx emission technologies to maximize independence.

To aid in its description, the Pareto frontier, it has been partitioned into 4 macro-regions, as shown in Figure 3d. While these regions do not possess defined boundaries and often blur with each other, they nevertheless help us to highlights groups of configurations that prioritize certain objectives at the expense of others. In region I, the solutions identified primarily focus on minimizing the economic objective. The system is configured to minimize investments in new infrastructure and relies mainly on importing electricity from the grid to fill local production deficits.

Region II contains configurations that minimize CO_2 and PMx emissions, characterized by investments in new renewable plants to reduce energy imports, and a heat production mainly entrusted to new heat pumps to avoid the use of CO_2 and PMx emitting boilers.

In region III, the configurations found are optimized to maximize independence from the grid. Like solutions in regions II, they are characterized by significant investments in renewables, which are sought after here to reduce the system dependence to outside import. However, heat production is mainly entrusted to oil and LPG boilers, avoiding additional energy purchase from the grid to power heat pumps, while being cheaper than biomass boilers. These configurations overall emit more CO_2 than other solutions on the frontier with similar economic investment, hence their position on the upper part of the frontier.

Finally, in Region IV, the solutions focus on minimizing CO_2 emissions, with less emphasis on particulate reduction.. Solutions in this region have a similar energy production mix to those in region II; however, they favor the use of biomass boilers rather than employing heat pumps bowered in part by imported energy, which is associated with a low but still present emission rate, resulting in increased particulate emissions and costs.

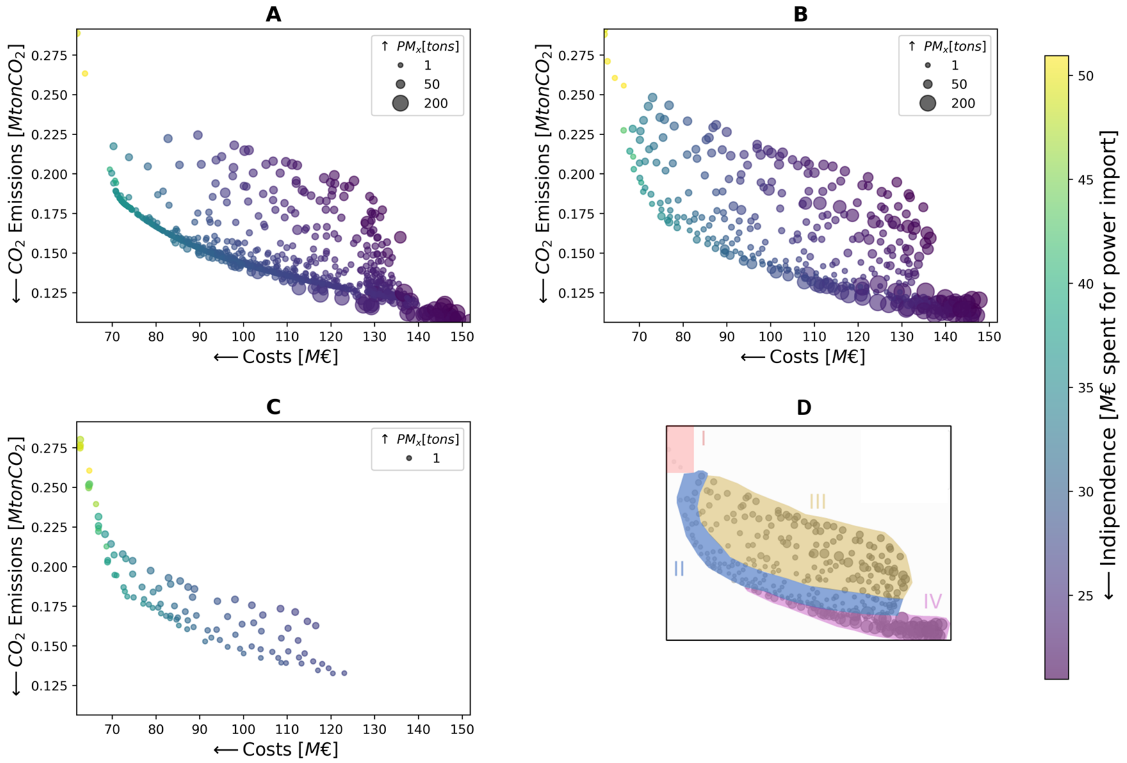

Figure 3. Pareto front obtained with the 3 methodologies described in the paper. a) Exhaustive method, b) evolutionary multi-objective optimization on weights, c) evolutionary multi-objective optimization on system configuration. d) visualization of the main macro-regions partitioning the extracted Pareto fronts.

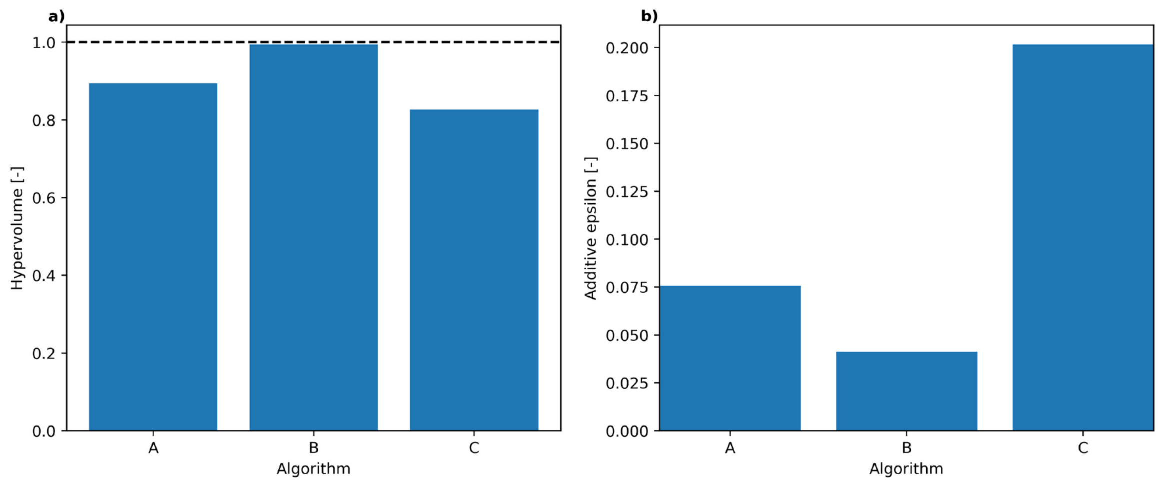

Figure 4. Metrics of performance for the three algorithms tested in this study: a) Hypervolume and; b) Additive epsilon indicator.

Figure 3 also allows for the comparison of the frontiers found using the three methodologies described above. The frontier in Figure 3a, referring to the exhaustive method, appears to be overall heterogeneous, with areas characterized by a low density of found solutions, such as zone I, alongside others where a high number of solutions with almost identical configurations are present (the lower band in zone II). In comparison, the use of method B) results in a more homogeneous and evenly-filled frontiers, with new configurations being found in previously unexplored areas characterized by high costs and filling the previously sparse region with low costs.

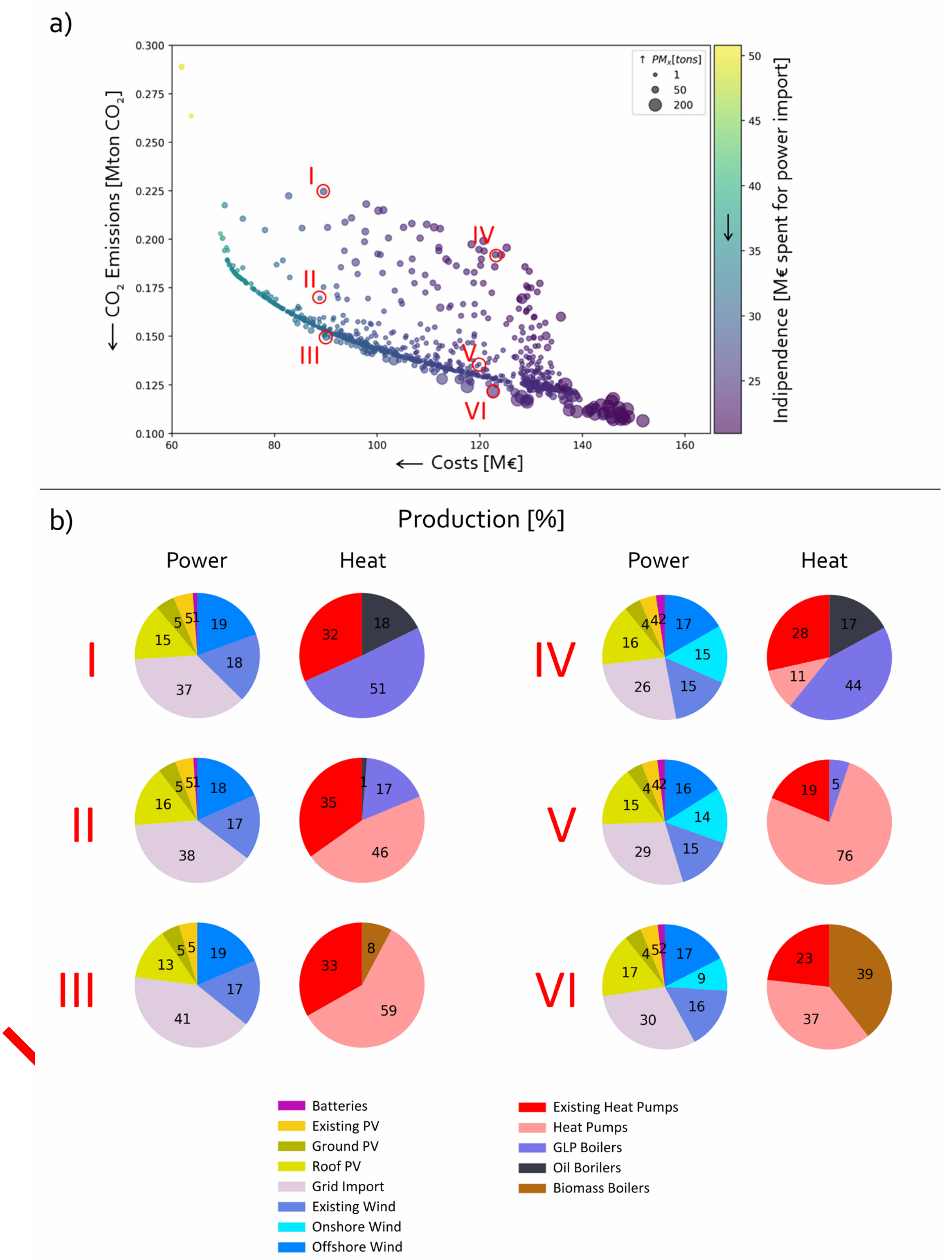

Figure 5 Details on the multi-energy system configurations found using the exhaustive method. Panel a) shows the The top-right figure identifies the macro-regions of the Pareto frontier used for its description. Panel b) presents six examples of optimized system configurations. Each solution shows

the percentage of total energy production for each present technology, for the electricity and heat energy vectors.

Finally, method c), even while having the highest number of FEs, return the most incomplete frontier, with many areas, especially those correlated with high costs, missing even a single non-dominated configuration. This is reflected by the values assumed by the metrics of performances, represented in Figure 4. Method b clearly outperforms both other techniques, dominating (hypervolume very close to one), and consistently covering (additive epsilon indicator close to zero) the entire objective space. Method a offers good performances as well, even though both less consistent and diverse. The low epsilon indicator performance of method c) suggest large portions of Pareto set unexplored. Moreover, further scrutiny into the configuration of the solutions reveal that many of them are still somewhat unoptimized, with multiple redundant heat generation technologies being included even when not needed to fulfill the demand.

Non-dominated system configurations

This section describes the features and composition of some non-dominated solutions to provide an overview of the optimal configurations found by CALLIOPE with different sets of weights.. The solutions are extracted from the Pareto front returned by the exhaustive method, as the other methods only returns the objective performance and decision variable values of the non-dominated solutions, requiring extensive computation to rerun CALLIOPE for each solution to extract the full details on the configurations.

Figure 5 shows the configuration of the energy system for six solutions identified by CALLIOPE for different weight sets. The examples are divided into two groups, presenting very similar cumulative costs (solutions I, II, and III in the first group, IV, V, and VI in the second).

Solutions I, II, and III are low-cost configurations, characterized by a similar mix of electrical production. In addition to existing technologies, ground and rooftop photovoltaic plants, and onshore wind turbines up to their maximum installable capacity, are included. Imports from the grid constitute more than a third of the annual production. As expected, solution I has the lowest grid import, as it focuses primarily on minimizing energy imports. The energy mix for heat production, however, is significantly different in the three solutions. In configuration I, in order to reduce electricity demand and thus the import needed from the grid, heat production is almost 70% derived from fossil fuel boilers. In solution III, with aims to only minimize CO_2 production, biomass boilers are used, which have a higher cost than other boilers and emit considerably more PMx. However, most of the heat production is via the new heat pumps installed. Solution II, finally, mostly focus on installing new heat pumps.

In solutions IV, V, and VI, the increase in invested capital is justified by the installation of offshore wind turbines, the most expensive available power generation technology. Regarding heat production, patterns similar to those observed in the previous three solutions are found. Configuration IV, like I, mainly invests in fossil fuel boilers to reduce both costs and the energy import. Solution V mainly uses heat pumps to meet the demand, while Solution VI favors the adoption en-masse of biomass boilers to minimize CO_2 emissions.

Figure 6 provides a visual indication of the adoption frequency of available technologies in the case study under consideration, depending on the weight given to the objectives considered and their relative importance in terms of total energy production. As can be seen, for renewable electricity generation technologies, generated power increases with increasing investment costs, moving from left to right, while it appears almost unchanged moving from top to bottom, or moving from solutions that prioritize grid independence to those that aim to reduce CO_2 and particulate emissions. Therefore, regardless of the prevailing objective, the sequence in which technologies are adopted with increasing investments appears similar, with the adoption of onshore wind and ground photovoltaic first, followed by rooftop photovoltaic, electrochemical storage batteries, and onshore wind.

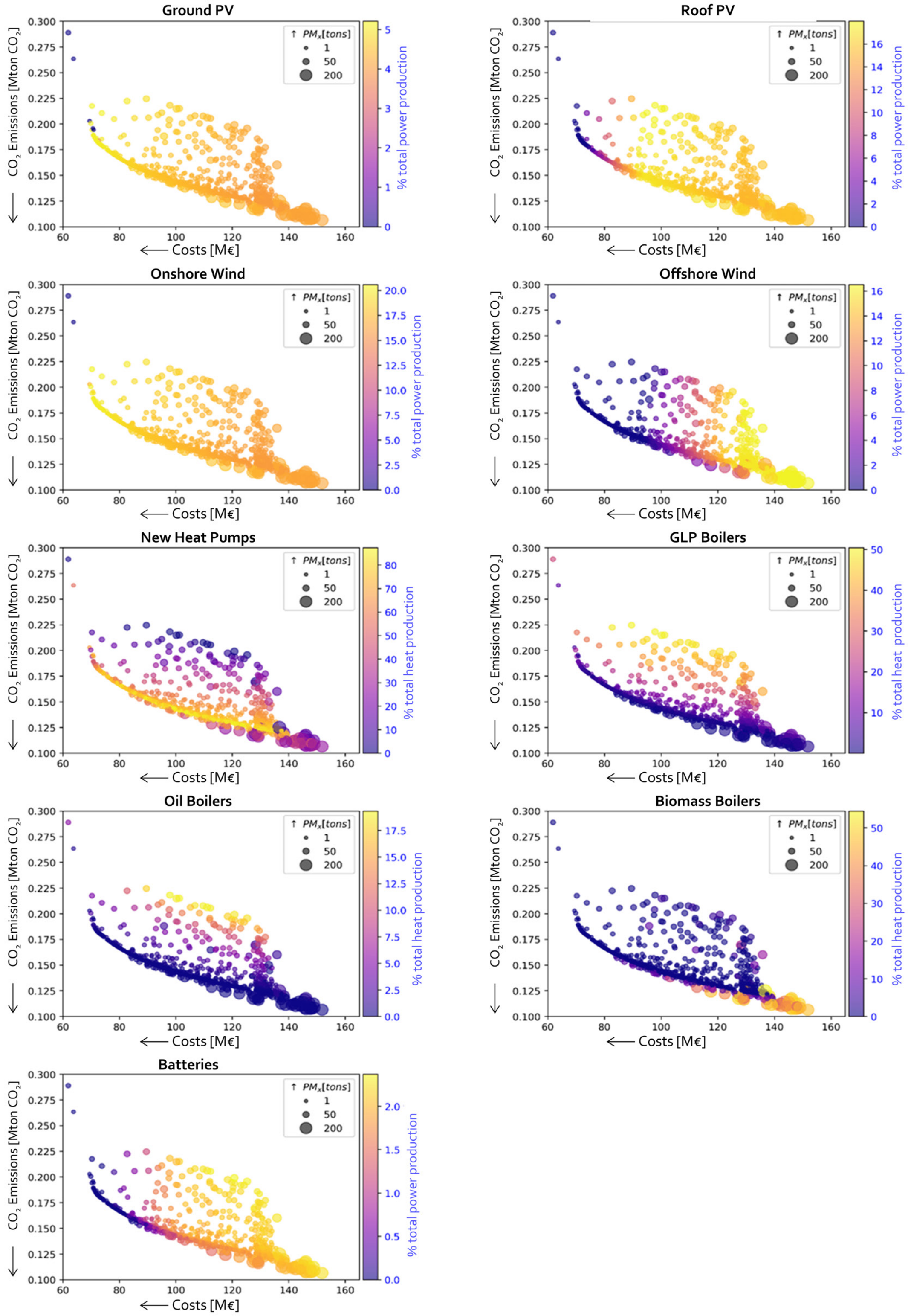

Figure 6. Fraction of energy generated by each of the available technologies for installation, for Pareto-efficient solutions found through the exhaustive method. The color of the indicators reflects the fraction of the annual energy production generated by the analyzed technology, relative to its primary output energy vector. The color scale represented by the color bar to the right of each graph has different values for each technology

The patterns appear different when considering heat generation technologies. In this case, the presence of different technologies is strongly influenced by the relative importance of the independence, CO_2, and particulate emission objectives. On the graph, this results in an increase or decrease in energy production by moving vertically on the frontier. Returning to the zone partitioning in Figure 3d, GPL and oil-fired boilers are mainly adopted in configurations that focus on independence (at the top of the Pareto frontier, in zone III and IV). In contrast, biomass boilers dominate heat production in solutions that aim only to reduce CO_2 emissions. The new heat pumps, present in almost all solutions, in configurations in zone II emerge as the predominant heat source in the system, as they avoid direct CO_2 and particulate emissions resulting from boiler use.

DISCUSSION AND FUTURE RESEARCH

The methodologies showcased in this paper represents a decisive step forward towards the creation of truly multi-objective optimization model of multi-energy systems. The results presented in this paper demonstrate that is possible to integrate the single-objective modelling tools already available, like CALLIOPE, into an external multi-objective framework, and achieve the same results of a fully multi-objective model, i.e the identifications of non-dominated solutions which showcases significant trade-offs between the objectives,

The methodologies outlined above can be compared based on their input data requirements, algorithm computational demand, and their ability to explore the decision space and provide a diverse set of optimal system configurations (and thus a more accurate approximation of the full Pareto front). The latter goal guarantees that the optimal configurations obtained highlight all possible trade-offs between non-comparable objectives.

From the results, it emerges that the exhaustive method (A) does allow to obtain a sufficiently heterogeneous Pareto frontier, which is however still heavily dependent on the size and distribution of the initial sampling. The identification of the latter, however, requires the user to already have prior knowledge of the system and how the performance indicators of the objectives relate to each other. For this reason, the extraction of weight sets represents an evident point of criticism in this methodology. Moreover, exhaustive methods like the one described run the risk of being particularly inefficient in utilizing available computational resources. In fact, looking at the resulting Pareto front, it is observed that, especially in zone II in Figure 3d, different combinations of weights converge on configurations that are particularly similar or practically identical to each other's, with comparable objective performances, which constitute a waste of resources that could be used to explore more interesting configurations. In zone I and III, the system configurations instead appear extremely sensitive to the slightest variation in the associated weights, and therefore the broad sampling of the space of weight combinations result in large portions of the Pareto frontier being left unexplored. Consequently, the method does not fully utilize the allocated computational resources, with areas of the objective space virtually unexplored and others characterized by an elevated density of mostly similar configurations.

Multi-objective evolutionary optimization on weights (B) ensures a heterogeneous exploration of the Pareto frontier, with better results than the exhaustive method. The resulting frontier appears more complete and evenly distributed. Although this method still requires the a priori definition of value range to assign to the weights, the use of MOEAs allows for the use of wider ranges, reducing the need for prior knowledge of the system. In fact, the ability of MOEAs to gradually evolve across their iterations to better explore the decision space in the search for interesting new non-dominated solution guarantees a more efficient use of the available computational resources. However, this method still requires prior knowledge of the system to define the weights feasibility spaces.

Finally, the Pareto frontier extracted with the multi-objective evolutionary optimization of system configuration method(C) appears populated by configurations that are not fully optimized and devoid of entire areas explored by the other methods. Indeed, it appears that the method has a clear limitation in its high computational demand. MOEAs typically require multiple iterations before returning optimized solutions to the problem. At the start of the algorithm and for the initial generations, the system configurations are random or extremely suboptimal, but are nevertheless run through CALLIOPE to extract objective performances, with great expense of computational resources. This is necessary to allow the evolutionary algorithm to learn which configurations are more efficient and converge towards Pareto-optimal solutions. However, depending on the complexity of the problem, these solutions may only be identified after a very high number of iterations. In comparison, in the previous two methods, the configurations returned by CALLIOPE for each weight set are all Pareto-efficient, with the only risk being their redundancy. Furthermore, the MPC method for optimizing management is the operation that demands the most computational resources in CALLIOPE. Therefore, removing the need to use MILP algorithm for planning optimization does not result in a significant reduction in computational load, which could have compensated for the increased number of iterations required. In summary, method C, although theoretically representing the most robust method as it does not require the use of weights to compare objectives, results relatively ineffective and inefficient compared to the previous ones, despite significantly more computational resources being allocated.

In general, method B appears as the most effective for optimizing multi-objective energy systems. Thanks to evolutionary algorithms, it allows for optimal use of computational resources and uniform and heterogeneous exploration of the objective space. The main limitation of the method, namely the need for prior knowledge of the system to define the feasibility space of weights, is partially limited by the convergence speed of the algorithms, which allows for the definition of wider ranges. However, it is important to mention how method C goes beyond this limitation, and although it has proved ineffective in the case study examined, it could be effective for less complex systems with fewer decision variables.

The different system configurations described in Figure 3 and Figure 4 show a high degree of variance in both the type and capacity of the technologies installed. This heterogeneity showcases the multiple trade-offs emerging among the objectives, and the relative importance of each technology according to the relevance attributed to each objective.

As the main goal of this research was the identification and analysis of different multi-objective multi-energy system configuration models, the methodologies were tested on a synthetic case study with data series taken for a single sample year. Naturally, when planning for a real case study, it becomes fundamental to include multiple years of data, as well as tools to consider and incorporate uncertainties in the analysis. Future developments in this line of research might focus on applying the identified paradigm found here to a real case study and analyzing the impact of climate, socio-economic, and technological uncertainties on the system and extracting optimal configurations to identify solutions that are not only optimal but also robust against sensitive inputs. A possible paradigm in this direction might be the one proposed by [36], which would allow the sensitivity of the optimization objectives to multiple uncertainty sources. New evaluation metrics, such as those presented in [37], can also could be introduced to identify optimal solutions that are resilient to uncertainties in the system and future changes.

CONCLUSION

The transition from traditional energy systems to multi-energy systems is considered vital for achieving decarbonization goals. Multi-energy systems allow for more efficient use of available resources through greater flexibility derived from the integrated management of the entire system and interaction among different energy vectors through storage and conversion technologies. They are particularly suitable for addressing the challenges of massive integration of non-programmable renewable sources into energy systems and adapting to local resources.

The integration of processes and energy vectors traditionally kept separate in these systems, however, makes planning and management particularly challenging. Therefore, to ensure efficient system configuration, the support of modeling tools that allow exploration of different alternatives and extraction of optimized solutions is necessary.

Many of these models, often have a single-objective perspective, maximizing the monetary profit of the system, resulting from the influence of traditional energy system planning paradigms, which typically favored economic objectives as the single or predominant evaluation metric. The work contained in this paper aims to overcome this limitation and develop multi-objective planning systems for multi-energy systems by coupling the single-objective multi-energy model CALLIOPE with multi-objective optimal solution search tools.

To this end, three different methods have been considered and explored and applied to a synthetic case study. The first method involves coupling CALLIOPE with an exhaustive weight sampling procedure, the second involves optimal search for relative weights through integration with evolutionary optimization algorithms, and the third uses these algorithms for both energy planning problem resolution and multi-objective evolutionary optimization of system configuration.

All three methods return multiple and diverse configurations of the multi-energy system, which allows for the identification of the interplay between technologies and objectives. However, the performance indicators highlighted how the employment of multi-objective evolutionary algorithm for the weights space exploration (method b) constitutes the better methodological paradigm for optimizing energy systems planning and operation, given its ability to thoroughly explore the Pareto front and extract heterogeneous system configurations.

Finally, all three methodologies have been designed to be easily integrated with other widely available MESs planning and management systems which use single-objective matrices to optimize the system configuration, such as PyPSA [26], H2RES [27] and MUSEPLAN [28]

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NOMENCLATURE

GHG	Greenhouse Gas
MES	Multi-energy System
MILP	Mixed-Integer Linear Programming
MOEA	Multi-Objective Evolutionary Algorithm
MPC	Model Predictive Control
OMOPSO	Optimized Multi-objective Particle Swarm Optimization
PM	Particulate Matter

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