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Evaluating near-optimal scenarios with EnergyPLAN to support policy makers

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ABSTRACT

Energy system modelling may support policymakers in their energy planning efforts. Energy system modellers usually identify the optimal system configuration based on an economic objective function, or in multi-objective optimization, a combination of multiple objectives such as greenhouse gas emissions and total system cost. However, there could be political, socio-economic, or environmental reasons justifying a policymaker's selection of a solution that is slightly more costly or greenhouse gas polluting than the uniquely optimal solution. Solely focusing on the uniquely optimal solution disregards potentially diverse alternatives, which based on different evaluation metrics could even be preferable. In response to this challenge, the evaluation of near-optimal solutions is gaining attention in the energy system modelling field as an extension of traditional multi-objective optimization studies and as a way to bridge the gap between simulation and optimization approaches. In this study, we explore near-optimal solutions, outline the diversity of near-optimal solutions, and evaluate the relevance of these solutions in the context of energy planning. The proposed methodology is applied to the Italian case to determine its potential as a tool to support policymakers in evaluating energy system scenarios from a selection of optimal and near-optimal solutions.

1. Introduction

Energy system modelling and energy system scenario-making have become increasingly important tools for policymakers in their energy planning efforts. Chang et al. [1] identified three main trends in the energy system modelling research field: increasing modelling of cross-sectoral synergies, growing focus on open access, and improved temporal detail to deal with high levels of variable renewable energy sources. Energy system modelling aims to determine the best system setup and capacity expansion by using an economic objective function or a mix of multiple objectives, such as minimizing greenhouse gas emissions and total system cost [2]. Nonetheless, policymakers may choose a solution that is marginally more expensive or environmentally damaging than the optimal solution due to political, socio-economic, or environmental reasons [3]. This is where near-optimal solutions come into play.

In recent years, the evaluation of near-optimal solutions has gained attention in the energy system modelling field as an extension of traditional multi-objective optimization studies and as a way to bridge the gap between simulation and optimization approaches [4]. The near-optimal solutions provide an opportunity to explore a wide range of alternatives that can be evaluated based on different metrics, such as socio-economic and environmental impacts. This approach allows policymakers to consider not only the most efficient solutions, but also solutions that are more sustainable, resilient, and equitable. Chang et al. [5] stated that a challenge of the energy system modelling research field is a better understanding of the near-optimal solutions space and studying these solutions going beyond the usual criteria for optimization.

The objective of this study is to explore the potential of near-optimal solutions in the context of energy planning. We propose a methodology to produce and evaluate near-optimal solutions using the EnergyPLAN software [6], which is a widely used energy system modelling tool. Although there are several existing articles on the topic of evaluating near-optimal solutions (see Table 1), all of them focus on the coupling of a linear programming energy system model and a modelling technique to generate alternatives or a similar approach. This article, however,

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Nomenclature

k	Index of the decision variables
K	Vector of the decision variables
DV_k	Generic decision variable k
$DV_k^{(L)}$	Lower bound for decision variable k
$DV_k^{(U)}$	Upper bound for decision variable k
i	Index of the solutions
I	Vector of the solutions
f_i^E	New value of the fitness of solution i resulting from equality function
E^*	Optimal fitness value for a certain constraint of CO_2 emissions
E_i	Fitness value of solution i
ε	Defines the space of near-optimal solutions
f_i^S	New value of the fitness of solution i resulting from sharing function
σ_s	Threshold of dissimilarity
$d_{i,j}$	Euler distance between solution i and a generic solution j
P	The penalty that is applied if the solutions are too similar
DoS_i	Diversity of energy supply indicator
$g_{m,i}$	Electricity generation of source m in solution i
G_i	Total electricity generation in solution i
m	Index of the sources
M	Vector of the sources
LU_i	Land use indicator for solution i
JC_i	Jobs creation indicator for solution i
$P_{m,i}$	Installed power of source m in solution i
lu_m	Land use factor for source m
jc_m	Job creation factor for source m

Acronyms

IAM	Integrated Assessment Model
MGA	Modelling to Generate Alternatives
MAA	Modelling All Alternatives
MOEA	Multi-Objective Evolutionary Algorithm
PES	Primary Energy Supply
SSD	sum of squared distances
HRE4	Heat Roadmap Europe 4
DHW	Domestic Hot Water

takes a different approach by implementing the evaluation of near-optimal solutions through a Heuristic method and introducing an Equality function and Sharing function. This approach allows for the identification of near-optimal solutions not only for a particular CO_2 emissions constraint but for all CO_2 emissions reduction levels among the optimal Pareto front solutions. Additionally, a set of indicators are utilized to enhance the transparency of the results for policy makers by exploring socio-economical aspects. The approach also incorporates a clustering technique to better understand the differences and similarities of the found optimal and near-optimal solutions, providing policy

Table 1
Existing literature exploring near-optimality in energy system modelling. Method to analyse the identified near-optimal solutions are explained in Ref. [7].

	Pub. year	Model on which is applied near-optimality	Programming technique of the model on which is applied near-optimality	Application case study	Method to implement near-optimality	Method to analyse the identified near-optimal solutions
De Carolis et al. [4]	2016	Temoa	Linear programming (minimize the system-wide costs)	US single node (electricity and transport sectors)	Modelling to generate alternatives (MGA)	Statistical analysis of decision variables in the near-optimal space
Price et al. [8]	2017	E3 model (IAM) - TIMES	Linear programming (minimize total system cost)	Global (sector coupling) 16 regions. Time horizon 2005–2050 (5 years periods)	Modified MGA	Statistical analysis of decision variables in the near-optimal space
Berntsen and Trutnevyte [7]	2017	EXPANSE	Linear programming	Swiss electricity system	MGA	Distance-to-selected approach
Hennen et al. [9]	2017	SPREAD	Linear programming	Small system with one heating demand and one electricity demand	MGA	Statistical analysis and correlation calculation of decision variables in the near-optimal space
Nacken et al. [10]	2019	PyPSA-Eur-Sec	Linear programming	Germany (Sector coupled energy system model)	MGA	Distance-to-selected approach
Lombardi et al. [11]	2020	Calliope (SPORES)	Linear programming	Italian power system	Extension to the MGA	Statistical analysis and correlation calculation of decision variables in the near-optimal space
Neumann and Brown [3]	2021	PyPSA-Eur	Linear programming	European power sector	MGA	Statistical analysis and correlation calculation of decision variables in the near-optimal space
Pedersen et al. [12]	2021	PyPSA-Eur	Linear programming	European power sector	MGA	Statistical analysis and correlation calculation of decision variables in the near-optimal space
Pickering et al. [13]	2022	Calliope (SPORES)	Linear programming	European energy system	Extension to the MGA	Statistical analysis of decision variables in the near-optimal space
Grochowicz et al. [14]	2023	PyPSA-Eur	Linear programming	European power sector	MGA and Modelling All Alternatives (MAA)	Statistical analysis and correlation calculation of decision variables in the near-optimal space
This study	–	EnergyPLAN, EPLANopt	Heuristic approach	Italian energy system (sector coupling)	Equality function and sharing function	Cluster analysis

makers with a transparent tool to make informed decisions.

In this paper, we will present the methodology and its application to a specific case study and discuss the potential of this approach to support local policymakers in evaluating energy system scenarios from a selection of optimal and near-optimal solutions. This study will contribute to the ongoing debate on the trade-offs between technical efficiency, social and environmental sustainability, and resilience in energy planning.

Policy or industry users of energy scenarios usually prefer a concise and informative collection of scenarios [15]. Thus it is important to reduce the large amount of scenario results to a small, diverse set of solutions [7]. There are available methods to characterize and filter a vast number of scenario results to derive a small and diverse set of scenarios. Berntsen and Trutnevyte [7] reports a list of methods for choosing a small, diverse set of scenarios among optimal and near-optimal solutions. The distance-to-selected approach, also used by Berntsen and Trutnevyte [7], searches for scenarios that are most dissimilar from the initial scenario in terms of their attributes. The difference from the initial scenario is calculated as the squared Euclidian distance. A cluster analysis allows for the identification of groups of similar solutions in the near-optimal space. One scenario in each cluster is selected to represent that cluster. Many methods do not use a technique to pick a small set of distinct solutions from the near-optimal solutions for analysis. Instead, they conduct statistical analysis on the decision variable values within the near-optimal space. Some of these methods also perform correlation analysis among the decision variables. Price et al. [8] applied a statistical analysis to understand how decision variables vary in the near-optimal space. The authors also stated that adding additional criteria to the identified near-optimal scenario and transition pathways may be of interest to decision makers.

The proposed article contributes novelty to the field of energy system modelling and planning by introducing two key elements in the methodology for evaluating near-optimal scenarios. Firstly, a heuristic approach is employed through a multi-objective genetic algorithm with equality and sharing functions to evaluate the near-optimal space. This approach allows for the identification of near-optimal solutions across all CO_2 emissions reduction levels among the optimal Pareto front solutions. Secondly, the adoption of cluster analysis is used to select representative solutions and analyse the identified near-optimal solutions with the introduction of additional criteria to better drive the decisions of policy makers. This approach enhances the transparency of the results for policy makers by exploring socio-economic aspects and provides a concise and informative collection of scenarios to aid decision-making. The novelty of the proposed method lies in the unique combination of these two elements, which distinguishes it from existing literature on the evaluation of near-optimal solutions in the energy system modelling field.

The structure of the article is as follows: in the second section, we describe the material and methods used in this study, including the EnergyPLAN software, the EPLANopt model implementing a Multi-Objective Evolutionary Algorithm (MOEA), the technique to implement near-optimal evaluation through this method as well as the additional evaluation indicators and clustering analysis to better analyse the final results. In the third section, we present the case study to which the methodology is applied including a baseline scenario from 2019 and the decision variables considered. In the fourth section, we provide results of our methodology applied to an Italian case study, and a discussion of the results, highlighting the key findings and implications. Finally, in the conclusion section, we summarize our contribution and suggest directions for future research. The appendix provides a detailed description of the clustering analysis method used in this study.

2. Material and methods

This section provides an overview of the materials and methods used in the study. Section 2.1 highlights the EnergyPLAN software, the multi-model approach and its integration with the multi-objective evolutionary algorithm through the EPLANopt model. Section 2.2 explains the near-optimal evaluation process and how it is implemented in this application of EPLANopt through the use of equality and sharing functions. Section 2.3 details the additional indicators used to broaden the analysis to socio-economic and security aspects. Finally, section 2.4 outlines the clustering analysis used to classify and present the results in a clear and organized manner for policymakers.

The method is based on the following steps:

i) Application of the EPLANopt model which couples EnergyPLAN with a Multi-Objective Evolutionary Algorithm to the Italian case study (method described in section 2.1).
ii) Selection of the admissible range for near-optimality and application of equality and sharing functions to identify the near-optimal solutions, (method described in section 2.2).
iii) Application of a set of indicators to the near-optimal solutions to estimate their impact on socio-economic and environmental aspects (method described in section 2.3).
iv) Clustering analysis to understand the trends and common patterns of near-optimal solutions (method described in section 2.4).

2.1. EnergyPLAN software

The EnergyPLAN software was created in 1999 and has undergone continual improvement to accommodate new technologies and potential synergies across the different sectors of the energy system [16]. Developed by Aalborg University, EnergyPLAN is one of the first energy system models to implement the concept of smart energy systems. This concept is based on the idea of linking energy sectors and studying the potential exchange benefits and synergies among them [17]. EnergyPLAN allows the user to take a holistic approach to the analysis of the cross-sectoral interaction of the energy system, linking demand sectors like buildings, industry, and transport with supply technologies via electricity, gas, district heating and cooling grids. With EnergyPLAN, users can perform comparative and consistent analyses of both fossil fuel-based and renewable energy systems, calculating hourly energy system operation with supply and demand matching.

In 2021, Lund et al. [6] published a review of the EnergyPLAN software and the main findings are:

1. EnergyPLAN is a free energy system analysis tool designed to study and research future sustainable energy solutions with a focus on high shares of renewable energy sources.
2. EnergyPLAN enables the analysis of the whole energy system, linking different demand sectors (buildings, industry, and transport) with supply technologies (electricity, gas, district heating and cooling grids) to consider cross-sectoral interactions.
3. The tool can model the entire energy system, including electricity, heat, industry, and transport sectors and a wide variety of technologies.
4. EnergyPLAN allows the user to perform consistent and comparative analyses of energy systems based on renewable energy, fossil fuels, and nuclear power.
5. The tool can perform technical and market-economic simulations, and calculate the costs of the total system, including investments costs, operation costs, fuel costs, CO_2 costs, and other taxes.
6. EnergyPLAN can be executed from other platforms such as Excel, MATLAB or Python and can perform hourly operation analysis.

In 2022 Østergaard et al. [18] published a review and validation of EnergyPLAN software. They concluded that EnergyPLAN has been applied in 315 peer-reviewed articles, and its large-scale application serves as inferred internal validation. The study has highlighted the important role of EnergyPLAN in modelling integrated smart energy systems. Moreover, the study revealed that EnergyPLAN, while primarily utilized as a standalone energy system analysis tool, has also been integrated within multi-tool approaches in conjunction with other energy system models or optimization algorithms. The implementation of EnergyPLAN in these multi-tool setups further supports its credibility and reinforces its inferred internal validation.

Østergaard [19] found that the most common performance indicators applied in energy systems analyses with EnergyPLAN are Primary Energy Supply (PES), CO_2 emissions, excess power, and costs, which are in line with the goals of countries seeking to minimize impacts on the climate. The most dominant indicator for probing the technical workings and feasibility of a given energy system is excess power. Table 2 shows the different multi-tool approaches applied in existing literature.

The EPLANopt model is the outcome of merging the EnergyPLAN software [6,44] and an optimization algorithm for expansion capacity. The full source code of EPLANopt can be found atthis open repository [45]. EnergyPLAN is a deterministic simulation model capable of simulating future scenarios with high levels of variable renewable energy sources (VRES). It uses an hourly time-step to simulate a one-year period and incorporates all three primary sectors of the energy system. The EnergyPLAN model has been used in various scales, such as at the European level [46], national level [47–54], regional level [55,56], as well as for towns and municipalities [57,58] and small islands [59–61].

In this work, EnergyPLAN has been adopted with the following characteristics: i) EnergyPLAN version 16.1 is used, ii) a technical simulation strategy balancing both heat and electricity demands is chosen, iii) for electric mobility dump charge is chosen. A Multi-Objective Evolutionary Algorithm (MOEA) [62–64] was used to perform a multi-objective expansion capacity optimization, which evaluates the optimal solutions by considering both economic and environmental factors. The objectives chosen in this case were to minimize the total annual costs and minimize annual CO_2 emissions. Equation 1shows the objective functions of the multi-objective minimization problem. The main constraints to which the optimization is subjected describe how the value of the decision variables should remain in a fixed range defined by the lower $DV_k^{(L)}$ and upper $DV_k^{(U)}$ bounds of decision variable k. Other constraints such as balance between demand and generation at each time-step or storage behaviour with initial content equal to final content are defined within the EnergyPLAN software.

Optimization function	$\min_{DV} \begin{bmatrix} \textit{Total Annual Costs } [M€] \\ \textit{Annual } CO_2 \textit{ Emissions } [kt] \end{bmatrix}$	(1)
Subject to	$DV_k^{(L)} \le DV_k \le DV_k^{(U)}$	

The operational simulation of the year is performed through EnergyPLAN software, while the expansion capacity optimization is achieved through the MOEA. The MOEA starts by generating an initial population of random solutions, each of which is characterized by a set of decision variables K and a value for each of them defined between a minimum, $DV_k^{(L)}$, and a maximum bound, $DV_k^{(U)}$. EnergyPLAN is then used to evaluate each solution by substituting the decision variable values into EnergyPLAN reference scenario and calculating the values of the objective functions (total CO_2 emissions and total annual costs). By means of the operators that are typical of the genetic algorithms (such as selection, crossover and mutation) the optimization algorithm moves forward until the convergence is reached and the final Pareto front is found.

2.2. Near-optimal evaluation

This section provides an overview of the materials and methods used to adapt EPLANopt model to enable the evaluation of near-optimal solutions. Fig. 1 shows in a total annual costs-CO_2 emissions diagram, given a certain CO_2 emissions constraint, the single-optimal solution, the near-optimal solutions included in the space limited by the constraint on

Table 2
Existing multi-tool approaches with EnergyPLAN as energy system simulation model.

Author	Publication year	Tool coupled to EnergyPLAN	Scope
Bjelic and Rajakovic [20]	2015	GenOpt – single-objective optimization algorithm (MATLAB)	Perform a single-objective expansion capacity optimization
Bjelic et al. [21]	2016	GenOpt – single-objective optimization algorithm, EPOPT (MATLAB)	Perform a single-objective expansion capacity optimization
Komušanac et al. [22]	2016	Brute-force algorithm	Obtain a Pareto front of optimal solutions and apply a multi-criteria analysis
Mahbub et al. [23]	2016	Strength Pareto Evolutionary Algorithm (SPEA2) – multi-objective optimization	Obtain a four-dimensional Pareto front of optimal solutions
Mahbud et al. [24]	2016	Strength Pareto Evolutionary Algorithm (SPEA2) – multi-objective optimization	Obtain a Pareto front of optimal solutions by coupling domain knowledge with algorithms
Mahbud et al. [25]	2017	Strength Pareto Evolutionary Algorithm (SPEA2) – multi-objective optimization	Obtain multiple Pareto fronts for different time horizons and identify transient scenarios for a gradual transition
Prina et al. [26]	2018	EPLANopt – multi-objective optimization (Python)	Obtain a Pareto front of optimal solutions incorporating considering combined cycle gas turbine flexibility constraints
Prina et al. [27]	2018	EPLANopt – multi-objective optimization (Python)	Obtain a Pareto front of optimal solutions considering residential energy efficiency improvements
Prina et al. [28]	2019	EPLANoptTP – multi-objective optimization (Python)	Minimize cumulative costs and carbon emissions for an entire transition period and optimize the timing of capacity expansions
Bellochi et al. [29]	2020	Multi-objective optimization (MATLAB)	Obtain a Pareto front of optimal solutions to evaluate electrified transport and heating scenarios
Viesi et al. [30]	2020	Multi-objective optimization	Obtain a Pareto front of optimal solutions for evaluating regional energy scenarios
Menapace et al. [31]	2020	Multi-criteria decision analysis (MATLAB)	Evaluating 100% renewable urban energy systems
Fischer et al. [32]	2020	Multi-objective optimization	Obtain a Pareto front of optimal

(continued on next page)

Table 2 (*continued*)

Author	Publication year	Tool coupled to EnergyPLAN	Scope
			solutions for evaluating municipal energy scenarios
Prina et al. [33]	2020	EPLANopt – multi-objective optimization (Python)	Obtain a Pareto front of optimal solutions for evaluating national energy scenarios
Prina et al. [34]	2020	EPLANopt – multi-objective optimization (Python)	Obtain a Pareto front of optimal solutions for evaluating regional energy scenarios considering flexibility and excess electricity integration
Groppi et al. [35]	2021	EPLANopt – multi-objective optimization (Python)	Obtain a Pareto front of optimal solutions for evaluating sector coupling options for isolated island case
Laha and Chakraborty [36]	2021	EPLANopt (multi-objective optimization) and multi-criteria assessment	Obtain Pareto front of optimal solutions for electricity system configurations and evaluate based on a multi-criteria assessment
Prina et al. [37]	2021	EPLANoptMAC - hill climbing Single-Objective expansion capacity optimization (Python)	Obtain a marginal abatement cost curve to estimate the relationship between carbon emission reductions and relative costs
Vaccaro and Rocco [38]	2021	EPLANopt coupled with Input-Output analysis (IOA)	Obtain Pareto front of optimal solutions and process solutions in an IOA to evaluate regional economic and environmental impacts
Hasterok et al. [39]	2021	Grey Wolf Optimizer (meta-heuristic search process)	Optimize national energy system configuration
Groppi et al. [40]	2022	EPLANoptMAC - hill climbing Single-Objective expansion capacity optimization (Python)	Obtain a marginal abatement cost curve for the decarbonization of the maritime sector for an island
Herc et al. [41]	2022	EPLANopt (multi-objective optimization) and post-processing evaluation procedure	Determine optimal national energy system configuration based on post-processing procedure
Maigret et al. [42]	2022	Multi-objective optimization	Obtain Pareto front of optimal solutions for decarbonization of refinery considering resource availability
Johannsen et al. [43]	2023	EPLANopt - multi-objective optimization (Python)	Obtain Pareto front of optimal solutions for comparison to results obtained from a stepwise simulation approach

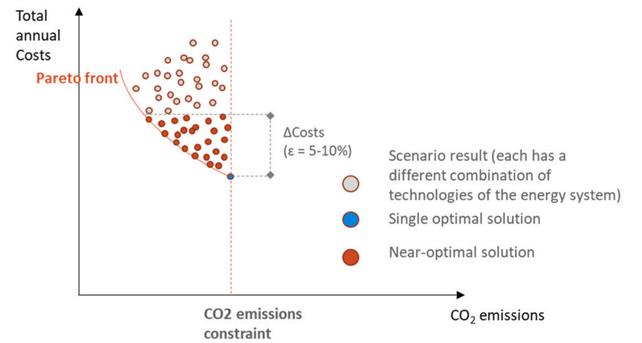

Fig. 1. Near-optimal evaluation representation in a total annual costs-CO_2 emissions diagram.

CO_2 emissions the Pareto front of optimal solutions and a given ε that defines the $\Delta Costs$ range.

Table 1 has shown that the most used method to implement the near-optimal analysis is Modelling to generate alternatives technique coupled to linear programming energy system models. This study makes use of the heuristic model, EPLANopt, and for this reason, a different approach is proposed to implement the near-optimal analysis. Liu et al. [65] introduced two functions for this purpose: the equality and sharing functions. Equality function to prevent individual solutions from converging into a single optimal solution. Sharing function to ensure diversity among optimal results.

Eq. (2) shows the mathematical formulation of the equality function. f_i^E is the new resulting value of the fitness of solution i (objective function on total annual costs) after applying the equality function. E^* is the optimal fitness value for a certain constraint of CO_2 emissions. E_i is the fitness value of solution i and ε defines the space of near-optimal solutions. This method is applied in this article to the Italian case study assuming an ε equal to 5%, a value in line with assumptions in similar studies, as highlighted by Neumann and Brown [3].

$$f_i^E = \begin{cases} E^* & E_i \geq (1+\varepsilon)E^* \\ E_i & E_i < (1+\varepsilon)E^* \end{cases} \tag{2}$$

In the sharing function, the fitness value of a solution is penalized when the solution is too similar to other solutions in the population. This penalty forces the spread of solutions in the decision space, allowing for the discovery of various optimal solutions and multiple non-optimal solutions. Eq. (2) shows how to calculate the sharing function. f_i^S is the new resulting value of the fitness after applying the sharing function. σ_s is the threshold of dissimilarity, $d_{i,j}$ is the Euler distance between solution i and a generic solution j. P is the penalty that is applied if the solutions are too similar. The sharing function penalizes the fitness value of a solution i if its fitness is too similar to an existing solution of the population.

$$f_i^S = \begin{cases} E_i & \min_j\left(d_{i,j}\right) < \sigma_s \\ E_i + P & otherwise \end{cases} \tag{3}$$

2.3. Additional indicators

The optimal and near-optimal solutions found by the method explained in sections 2.1 and 2.2 are by now characterized by two outputs: total annual costs and CO_2 emissions. In this phase, it is possible to apply to the found solutions a set of indicators to account for the impacts of these solutions on socio-economic, security of supply and environmental aspects. This is useful to better support policy makers in the choice of the most appropriate future energy system configuration. It is also possible to use other criteria, such as renewable energy share, reliability, the amount of energy demand that can be satisfied by renewable sources, or the level of electrification of the system, to further assess the performance of the solutions found by the model. Some other examples could be reliance on import of electricity and fuels, land use, particle emissions, local investment and employment opportunities, system flexibility, and resilience towards future price changes.

In this study, three indicators are introduced to expand the solutions impacts on socio-economic aspects: land use, job creation, and diversity of energy supply. It should be noted that these indicators are just examples of commonly used criteria and that other indicators could also be applied in this phase. The choice of indicators should depend on the specific context and objectives of the energy planning exercise, as well as the available data and resources for their calculation. Eq. (4) shows the mathematical formulation of the diversity of energy supply indicator DoS_i for solution i based on the Shannon-Wiener Index. $g_{m,i}$ is the electricity generation of source m in solution i. M is the list of electricity generation resources. G_i is the total electricity generation in solution i. The range of values for this index is from 0 to infinity. A value of 0 represents a complete lack of diversity, where a single power source is used to meet the entire electricity demand. On the other hand, a value of infinity represents a perfectly diversified electric system, where the electricity demand is met by an equal proportion of all available power sources. In general, the greater the diversity of power sources used in the system, the higher the value of the diversity indicator, which reflects the reduced dependence on a single power source.

$$DoS_i = -\sum_{m}^{M} \frac{g_{m,i}}{G_i} \bullet \ln\left(\frac{g_{m,i}}{G_i}\right) \tag{4}$$

Eq. (5) shows the mathematical formulation of the land use indicator. LU_i is the land use indicator for solution i. lu_m is the land use factor for source m (see Table 3 for the assumed values) [66]. $P_{m,i}$ is the installed power of source m in solution i.

$$LU_i = \sum_{m}^{M} P_{m,i} \bullet lu_m \tag{5}$$

Eq. (6) shows the mathematical formulation of the job creation indicator. JC_i is the jobs creation indicator for solution i. jc_m is the job creation factor for source m (see Table 3 for the assumed values) [67, 70].

$$JC_i = \sum_{m}^{M} P_{m,i} \bullet jc_m \tag{6}$$

Table 3
Land use and job creation factors.

Technology	Land use, lu_m, [m^2/MW] or [m^2/MWh] for Lithium-ion Batteries and Hydrogen storage	Ref.	Job creation, jc_m, [jobs-years/MW] or [jobs-years/MWh] for Lithium-ion Batteries and Hydrogen storage.	Ref.
On-shore wind power	14548 (8.4 for generated MWh)	[66]	8.92	[67]
Off-shore wind power	62750 (25.0 for generated MWh)	[66]	26.79	[67]
Rooftop PV	3780 (3.0 for generated MWh)	[66]	35.31	[67]
Utility-scale PV	23940 (19.0 for generated MWh)	[66]	21.20	[67]
Lithium-ion Batteries	139.6	[68]	28.90	[67]
Electrolyser	25.0	[69]	2.72	[70]
Fuel cell	30.0	[71]	2.17	[70]
Hydrogen storage	5.0	[69]	0.06	[70]

2.4. Clustering analysis

The outcome of section 3.3 is a collection of optimal and near-optimal solutions, each of which is also analysed in terms of land use, job creation, and energy supply diversity. With such a large number of solutions, it becomes necessary to utilize statistical analysis to gain a deeper understanding of their characteristics and see if they can be grouped into smaller sub-groups or clusters. Clustering Analysis is a data mining technique used to partition a dataset into groups (also known as clusters) based on their similarity. In this study, the K-Means method was used for clustering analysis [72]. The K-Means method is a popular and widely used clustering algorithm that partitions a dataset into K pre-defined number of clusters based on the mean distance between the data points and the cluster centroid [73]. This distance metric used to measure the dissimilarity between solutions is based on the Euclidean distance. To determine the optimal number of clusters, two evaluation metrics were used in this study: the Elbow Method and the Silhouette Score.

The Elbow Method [74] is based on the idea that the optimal number of clusters is the value of K at which the increase in explained variance starts to decrease and becomes marginal. The explained variance can be represented by the sum of squared distances (SSD) between the data points and their assigned cluster centroid. The Silhouette Score [75] measures the similarity between a data point and the data points in its own cluster compared to those in other clusters. It ranges from −1 to 1, with a score close to 1 indicating that the data point is well-matched to its own cluster and poorly matched to other clusters. In this study, the optimal number of clusters was selected based on both the Elbow Method and Silhouette Score.

The clustering analysis is performed on each of the selected solutions, both optimal and near-optimal, by taking into account the values of five indicators: total annual costs, annual CO_2 emissions, land use, job creation, and energy supply diversity.

A representative solution has been selected for each cluster based on the closest to centroid criterion. Selecting the closest to centroid solution ensures that the representative solution is a good representative of the cluster as a whole, as it is located at the centre of the cluster in terms of its decision variable values. This method also simplifies the process of selecting representative solutions, as it is based on a single criterion that is easy to calculate. It should be noted, however, that other criteria could also be used for selecting representative solutions, such as the most extreme solution or the solution with the highest weight in a weighted average of the solutions in the cluster. The choice of criterion should depend on the specific objectives of the energy planning exercise and the characteristics of the solutions and clusters being analysed. More details of the clustering analysis are reported in Appendix A. The results of the clustering analysis and the selection of the optimal number of clusters are discussed in the results section of the article.

3. Italian case study

The previous chapter outlines the general model formulation and optimization process. This chapter focuses on the application case study, detailing the input variables, parameters, and decision variables selected for the case study which is the Italian energy system. Furthermore, it is important to emphasize that the purpose of the article is to test the proposed methodology on a case study, rather than to study in depth the

Table 4
Baseline 2019 main additional sources in the power sector to HRE project data [76].

Data	Source
Installed capacity for VRES	GSE [80], Terna [81]
Hourly distribution for VRES	GSE [80], Terna [81]
Installed capacity for other technologies	Terna [81], HRE [77]

decarbonization options and scenario results of the selected case study. The chapter is divided into two sections. The first section presents the assumptions made in the Baseline scenario, which represents the current state of the energy system. The Baseline was created for the year 2019, and the EPLANopt expansion capacity optimization model was run for the future target year 2050. The second section discusses the decision variables considered in the optimization problem.

3.1. Baseline 2019

A Baseline 2019 energy system is created based on Heat Roadmap Europe 4 (HRE4) [76]. A 2015 EnergyPLAN input file is provided by this project for 14 EU member countries (including Italy) [77]. Based on more precise data from Italian authorities: GSE [76], RSE [78] and Terna [79], this 2015 HRE4 baseline has been modified and updated to 2019 (see Table 4 for more details). The following publication [33] provides more information about the Baseline 2015.

The costs of various technologies have been updated using different sources. This previous study [33] lists all the different assumptions, emissions factors, technology costs, and fuel costs for the year 2050 in the Italian energy system.

3.2. Decision variables

The decision variables are the decarbonization measures on which the expansion capacity optimization is performed. The relevant decarbonization measures for the specific case study must be determined, considering the potential synergies between different sectors. It is also important to define their bounds. $dv_k^{(L)}$ corresponds to the current state of the decision variable while $dv_k^{(U)}$ is the upper bound and corresponds to its maximum potential.

The considered decision variables are listed in Table 5 and are chosen from different energy sectors.

- Onshore Wind power. Tröndle et al. [82] provide the technical potential of Onshore wind power for European countries.
- Offshore Wind power. Tröndle et al. [82] provide the technical potential of Offshore wind power for all European countries.
- Solar PV. For residential rooftop PV, a couple of studies, Taylor et al. [83] and Vartiainen et al. [84], together with internal studies of Eurac research based on the Solar Tyrol project [85] identified a share of 3 kW per person as maximum rooftop PV potential.
- Utility-scale PV. Tröndle et al. [82] provide the technical potential of Utility-scale PV for European countries.
- Electric storage. The maximum potential of lithium-ion batteries and hydrogen storage has been estimated through a series of simulations. It has been verified that a value higher than 500 GWh is typically not considered by the optimization because it brings a higher increase in costs without the balanced benefits in terms of renewable energy integration.
- The installation of heat pumps is allowed only after a deep energy refurbishment of buildings. This decision variable is the percentage of the overall buildings that have switched their heating system from boilers to heat pumps. For this reason, its maximum potential is 100%.
- The energy efficiency of buildings. The energy efficiency cost curve and the way it is implemented in the source code of EPLANopt are explained in a previous publication [27].
- The industry sector. Two decision variables are adopted in this field to replace the current fossil fuel consumption: electrification and adopting green gases. Thus, the system can substitute conventional fossil fuels in the industry sector depending on the share of electrification and green gases. A constraint is introduced to guarantee that the sum of the share of electrification and the share of green gases do not exceed 100%. The cost of green gases is assumed equal to 150 €/MWh [86,87].

Additional assumptions were made regarding the heating sector: the domestic hot water (DHW) in buildings that are connected to the district heating network is supplied by the district heating itself. For individual buildings, there are two separate demands: one for DHW and another for heating. Energy efficiency measures can decrease the heating demand, but they do not impact the DHW share. The optimization process determines the proportion of renovated buildings that should install heat pumps. In the individual sector, at the increase of the energy efficiency share, heat pumps substitute different types of boilers with the following priorities: 1) Coal boilers, 2) Oil boilers, 3) Electric boilers, 4) Natural gas boilers and 5) Biomass boilers.

The expenses associated with the establishment of electric vehicle charging infrastructure have been accounted for in the model. Based on the research conducted by Enel foundation [88], the cost of electric vehicle infrastructure was calculated for various levels of battery electric vehicle adoption. These costs encompass the cost of infrastructure for both urban and suburban areas, as well as the costs of different types of charging stations. Further details and the method used for interpolation are described in a prior publication [33].

The model also incorporates a decrease in energy consumption from the industrial sector. Utilizing historical data from the Odyssee-Mure database [89], a logarithmic interpolation was applied to examine the energy efficiency trend for the industrial sector in a "business as usual" scenario. This leads to a 15% decrease in energy consumption by 2050 compared to the energy consumption in 2019.

The following additional assumptions have also been made:

1) a constant demographic situation from 2019 to 2050,
2) transport demand in terms of miles driven and mode of transportation are assumed to be constant,

Table 5
List of decision variables per sector and type, their current state $dv_k^{(L)}$, their maximum potential $dv_k^{(U)}$.

Sector	Type	Name	Unit	Current state, $dv_k^{(L)}$	Maximum potential, $dv_k^{(U)}$
Power sector	Generation source	Residential photovoltaic	GW	15.8	178
		Utility-scale photovoltaic	GW	4.2	119
		Wind power	GW	10.2	68
		Offshore wind power	GW	0	46
	Balancing & storage	Batteries	GWh	0	500
		Electrolyzer	GW	0	50
		Fuel cell	GW	0	50
		Hydrogen storage	GWh	0	500
Heating sector	Energy refurbishment	Energy efficiency	%	0	60
	Generation source	Heat pumps	%	0	100
Industry sector	Generation source	Electrification	%	0	100
		Green gases	%	0	100

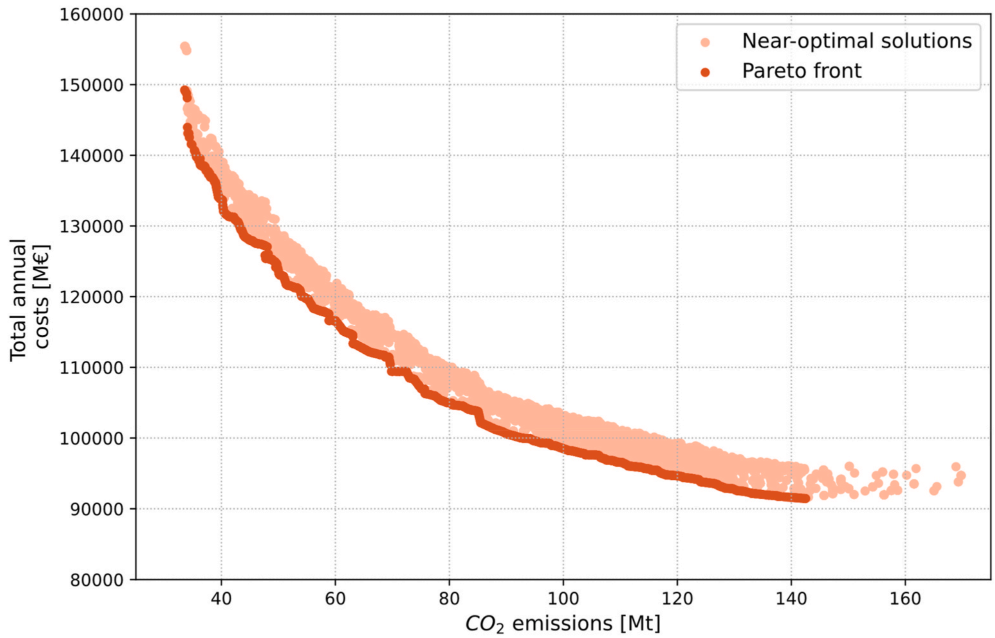

Fig. 2. Pareto front optimal and near-optimal solutions for the Italian case study in 2050.

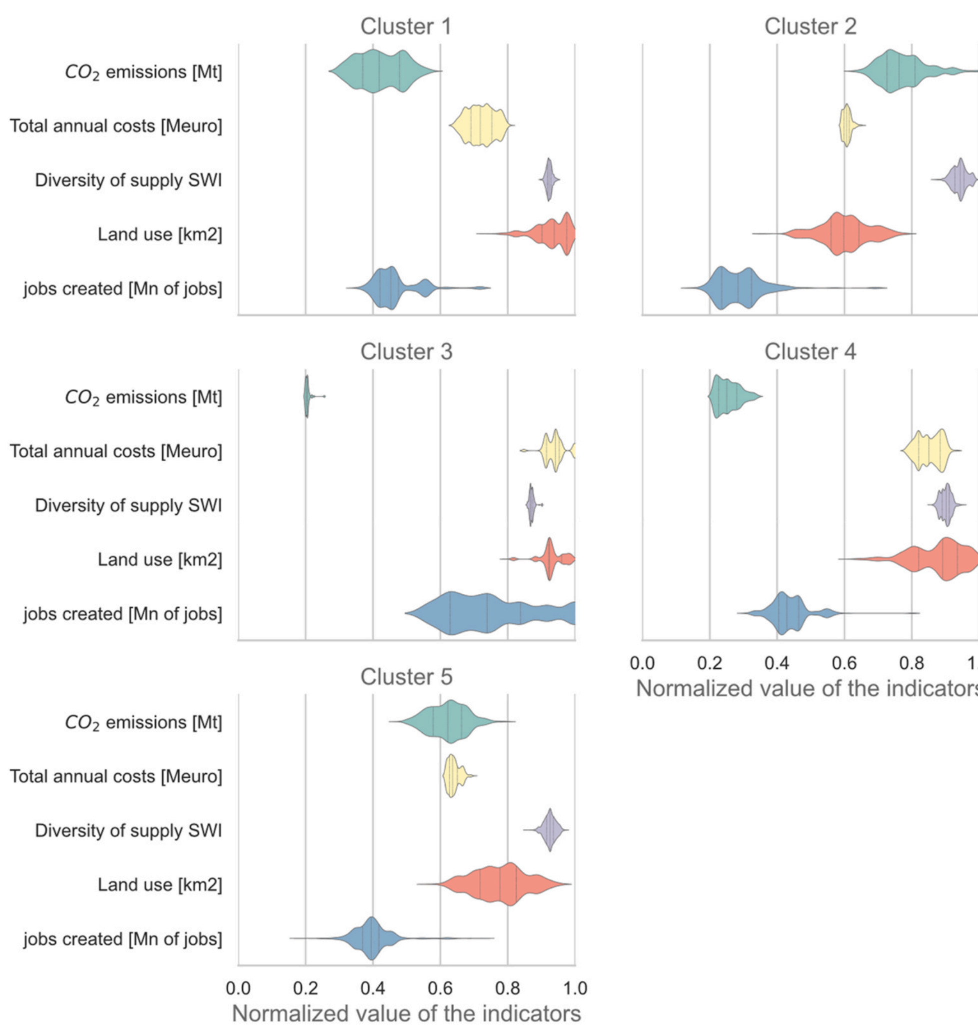

Fig. 3. Results of the clustering analysis with five clusters.

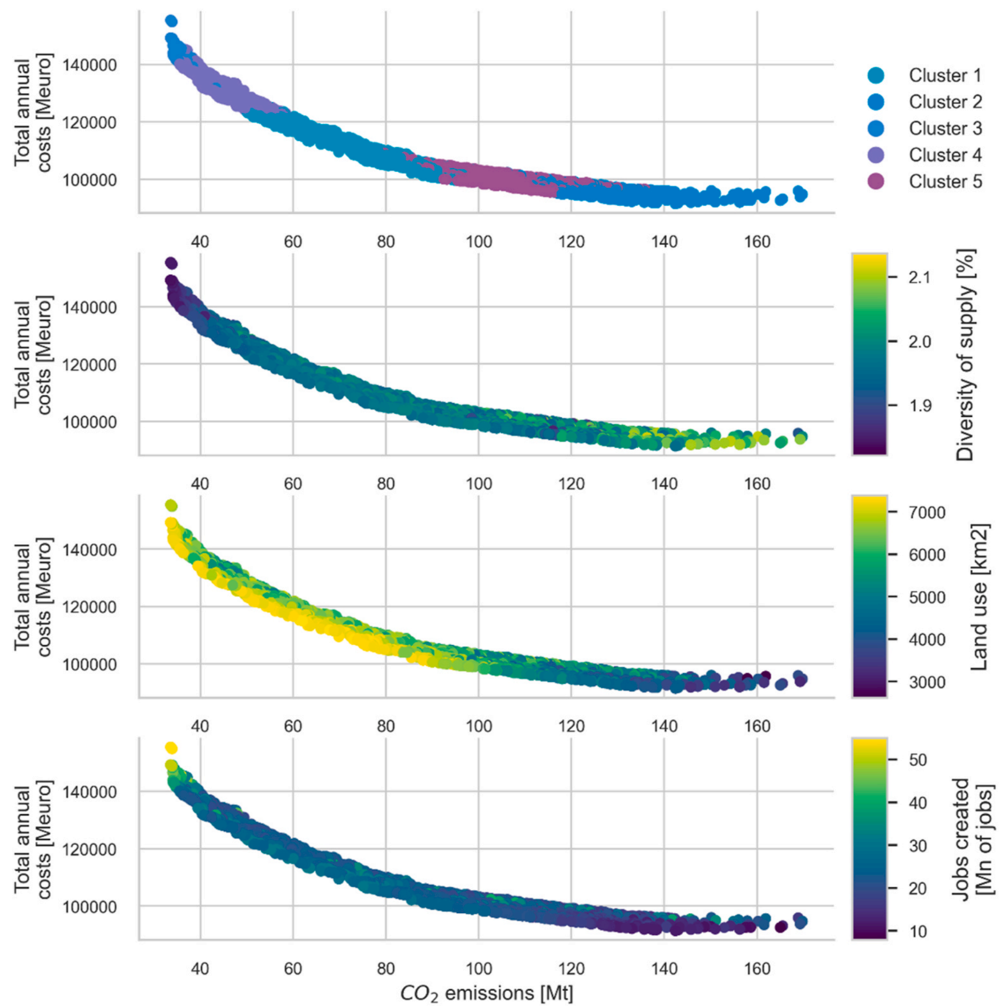

Fig. 4. Results of the clustering analysis with five clusters among all optimal and near-optimal solutions (first subplot on the top), the values of diversity of supply for all these solutions (second subplot from the top), the land use for each of these solutions (second subplot from the bottom) and jobs created (first subplot from the bottom).

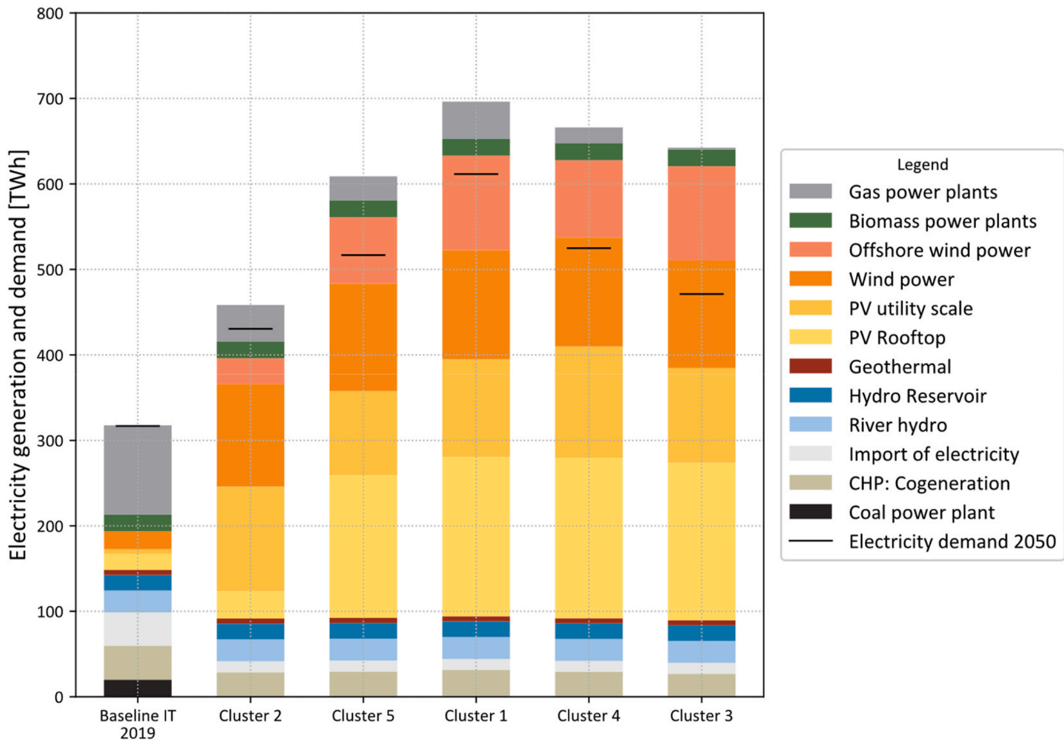

Fig. 5. Electricity generation mix in the closest solutions to centroids for each cluster.

3) fixed proportions of battery electric vehicles have been assumed for the future target years (100% for the year 2050),
4) complete elimination of coal and oil by 2030,
5) learning curves for certain key technologies are based on data from past years. Based on different publications on the development of these learning curves in the years to come average data have been calculated for 2050 [33].
6) trends in electricity costs are not considered, electricity prices are assumed to remain constant,
7) emission factors are taken from IPCC (biomass emission factor is equal to 0),
8) electricity consumption accounts for losses in the grid and
9) costs of electric vehicles are assumed to be equal or lower than the costs of conventional cars by 2050 (Bloomberg in the electric vehicle outlook of 2018 [90]).

Additionally, the calculation of final energy consumption only accounts for combustion processes, with emissions from fermentation processes not taken into account, and the consequences of global warming, rebound effect and disruptive technologies are not considered.

4. Results and discussion

In this study, we aimed to explore the near-optimal solutions and their relevance in energy planning. To achieve this, we applied the proposed methodology to the Italian case and evaluated energy system scenarios from a selection of optimal and near-optimal solutions. The results of our analysis are presented in the following section.

Fig. 2 shows the resulting Pareto front of the optimal solutions and the near-optimal solutions for the Italian case in 2050 in a chart with total annual costs on the y-axis and annual CO_2 emissions on the x-axis. The Pareto front represents the trade-off between the total annual costs and the annual CO_2 emissions and provides a visual representation of the different near-optimal solutions that are available. The near-optimal solutions are the points that are located close to the optimal solution and provide alternative options that are only slightly more expensive or emit slightly more CO_2. These solutions represent a diverse range of options that can support and guide policymakers in their energy planning efforts. The optimal and near-optimal solutions found are in total 8434.

Fig. 3 presents the results of the clustering analysis applied to the optimal and near-optimal solutions for the Italian case study. The clustering analysis considered five indicators: total annual costs, annual CO_2 emissions, land use, job creation, and energy supply diversity. Using the elbow method and Silhouette score as described in Appendix A, five clusters were identified as the optimal number for this analysis.

The five clusters shown in Fig. 3 represent a range of options that policymakers can consider when evaluating energy system scenarios. Cluster 2 represents the solutions with the lowest CO_2 emissions reduction, the lowest total annual costs, and the best diversity of supply. This cluster could be a suitable option for policymakers who prioritize cost savings and energy supply diversity over reducing CO_2 emissions. On the other hand, Cluster 3 represents the solution with the highest CO_2 reduction, the highest total annual costs, the worst diversity of supply, and the highest land use and job creation values. This cluster could be a suitable option for policymakers who prioritize reducing CO_2 emissions and creating jobs but are willing to accept higher costs and less diversity of energy supply.

The other clusters, 1, 4, and 5, represent solutions that fall in between the extremes of Clusters 2 and 3. Cluster 5, for example, has lower CO_2 emissions than Cluster 2 but higher costs, worse values of diversity of supply and land use and better in terms of jobs created. Cluster 1 has lower CO_2 emissions than Cluster 5, higher costs, worse values of diversity of supply and land use and better in terms of jobs created. Cluster

4 has lower reduction of CO_2 emissions compared to cluster 3, lower costs, better values in terms of diversity of supply and land use but worse in terms of jobs created.

Overall, the results of the clustering analysis show the diversity of near-optimal solutions available for energy planning in the Italian case study. The results highlight the trade-offs between different indicators, and how policymakers can prioritize different objectives depending on their policy goals and constraints. The analysis also provides a way to bridge the gap between simulation and optimization approaches and support policymakers in evaluating energy system scenarios from a selection of optimal and near-optimal solutions.

Fig. 4 consists of four subplots, where the first one displays the clustering results in the CO_2-costs chart. It indicates that the clusters are nearly sequential from low to high CO_2 emissions reduction, with clusters 2, 5, 1, 4, and 3 arranged from right to left. The second subplot represents the diversity of supply for all optimal and sub-optimal solutions, showing a decline in supply diversity from right to left. This is because solutions with high CO_2 emissions reduction involve extensive installation of few variable renewable energy technologies, resulting in a reduction of electricity generation from conventional power plants. As a consequence, land use increases from right to left due to the significant ground occupied by renewables, leading to an increase in land use indicator values. Similarly, jobs created by the installation of renewables also rise from right to left due to the same reason. Overall, the figure suggests that high CO_2 emissions reduction comes at a cost of decreasing supply diversity, increasing land use, but also correlates to an increase in and job creation.

The results presented in Fig. 4 have important implications for policymakers in terms of designing and implementing effective energy policies. Policymakers can use the clustering results in the CO_2-costs chart to identify the most cost-effective clusters that can achieve the desired level of CO_2 emissions reduction. The decline in supply diversity and increase in land use and job creation associated with high CO_2 emissions reduction should also be considered by policymakers when designing energy policies. They need to balance the trade-off between CO_2 emissions reduction and the impacts on supply diversity, land use, and job creation. Policymakers may consider implementing policies that encourage the deployment of a diverse range of renewable energy technologies to maintain a balanced energy mix and avoid over-reliance on a single technology. Moreover, policies that promote the development of low-carbon technologies with low land use requirements can help mitigate the impact on land use. Finally, policymakers can take into account the potential increase in job creation associated with high CO_2 emissions reduction to create employment opportunities and support the transition to a low-carbon economy.

In Fig. 5, the electricity generation and demand for the baseline and each cluster's closest scenario result are displayed. Moving from lower to higher CO_2 emission reductions, the electrification of transport, heating, and industry sectors leads to an increase in electricity demand, along with a rise in electricity generation from variable renewable energy sources. Despite the reduction in gas power plant generation compared to the baseline, it does not vanish. The last two clusters with the highest CO_2 emission reductions experience a decrease in electricity demand, primarily due to investments in green gases in the industry sector instead of electrification, which is costlier for the system. Furthermore, the generation of electricity from gas power plants decreases due to high variable renewable energy source generation and storage options' investments, which raise the system's costs.

5. Conclusions

In this study, we proposed a novel modelling approach to support the optimal planning of energy systems. This approach integrates multi-objective optimization, near-optimal solutions evaluation, the application of environmental and socio-economic indicators and clustering analysis to better understand the dynamics between main decarbonization measures. The method has been applied to the Italian case study and scenario results for the year 2050 have been developed.

The results of the application of our approach showed that it is possible to achieve a significant reduction in CO_2 emissions and improve the diversity of energy supply while minimizing the overall system costs. Our approach also allowed us to identify different clusters of optimal and sub-optimal solutions, which provided insights into the trade-offs between different objectives and the role of different renewable technologies in achieving these objectives.

The analysis of the environmental and socio-economic indicators also revealed the importance of considering these aspects in the planning of renewable energy systems. We found that the expansion of renewable energy systems can have both positive and negative impacts on the environment and society, depending on the technology mix and the location of the installations. Our approach provided a useful tool to evaluate these trade-offs and identify optimal and near-optimal solutions that minimize negative impacts and maximize positive ones.

Overall, the results of our study demonstrate the effectiveness of exploring near-optimal scenario results and supporting the optimal planning of renewable energy systems at the national level through additional indicators. Our approach can be applied to other countries and regions to support the transition to a more sustainable and low-carbon energy system and could in future studies be expanded to include additional indicators.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. clustering analysis

In this appendix, we provide a detailed explanation of the clustering analysis conducted in the study to identify the optimal number of clusters for the Italian case study. We used two methods, namely the elbow method and the silhouette score indicator, to determine the number of clusters that would best represent the data.

Figure A1 shows the elbow method's results for a variable number of clusters. This allows us to identify a first range for the optimal number of clusters in the range of 4 and 18. The elbow method is a common technique used to identify the optimal number of clusters in clustering analysis. It is based on the observation that the variance explained by the clusters increases with the number of clusters, but at a certain point, the gain in variance explained decreases significantly. This point is called the elbow point and represents the optimal number of clusters.

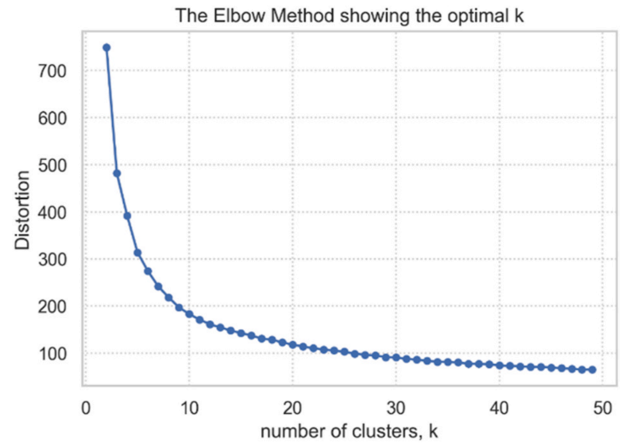

Fig. A.1. Results of the clustering analysis with six clusters.

Figure A2 shows the values of the silhouette score for a variable number of clusters. The silhouette score measures the quality of the clustering and ranges from −1 to 1, where a score of 1 indicates that the data point is well-matched to its own cluster and poorly matched to neighbouring clusters. We identified the optimal number of clusters to be five based on the highest average silhouette score in the range between 4 and 18.

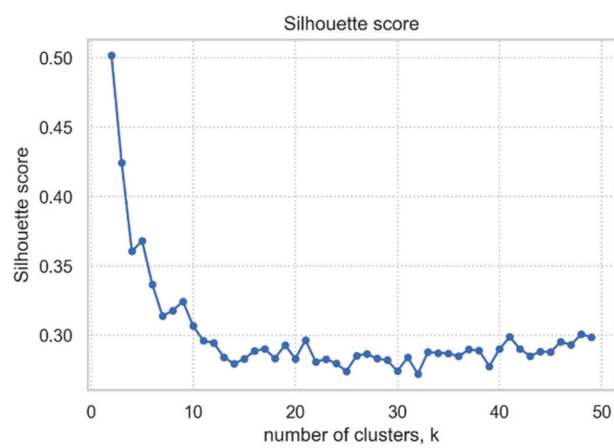

Fig. A.2. Results of the clustering analysis with six clusters.

Figure A3 reports the characterization of the clusters for a variable number between 4 and 18. We used the k-means clustering algorithm to create the clusters and characterized them based on the values of the indicators (total annual costs, annual CO_2 emissions, land use, job creation, and energy supply diversity). In the chart, the x-axis shows the silhouette score values, while the y-axis shows the cluster labels. Each bar on the chart represents a solution, and the colour indicates the corresponding cluster. The distribution of the bars in the chart can give insights into the quality of clustering. Ideally, the chart should show distinct, well-separated clusters with a high average silhouette score. The chart also includes a breakdown of the composition of each cluster. This can help to understand the characteristics of each group and how they differ from one another.

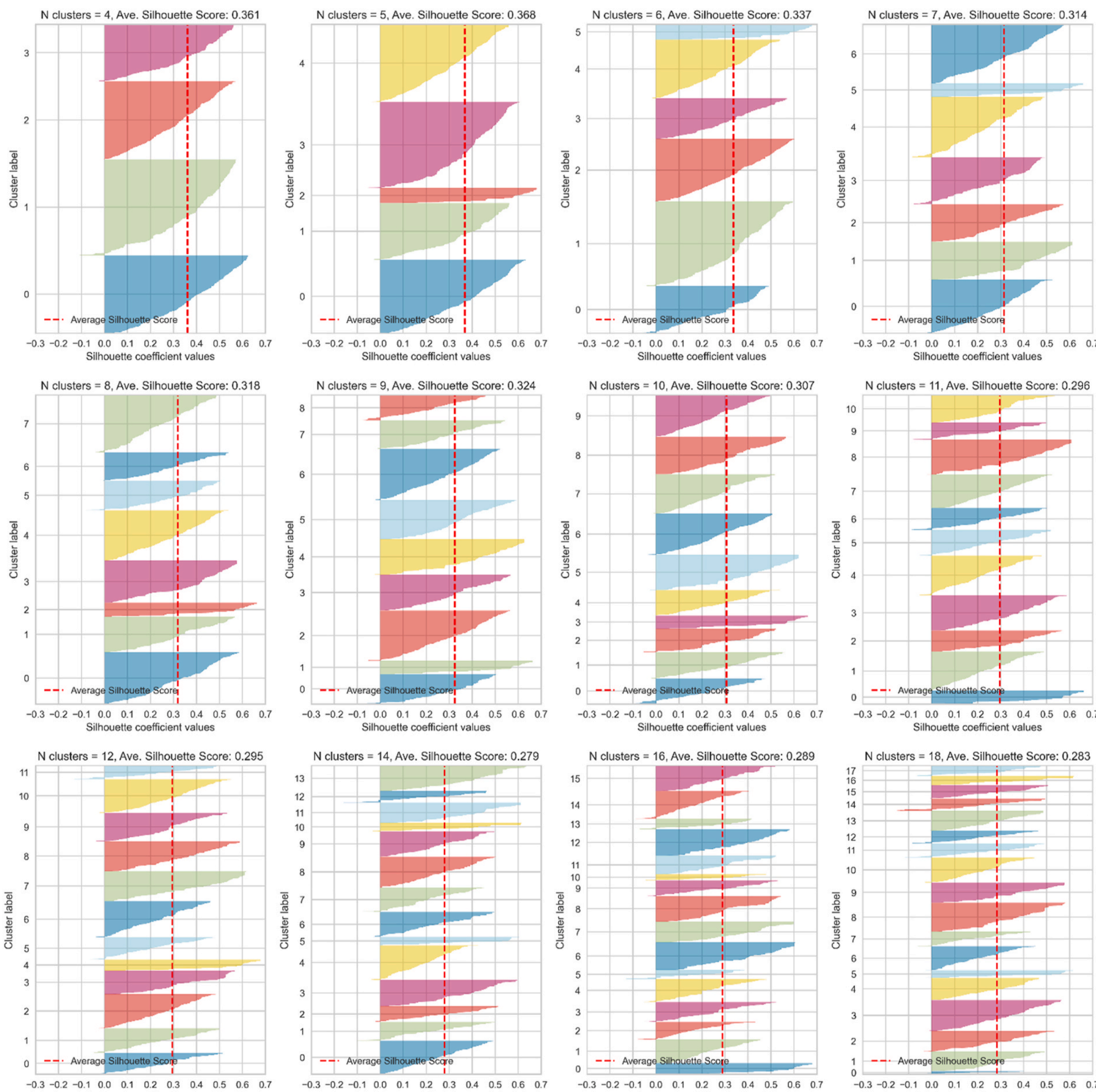

Fig. A.3. Results of the clustering analysis with six clusters.

Figure A4 shows the results of the clustering analysis with five clusters through a violin plot that displays the values of the indicators for each cluster. The violin plot provides a visual representation of the distribution of the data and allows us to compare the clusters based on their values for the different indicators. Overall, this analysis allowed us to identify distinct groups of solutions based on their characteristics and helped us to draw meaningful conclusions from the results.

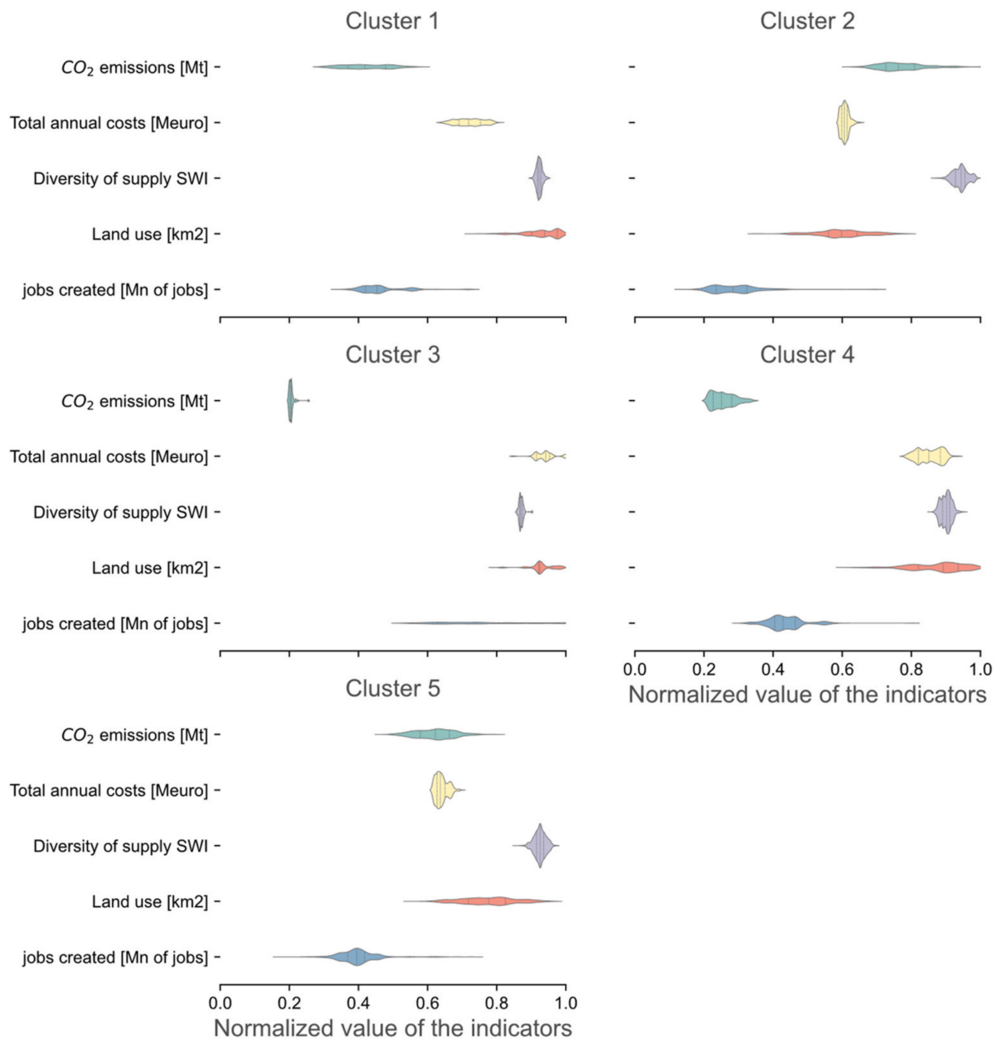

Fig. A.4. Results of the clustering analysis with six clusters.

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