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Research paper

How much do carbon emission reduction strategies comply with a sustainable development of the power sector?

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ABSTRACT

Current efforts toward the necessary energy transition are predominantly focused on climate change mitigation in relation to decarbonization measures, mainly on the energy sector, but may not succeed in satisfying the goals of reaching the full sustainability of human activities, which should foster social equity, economic stability, and security of supply. Energy System Optimization Models, used as a key tool in guiding energy transition strategies through the formulation of energy scenarios, mostly focus on economic aspects and emissions reduction objectives only, completely neglecting the critical issues of the multifaceted "sustainability" concept. In response to that, the aim of this research is to develop an all-encompassing metric for evaluating the sustainability of decarbonization scenarios. It incorporates twelve key indicators pertaining to environmental, social, and security dimensions that are weighted and combined into a sustainability index (SI) for evaluating power sector technologies. The open-source TEMOA-Italy model is employed to create a baseline scenario and a decarbonization scenario. The computed evolution of the power sector is evaluated through a singular, multi-dimensional SI trend, enabling the monitoring of sustainability progress over time. The impact of alternative prioritization of the various sustainability factors is analyzed by exploring thousands of weights assigned to those factors within the SI. The obtained SI profiles are analyzed employing both unsupervised and supervised data analytics techniques, with the aim to extract and characterize the most representative patterns in terms of profile magnitude and trend. Eventually, explainable artificial intelligence (XAI) methods are implemented to understand the set of key indicators that mostly affect those two features of the SI profile. It turns out that the reliability of power system, geopolitical considerations, and land use play a pivotal role in influencing the SI trend and magnitude.

1. Introduction

The decarbonization of the global economy requires addressing significant challenges, including energy saving, emission reduction, and the formulation of sustainable development pathways (Fawzy et al., 2020). Decarbonization strategies, pivotal in reducing emissions, encompass the development and implementation of actions aimed at reducing CO2 emissions across various sectors (Papadis and Tsatsaronis, 2020) These might include, according to the sector, renewable energy adoption, energy efficiency measures, carbon capture and storage or switching to carbon free primary fuels (IEA, 2022a). Within the framework of sustainable development, emission reduction usually serves as a necessary but not exhaustive (Fader et al., 2018) proxy for more comprehensive goals. The terms 'sustainability' and 'sustainable development' are frequently employed in both scientific literature and public policy in relation to the energy system. The presence of these terms has been recently emphasized with the introduction of the United Nations Sustainable Development Goals (SDG) (United Nations UN, 2022). However, there is still no consensus on standardized terminology and measurement metrics for these objectives, attributable to the broad range of existing interpretations and definitions (Barbosa et al., 2014). In its basic meaning, sustainability refers to a system's capacity to self-sustain at a certain level for a specified period. It is based on the principle that utilizing natural resources for current needs should not compromise the ability of future generations to meet their needs. Sustainability encompasses a spectrum of interdependent variables that integrate social, energy, security, economic, and environmental issues

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Nomenclature

Acronyms

AP	Acidification Potential
CHPR	Combined Heat to Power Ratio
EP	Eutrophication Potential
ESOM	Energy System Optimization Modeling
ETSAP	Energy Technology System Analysis Program
GHG	Greenhouse gas
GWP	Global Warming Potential
IAM	Impact Assessment Method
IEA	International Energy Agency
IAEA	International Atomic Energy Agency
LCA	Life Cycle Assessment
LCI	Life Cycle Impact
LCIA	Life Cycle Impact Assessment
LU	Land Use
MAVT	Multi-Attribute Value Theory
MCDA	Multi-Criteria Decision Analysis
MOO	Multi-Objective Optimization
NEEDS	New Energy Externalities Development for Sustainability
RES	Reference Energy System
PSI	Political Stability Index
PWR	Pressurized Water Reactor
SDG	Sustainable Development Goals
TSI	Technology Sustainability Index
TSS	Technology Sustainability Score
WEC	World Energy Council
WU	Water Use
A	Activity, or total output commodity flow
AS	Activity Share
CF	Capacity Factor
ER	Emission Reduction
GR	Growth Rate
$\overline{GR}$	Average Growth Rate
I	Parameter associated to indicator, $\mathbf{I} \in \mathbf{IND} = \{\mathbf{GWP}, \mathbf{AP}, ..\}$
LT	Lifetime
SS/SI	Overall Sustainability Score (or Sustainability Index)
W	Weight (associated with the sustainability dimension)
W	Weight (associated with the sustainability indicator)
H	Efficiency

Indices

I	Indicator index, $i \in IND = \{GWP, AP, ..\}$
J	Year index, $j \in J = \{\text{ESOM milestone years}\}$
K	Sustainability dimension index, $\mathbf{k} \in \mathbf{K} = \{\mathbf{Environment}, \mathbf{Equity}, \mathbf{Security}\}$
N	Lifecycle phase index, $\mathbf{n} \in \mathbf{N} = \{\mathbf{Construction}, \mathbf{Operation}, \mathbf{Decommissioning}\}$
NORM	Normalized
T	Technology index, $\mathbf{t} \in \mathbf{T} = \{\mathbf{Coal\ steam\ turbine}, \mathbf{Oil\ steam\ turbine}, ..\}$

(Apergis and Payne, 2010; Ntanos et al., 2018; Marinescu and Cicea, 2015). Sustainable development, therefore, can be defined as a pathway toward achieving sustainability as a long-term objective (Costanza and Patten, 1995). Consequently, it becomes crucial to consider synergies and trade-offs between emission reduction and broader sustainable development objectives.

However, the intricate nature of planning sustainable development paths in this domain presents substantial obstacles. First, a clear definition of sustainability is difficult to establish due to its multifaced and dynamic nature (Programme and On Governance, 2023). In the energy field, the existing literature extensively discusses sustainability, and although specific aspects may vary, there is a consensus on its broad scope. The existence of an environmental dimension is recognized, in relation to global warming, deforestation, air, land, and water pollution (Armeanu et al., 2021; Gayen et al., 2023), as well as an economic dimension accounting for profitability and affordability of energy (IEA, 2022a; United Nations UN, 2023a). In addition, there is increasing attention at the technical capacity of the system to provide energy (Debnath and Goel, 1995) and its security, both in the short term (grid security) and in the long term (geopolitical trades) conditions (Bompard et al., 2017). Finally, an emerging paradigm in several analyzed studies is the social sustainability, referred to as the effect of energy in society, comprehensive of aspects as acceptability and social impact (Algunaibet et al., 2019; Wüstenhagen et al., 2007). The sustainability ingredients commonly considered in the sustainability assessments are summarized in Table 1. It is then expected that a study, moving from the existing state of the art, should incorporate those elements as essential components when assessing the sustainability of energy systems.

Several selected studies (Nock and Baker, 2019; Buchmayr et al., 2021) have sought to incorporate indicators within the Social and Economic dimensions to address the capability of the energy system and grid to ensure a secure supply (internal factors), as well as concerns

Table 1
Review of current literature on Sustainability Assessment in the energy field.

Economic	Environmental	Technical	Social	Security	Year	Source
v	v		v		1997	(Suding, 1995)
v	v		v		1999	(Streimikiene et al., 2007)
v	v	v	v		2009	(Evans et al., 2009)
v	v	v	v		2012	(Iddrisu and Bhattacharyya, 2015)
v	v	v	v		2014	(Liu, 2014)
v	v	v	v		2014	(ESMAP and World Bank Group, 2024)
	v	v	v		2015	(Kılkış, 2018)
v	v			v	2016	(Teresa García-Álvarez et al., 2016)
v	v	v	v		2017	(Martín-Gamboa et al., 2017a)
v	v				2019	(Campos-Guzmán et al., 2019)
v	v	v	v		2019	(Nock and Baker, 2019)
v	v	v			2020	(Ranjbari et al., 2021)
v	v	v			2021	(Buchmayr et al., 2021)
v	v			v	2022	(Madurai Elavarasan et al., 2022)
v	v	v		v	2022	(Gunnarsdottir et al., 2022)
v	V	v	v		2022	(Saeid Atabaki et al., 2022a)

related to the safety of the energy supply chain (external factors). These considerations have further gained significance due to recent events such as the Ukrainian war (Zhou et al., 2023; Helbig et al., 2021a) and material crises (Helbig et al., 2021a), which have independently highlighted the importance of energy security. As a result, it is crucial to explicitly include this dimension, previously hidden in other categories, and allocate specific attention to it to achieve a comprehensive sustainability assessment. Also, an Economic and the Technical dimensions is to be considered.

To evaluate the evolution of the energy system and the expected energy transition, several tools are available characterized by different for sectorial coverage, time horizon and time steps, spatial scale and modeling method (Chang et al., 2021). Among them, Energy System Optimization Models (ESOMs) feature a detailed techno-economic description of the main technologies (or processes) belonging to the most energy-intensive sectors of the system. They are optimization models evaluating the minimum-cost configuration of the system (Loulou et al., 2022), according to the studied alternative socio-economic and policy scenarios and to the technology modules included in the model. Given such features, ESOMs have been widely used to assess the effects of decarbonization strategies or innovative technologies, focusing on several sectors (i.e., transport (Lerede et al., 2020), industry (Lerede et al., 2021), hydrogen (Balbo et al., 2023)) and regions (e.g., Belgium (Limpens et al., 2020), US (Eshraghi et al., 2018), EU (Barnes et al., 2022), World (Sofia et al., 2013a); Lerede et al., 2023). However, environmental issues are usually considered in ESOMs through the computation of greenhouse gas (GHG) emission levels only, while the interest for the overall sustainability of the energy system is raising (United Nations UN, 2023b), aiming to go beyond the mere impact on climate change. In this regard, it is important to observe that, in some cases, the decarbonization of energy systems may conflict with other essential sustainability aspects (Luderer et al., 2019). First, the energy sector is responsible for environmental impacts, such as water consumption, land occupation and air pollution (Luderer et al., 2019). Secondly, the electricity grid evolution required by the decarbonization presents geophysical, techno-economic, socio-cultural, institutional, and ecological issues, which in turn limit the capability to integrate clean energy resources without impacting other areas, as the conservation of land and water resources, protection of terrestrial and aquatic ecosystems, and preservation of cultural sites ((Su et al., 2021); Best, 2018; Wu et al., 2020, 2023). Furthermore, a sharp transition towards a low-carbon system could reduce energy reliability (IEA, 2018). For example, the intermittent nature of renewable energies generation creates demand fluctuations, often resulting in a mismatch between generation and demand, challenging grid stability (IEA, 2024). Finally, with the increasing penetration of renewable energy sources, emissions and resource consumption are shifted from the operational phase of the plants to the other steps of the production chain (Gibon et al., 2015), highlighting the necessity of a holistic impacts accounting framework as the Life Cycle Assessment (LCA) (ReCiPe, 2022). Therefore, robust capacity planning should complement the current economic-oriented paradigm by including sustainability dimensions to account for the above-mentioned aspects.

In the currently existing literature, alternative approaches exist allowing the integration of sustainability-related aspects within energy models. Attempts have been performed in the direction of a direct integration of sustainability paradigms in the optimization strategy (endogenous integrations), or by conducting sustainability assessments on the outcomes of energy models (ex-post analysis) (Blanco et al., 2020). Endogenous integrations can be realized by integrating sustainability variables in the energy model, subsequently performing a traditional economic optimization, a Multi-Objective Optimization (MOO), or an impact monetization (NEEDS, 2022). In the MOO, one or more target functions related to the sustainability aspects are integrated directly within the ESOM instance and optimized together with the traditional economic objective function. The different objectives can be integrated in the same formulation (weighted sum method (Kotzur et al., 2021)) generating a single solution, or computed separately, obtaining in both cases a Pareto front to estimates trade-offs between different objectives (Junne et al., 2021). In (Saeid Atabaki et al., 2022b), for instance, integrated social (job creation, human health, diversification) and environmental (water and land use, acidification, and global warming) criteria are considered in an ESOM together with the economic objective function in a weighted sum approach, analyzing scenarios for the Iranian power system up to 2050. The main limitation consists in the fact that the final solution is a compromise between the different objectives, strongly depending on their weighting (exogenously assigned). Moreover, the complexity of the model leads to a high (computational cost. In the impact monetization, economic damages of the different impacts considered in the analysis are quantified and subsequently integrated in the economic objective function of the model (Rafaj and Kypreos, 2007). Monetization of impacts is well-established in the context of power models, such as the NEEDS (NEEDS, 2022) and the ExternE (Spadaro and Rabl, 1998) European frameworks. Advantages are related to the adaptability of this method to already-existing modeling frameworks by a simple reformulation of the objective function, without the necessity to develop new and complex optimization tools (García-Gusano et al., 2016). The main disadvantages concern the uncertainties related to the monetization process, particularly social and security impacts.

Traditional models that rely on a single economic objective function are, on the contrary, very widespread, and lack a sustainability accounting dimension. Simple ex-post analyses, in which ESOMs results are integrated with LCA impacts databases to establish the energy system footprint, are already available in literature. Among them, (Blanco et al., 2020) developed an ex-post LCA analysis of results by the JRC-EU TIMES model (Sofia et al., 2013b) and estimated the environmental impact indicators across 18 categories in scenarios that achieve 80–95% CO2 emission reduction by 2050. A relevant outcome is the qualitative evaluation of the analyzed policies for each impact class. This may serve as a tool for policymakers in establishing the pros and cons of a strategy, but still lacks a unique quantitative method to identify the best alternative among a wide set of impact classes. Also, the authors of (Luderer et al., 2019) analyzed with a quantitative decision-making tool twenty European energy scenarios characterized by different degrees of decarbonization for twelve LCA environmental impact classes, concluding that there is a co-benefit between emission reduction and mitigation of environmental impacts. A consistent limitation of that study is related to the adoption of the LCA parameters as unique sustainability paradigm since the latter should not be restricted to the environmental component only (United Nations UN, 2022). Indeed, a useful decision-making tool, able to link the decarbonization targets of the energy models with their implications in terms of sustainability, should rely on a comprehensive metric, encompassing a comprehensive range of aspects (Namany et al., 2021). However, a robust, holistic, and flexible methodology that identifies to what extent power sector decarbonization strategies can be considered sustainable is still missing.

This paper aims to provide a comprehensive metric to measure the sustainability of decarbonization strategies. Environmental, social and security aspects have been included in a sustainability index (SI), by considering twelve parameters for the characterization of power sector technologies. Note that the inclusion of an Economic and the Technical dimensions is a minor concern here, since in ESOMs these components are already considered during the optimization process. A tool has been developed and implemented to apply such index to ESOMs results, and unlike other studies, the metric has then been tested evaluating the resulting technology mix. In particular, the open-source TEMOA-Italy model (Nicoli et al., 2022) has been used to generate a reference scenario and a decarbonization one. As the first novelty introduced by this study, the computed evolution of the power sector throughout the two scenarios is then translated into a unique multi-faceted SI trend for such scenarios, allowing the tracking of the sustainability evolution. As a second element of novelty, since different stakeholders may weight sustainability aspects differently according to their preference, the role of the weights assigned to the different aspects within the SI is assessed through a post-mining analysis. Specifically, several thousand combinations of weights associated to the indicators included in the calculation of the SI are analyzed through supervised and unsupervised data analytics techniques together with explainable artificial intelligence methods with the aim of extracting significant patterns explaining the role of specific indicators in influencing the sustainability score.

The proposed methodology and the outcomes of its application are presented respectively in Section 2 and Section 3. Finally, the results are critically discussed in Section 4 also in the light of future improvements.

2. Methodology

This section introduces the methodological framework for the development and the interpretation of the proposed sustainability index. According to Fig. 1.

- **TEMOA-Italy model and scenario definition**: The objective of this step is to define two different decarbonization scenarios by means of the TEMOA-Italy model. Section 2.1 provides details about the model set-upand its relevant outcome for the following analysis.
- **Identification of relevant sustainability indicators**: The objective of this step to identify the most relevant indicators to be considered for the development of the proposed Sustainability Index (SI). The selection process is detailed in In Section 2.2.
- **Development of Sustainability Index (SI):** The objective of this step is to develop the sustainability index through a structured combination and weighting of the previously identified indicators. Section 2.3 provides details about the mathematical formulation of the SI
- **Post mining analysis**: The objective of this step is to conduct a sensitivity analysis on the two evaluated decarbonization scenarios, to assess the impact of indicator weights on relevant features of the SI. Details about the employed data analytics techniques are reported in Section 2.4.

2.1. The TEMOA-Italy model and scenarios

ESOMs are generally based on a virtual representation of the energy system under analysis, named Reference Energy System (RES). The RES encompasses the description of the techno-economic features of all the technologies, commodities, and their interconnections throughout the different sectors of the system. Fig. 2 shows the main supply- and demand-side sector typically constituting each RES. Supply-side sectors (upstream and power sector) are devoted to the production of primary and intermediate energy commodities (such as fossil fuels, renewable potentials, electricity, heat, etc.) consumed by the demand-side of the energy system (buildings, transport, and industry) to satisfy final energy service demands. Such models are usually calibrated on a specific base-year, while the optimal configuration of the system (according to the minimum cost criterion) is evaluated for the future years according to the studied scenario.

The model selected for the present study is TEMOA-Italy (Release 3.0, (MAHTEP Group, 2023a)), developed within the TEMOA modelling framework (Nicoli et al., 2022; MAHTEP Group, 2023b). Since a specific methodology for emissions accounting was recently implemented in TEMOA-Italy and the model behaviour was precisely tested in a reference (Nicoli et al., 2022) and in a low emissions scenario (Colucci et al., 2023), this works aims to extend the analysis to evaluate the overall sustainability level for the evolution of the power sector computed throughout the two scenarios. The TEMOA-Italy RES represents the Italian energy system with a single spatial region and across a time horizon that spans from 2006 (base year) to 2050. A schematic representation of the TEMOA-Italy RES is provided in Fig. 3.

Energy imports/exports are modelled in TEMOA-Italy with a single technology per each imported/exported commodity, representing the average import/export price according to World Bank historical data (World Bank, 2023) and the World Energy Outlook 2022 future projections (IEA, 2022b). Constraints for imported and exported commodities are from Eurostat (Eurostat, 2022) for the historical period 2006–2020 and progressively relaxed for future years. The demand projection for future years is presented in (Oliva et al., 2021). The set of hurdle rates is from (Laera et al., 2024).

Together with the traditional energy sectors already reported in Fig. 2, TEMOA-Italy also includes technologies for hydrogen production (grey, blue, green, and yellow hydrogen, as reported in (Balbo et al.,

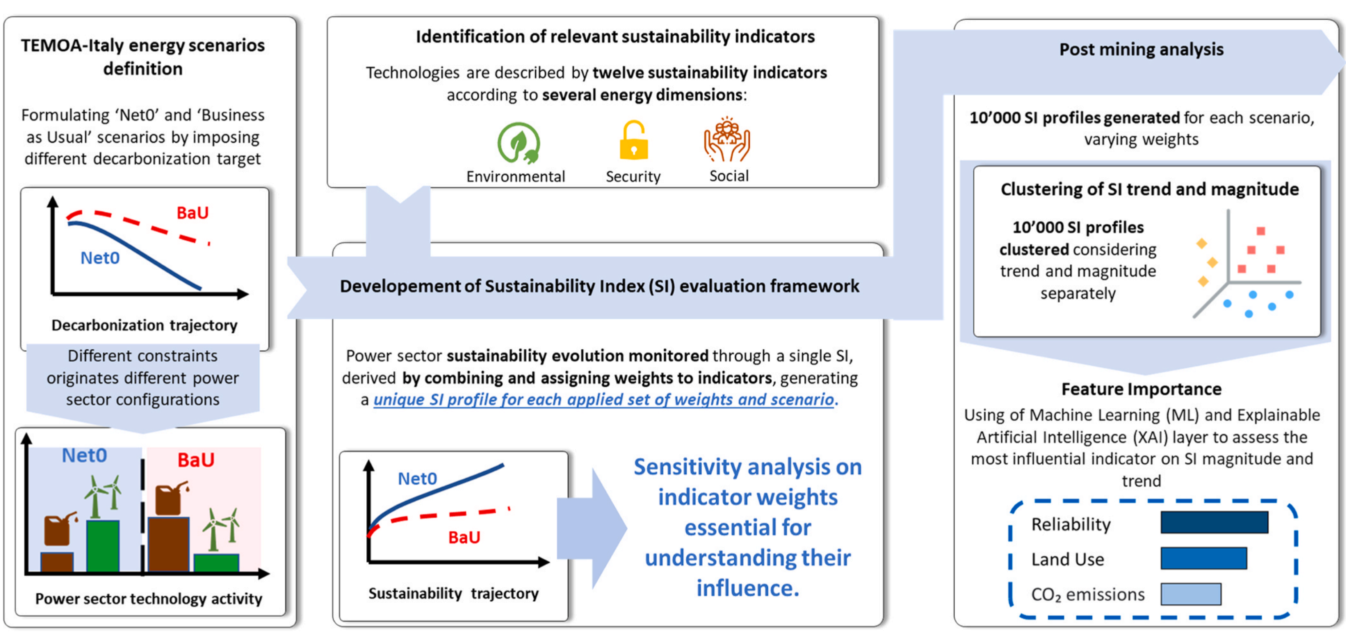

Fig. 1. Workflow of the methodology.

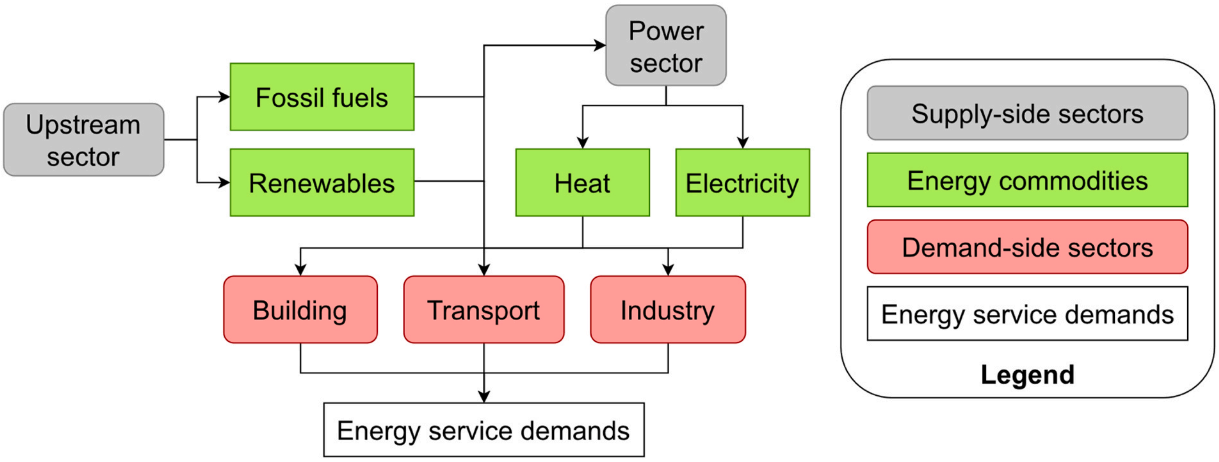

Fig. 2. Schematic representation of the general Reference Energy System of a bottom-up energy system optimization model (MAHTEP Group, 2023a).

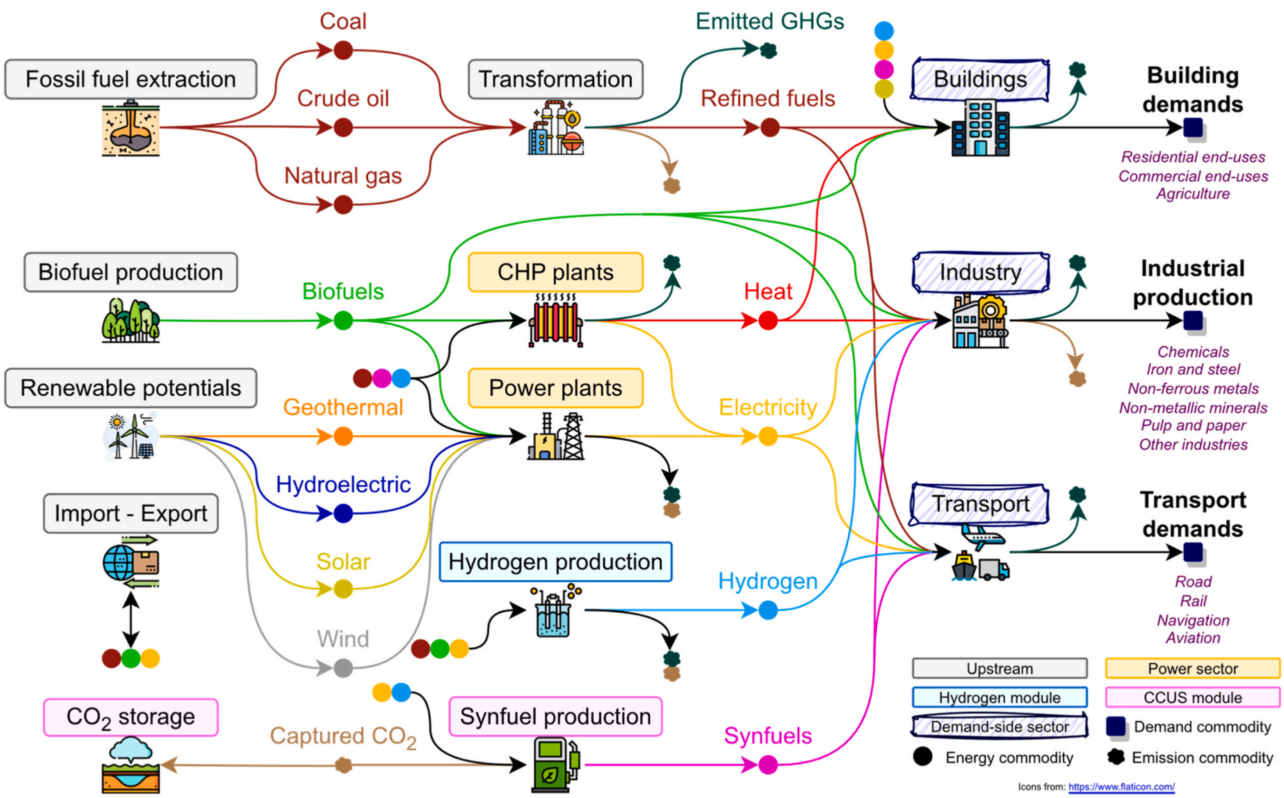

Fig. 3. The TEMOA-Italy Reference Energy System (Colucci et al., 2023).

2023)), final consumption (transport, industry and blending with natural gas) or transformation processes involving hydrogen. Indeed, the CCUS modules also includes synfuels production options (syndiesel, synkerosene, synmethanol, and synmethane) and technologies for CO2 capture and storage (as discussed in (Colucci et al., 2023) and (Colucci et al., 2022)).

Focusing on the power sector (the object of this study), Fig. 4 shows the main technology groups and their input/output commodities, also highlighting the connections with the other sectors of the model and, namely, the hydrogen and CCUS modules and the demand sectors (including electricity and heat consumption options). A major distinction in the power sector is present for existing and new technologies, since the same technology (e.g., natural gas combined cycle power plant) may present different parameters value (e.g., efficiency, capacity factor) according to its existing or new version. Table 2 shows a summary of the main parameters used for the existing technology modeling (as discussed in (Nicoli, 2022)), aggregated by plant category (power, CHP, and heat production plants) and input resource (more than one technology is associated to each resource). The capacity of existing technologies lead to a total gross capacity in 2006 equal to 91.80 GW (including heat plants), correspondent to statistics by TERNA (Ntanos et al., 2018).

The complete techno-economic characterization of new technologies is available in Table 2. While the overall technology categories are power plants (devoted to electricity production), CHP and micro-CHP plants (devoted to combined electricity and heat production) and heat plants (devoted to heat production), several technology options are available. More specifically, the possible energy inputs for the TEMOA-

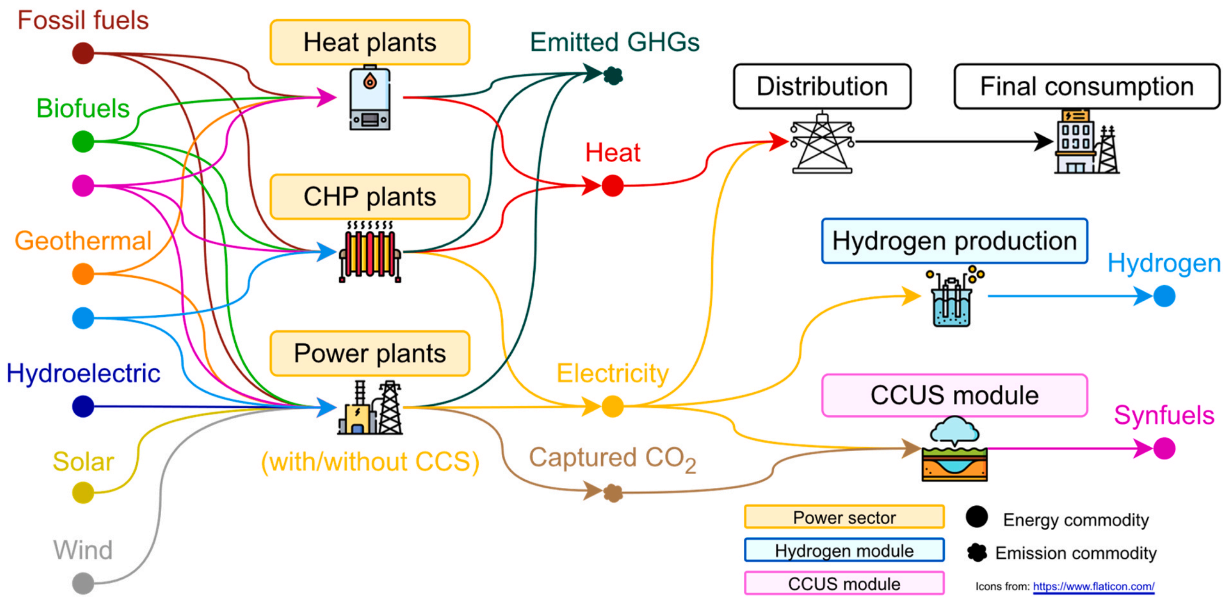

Fig. 4. The power sector as represented in TEMOA-Italy.

Table 2
Techno-economic characterization of existing technologies in the TEMOA-Italy power sector (MAHTEP Group, 2023a).

Category	Resource	Efficiency (%)	Existing Capacity (GW)	End of Life	Fixed O&M Cost (M€$_{2009}$/GW)	Variable O&M Cost (M€$_{2009}$/PJ)	Capacity Factor (%)
	Coal	32	7.73	≈ 2030	31	0.46	
	Oil Products	35	9.28	≈ 2030	32	0.47	
	Natural Gas	46	28.03	≈ 2050	18	0.49	
	Biofuels	27	0.76	≈ 2030	13	0.36	
	Geothermal	10	0.79	≈ 2030	94	3.48	≈ 40
	Hydroelectric		21.38		25	0.08	
Power	Solar		0.02	≈ 2025	31	13.89	
Plants	Wind		2.12	≈ 2020	34		
	Coal	37	0.91	≈ 2030	221	0.83	
	Oil Products	35	3.23	≈ 2020	32	0.47	
	Natural Gas	48	14.83	≈ 2050	29	0.61	
CHP Plants	Biofuels	39	0.82	≈ 2050	221	0.83	≈ 60
	Natural Gas	80	0.77	≈ 2035			
Heat Plants	Geothermal	80	1.13	≈ 2035			50

Italy power sector are fossil fuels, biofuels, renewables, and hydrogen. No nuclear options are currently included in the model database, neither fission nor future fusion facilities.

The main sources of data for the applied set of constraints are:

- TERNA Statistics (Terna, 2023), Eurostat Energy Balances (Eurostat, 2022) and GSE Statistics (GSE, 2023) for the calibration on the historical period 2006–2020.
- National Integrated Plan for Energy and Climate (PNIEC) (Ministry of Economic Development, 2019), Long term Italian strategy for greenhouse gas emission reduction (LTS) (Ministry of Economic Development, 2021), Fit for 55 (European Council, 2023) with respect to stated future policies implemented in the model. This includes the phase-out of coal power plants no later than 2030.
- Elaboration from ENSPRESO Database (Ruiz et al., 2019), for renewable future potentials.

To apply the presented methodology to the Italian long-term strategy on emission reduction (Ministry of the Environment and Land and Sea Protection, 2021) two alternative scenarios were developed within TEMOA-Italy, spanning on a time horizon from 2020 to 2050. The Reference scenarios was developed including a projection up to 2050 of the PNIEC 2019 (Ministry of Economic Development, 2019) minimum targets for renewables development, while the Decarbonization scenario reflects the net zero emission target in 2050 (MAHTEP Group, 2023a). For the 2025–2030 period, the PNIEC targets concerning renewable production (Fig. 5) are implemented as constraints for the model. In the Reference scenario, the PNIEC policies are imposed as five constraints, forcing the model to exactly reproduce them. Differently, in the Decarbonization scenario, they are implemented as a set of minimum targets, allowing for higher values in the final electricity production mix. This approach, in synergy with the 2025–2050 carbon emission constraint reported in Fig. 5(b) allows to reach a configuration that should lead close to carbon neutrality by 2050 (around 29 $MtCO_{2\ eq}$ residual).

According to Fig. 5(a) an increasing trend is highlighted for all the renewables, except for hydroelectric and geothermal, with a 40% increase in the electricity produced from solar and 20% for wind in 2030. The geothermal and hydroelectric resources are already exploited at the maximum level, and no increase is forecasted in the period 2025–2030, causing a flat trend. The constraints for the period 2030–2050 are defined by the extension of the renewable electricity production until 2050, preserving the same annual growth rate observed in the period 2025–2030.

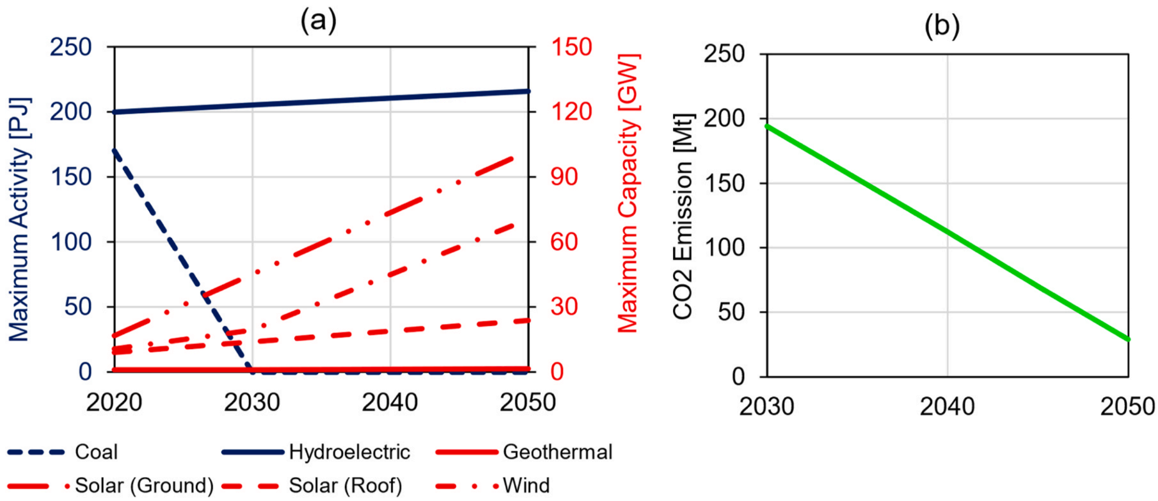

Fig. 5. Targets for renewables development of the (a) Reference scenario (PNIEC targets projected up to 2050). (b) Overall gross emissions constraints implemented in the Decarbonization scenario.

2.2. The sustainability metric: indicators selection and data inventory

To adequately address the extensive scope of each sustainability dimension, a comprehensive set of indicators are needed to accurately describe the associated problems. Since an energy system is a systemic concept that encompasses various energy processes and commodities, it is then crucial for the metric to establish a hierarchical structure (UNECE, 2021), where indicators and technologies are linked and constitutes the starting point. Therefore, each power sector technology has been characterized in terms of each included indicator, according to these general pillars:

1. *Accordance with previous literature*, Selected indicators should reflect the actual body of knowledge about sustainability as specified in Table 1.
2. *Avoidance of double counting*: It is crucial to avoid including sustainability aspects that are already accounted for in Energy System Optimization Models (ESOMs). For example, if the models already aim at minimizing generation costs, there is no need to include indicators such as Levelized Cost of Electricity (LCOE) that reflect the same aspect.
3. *Associability of indicators to energy technologies*: The selected indicators should be tailored to the operation of the different technologies of the power sector. This link between indicators and technology can be direct, as for instance, pollution indicators, which can directly relate to the quantity of pollutants produced per unit of electricity generated. However, some indicators may require mathematical elaborations, as is the case with security indicators.

For the **environmental** dimension, the selected parameters affect different areas of the environment. The *Global Warming Potential* (GWP), *Acidification* and *Eutrophication Potentials* (AP, EP) are linked to the provoked damage, and they mainly depend on emissions from fossil-based plants. On the other side, *water consumption* and *land use* refer to the natural resources consumed by the power sector technologies. To preserve the comprehensive cradle-to grave approach of the metric in the accounting of these five elements, the Life cycle assessment (LCA) assessment framework is used (ISO 14005, 2023). That is a standardized method defined by the ISO 14040 series (ISO, 2023) and widely used for evaluating the environmental impact of technologies. The ISO 14040 series ensures reproducibility and transparency in LCA studies, although direct comparability between ISO-compliant studies may not be guaranteed (ISO 14005, 2023). To mitigate this uncertainty issue, LCA indicators are derived from the UNECE Report "Integrated Life Cycle Assessment of Electricity Sources" (UNECE, 2021), which represent the most recent and significative effort in creating a comprehensive power sector LCA database at a European level. However, there are limitations related to the use of the UNECE report mainly related to the different modelling of power sector technologies, which requires an "alignment" between data A comprehensive explanation of the assumptions employed during this "alignment" phase and a detailed discussion of the data are available in Appendix A.

The **security** of an energy system encompasses several aspects (Gracceva and Zeniewski, 2014): among these, there is a stable and uninterrupted supply by the energy infrastructures, including the power sector (Ang et al., 2015). In this regard, ESOMs usually rely on a poor representation of the power system, not considering the dispatchability issues of VRES if not in a rough manner (Kotzur et al., 2021). Therefore, it is not guaranteed that a feasible ESOM scenario also provides feasible and well-performing solutions when simulated on dispatch models (Deane et al., 2015). Therefore, the indicators in this dimension must necessarily involve the reliability issue, here expressed by the technology's capacity factor, in accordance with existing literature (Nock and Baker, 2019; Martín-Gamboa et al., 2017b). Considering the long-term side, a secure energy infrastructure also depends on the import availability, with possible disruptions to be mitigated (Ang et al., 2015). The spread of VRES and more in general clean energy technologies is beneficial for energy security, since it decreases the fossil fuel import reliance that many countries have been experiencing until today: however, the expected massive penetration of renewables could lead to new import dependencies, that must be strategically faced before they overcome the above-mentioned energy security benefits (Hache, 2018). Clean energy technologies (e.g., batteries, solar panels, wind turbines) present high geographical concentration in some countries (mainly China (IEA, 2023)) along the whole value chain, from raw material extraction to technology assembly, increasing the risk of possible value chain bottlenecks (JRC, 2020). Therefore, this analysis has been narrowed down to technologies that pose concerns for energy security: fossil fuel plants, photovoltaic, and wind energy, as corroborated by the literature (JRC, 2020, 2023). This selection is predicated on the fact that both fossil and renewable technologies involve the import of "critical" commodities. Although other plants also entail dependencies (e.g., steel, cement, foreign components), there is no supporting evidence justifying the inclusion of these materials as critical. Therefore, the assumption is that other technologies and electricity imports do not pose security concerns. In this regard, for energy carriers and critical materials (both considered critical commodities for the security of supply) three indicators are considered: the *volume shortage risk*, *the import dependence*, and the *geopolitical stability*. The rationale behind this choice is to quantify both the quantity of import (*import dependence)* and its quality (volume *shortage risk*, representing the diversification of the mix), and *geopolitical stability*, that quantify reliability of energy partners. Data for these indicators are quantified and gathered differently:

- *Reliability (Capacity factor):* The capacity factor (CF) of power sector technologies (*reliability* indicator) is derived from the TEMOA-Italy database (MAHTEP Group, 2023a). CF is already present for all the technologies. For new technologies, data are reported and discussed in Table 3, together with the data sources.
- *Import dependence (% of imported commodity):* The import dependence is quantified by the percentage of imported fuels and import reliance along the whole clean energy technology supply chain. In the TEMOA-Italy model, the import of energy commodities is modelled without distinguishing between the different supplier countries (e.g., generic import of natural gas), while material flows are not included. This is the reason why external sources were used. For each fuel and technology supply chain phase included in the analysis, supplier countries are described by their share on the overall import (at the Italian and the European level, respectively). Since both energy carriers and critical materials are commodities, but the latter requires a more complicated elaboration, a detailed explanation of this indicator and the data description is found in Appendix A.
- *Volume shortage risk (N-1% residual supply):* Once obtained the import share by nation, these shares are then used to quantify the volume shortage risk. Both for critical materials and energy commodities, the Volume Shortage Risk, is quantified applying the "N-1" criteria (Carrión et al., 2021), representing the remaining percentage of supply if a failure of the biggest supplier happens. The math for this index is reported in Eq. (1) and data are found in Appendix A:

$$N-1=\sum_{i=1}^{N_{importer\quad countries}} \%of \quad tot.imp.fuel-\left(\%imp.fuel_{\quad largest \quad supplier}\right) \tag{1}$$

- *Geopolitical stability (Political Stability Index):* Geopolitical stability is calculated from the Political Stability Index (World Bank Group, 2023) (PSI) of the supplier countries. At this point, importer countries are characterized by their import share (for each critical commodity) and their PSI. Then, an average PSI for each energy commodity or material supply chain is derived, starting from the PSI of the supplier countries and their weights in the import share. This is done through a weighted average process as in Eq. (2):

$$PSI_{commodity}=\sum_{i=1}^{N_{importer\quad countries}} PSI_{country(i)} * import \quad share_{country(i)} \tag{2}$$

Power sector technologies are finally characterized by a PSI of the energy commodity/material they consume. Fossil fuel plants are associated with the commodities they require (e.g., PSI of natural gas for combined cycle power plant). For renewables, an overall PSI including the whole supply chain, from raw material extraction to component assembly, was computed for, with a detailed description of the procedure in Appendix A. Again, the need to link with the technology activity bring limitations and the need for a mathematical formulation, both discussed in Appendix A.

For the Social dimension, intended as the ability of an energy system to provide safe, clean, and affordable electricity (World Energy Trilemma Index, 2023), the choice of the indicators should reflect the wideness of this definition. Indeed, three sub-aspects are selected. The Quality of labor indicator refers to the unsustainability associated with poor labor conditions in the countries supplying the primary commodities required for energy systems. Specifically, this indicator addresses the labor conditions related to fossil fuels and critical materials, which are predominantly extracted in less developed countries. Considering that the case study focuses on Italy, the countries from which Italy imports these commodities were considered. The Quality of labor is assumed to be proportional to the Human Development Index (HDI) of the countries associated with the supplier country. As Italy is a developed country, the quality of internal jobs was not considered as a concern. The HDI values associated with a particular technology are linked to the specific commodity required by that technology. A mathematical formulation, explained in detail in Appendix A, was developed to properly calculate this indicator. Then, human health impacts are accounted for through the Human Health Damage (HDD) indicators. This is a LCA end-point kind (ReCiPe, 2022) (different from the environmental ones, which are midpoint) because it directly relates the electricity production of a plant to the human health implications, expressed in Disability Adjusted Lifetime Years (DALY), the impact assessment unit for overall disease burden, expressed as the number of years lost due to ill-health, disability, or early death (Salomon, 2014). Data for HHD are again derived from the UNECE Report (UNECE, 2021) and their detailed description is reported in Appendix A. Finally, fatalities derived by power plants hazards are added because they represent another kind of damage to human, not related to hill but to unpredictable hazards happening over the whole life cycle of the plant, even if evidence is not clear on the proportion of fatalities that occur during construction versus during operation (in developed countries) (Nock and Baker, 2019). Source values are taken from (Klein and Whalley, 2015), a well-established reference in literature. The inclusion of HHD, quality of labor, and fatalities is in line with many of the sampled work, where internal factors like fatalities and pollution were considered (e.g., (Nock and Baker, 2019; Madurai Elavarasan et al., 2022; Gunnarsdottir et al., 2022)) together with external issues as human rights and labor conditions (Nock and Baker, 2019).

It is also important to notice that the unit of measurement of indicators differs and some amounts are directly proportional to sustainability (e.g., Capacity factor for *reliability*), while others are in opposition (e.g., emissions, resource consumption). We categorize our indicators into two groups: 'The Lower the Better' (TLTB), where the lowest value signifies maximum sustainability (scored as 1), and the highest denotes minimum sustainability (scored as 0), and 'The Higher the Better' (THTB) indicators, which present the opposite scenario. The sustainability indicators and their related dimensions are summarized in Table 4.

As discussed, data sources are uniform for the environmental dimension and the HHD, while for the other is a mixture of TEMOA model input data and external references. All the indicators in Table 4 have a value for each technology and for each milestone year of the model that are reported in Appendix A.

2.3. MCDA framework for sustainability evaluation of energy scenarios

The optimal technology mix derived for the power sector by the results of the adopted ESOM and the indicators from data inventory are combined in a proper framework to obtain a separate SI for each scenario. The process can be divided into three phases: database creation, normalization and weighting, and sustainability evaluation of energy scenarios. An overview of the dataflows is provided in Fig. 6.

2.3.1. Database creation

The aim of the first phase is to create a dataset with twelve indicators for each technology and milestone year in ESOM.

The impact values for sustainability indicators are collected not only at the ESOM base year (see Appendix A), but throughout the entire time horizon of the model. While parameters independent of technological improvement are assumed constant over the years, those related to specific technological parameters derived from ESOM data, namely efficiency (η), lifetime (LT), or capacity factor (CF), are calculated to consider the reduction in impact caused by improved technological performance over time. Improvements in technical parameters generally

Table 3
Techno-economic characterization of new technologies in the TEMOA-Italy power sector (Release 3.0 (MAHTEP Group, 2023a)).

Category	Resource	Technology	Efficiency (%)	Lifetime	Investment Cost	Fixed O&M Cost	Variable O&M Cost	Discount Rate (%)	Capacity to Activity	Capacity Factor (%)	Capacity Credit (%)	CHPR	Source
	Natural Gas	Gas Cycle	35 ~ 49	30	703 ~ 922 $M\$_{2020}/GW$	21 $M\$_{2020}/GW$	1.39 $M\$_{2020}/PJ$			95			
		Combined Cycle	54 ~ 59	30	838 ~ 1038 $M\$_{2020}/GW$	28 $M\$_{2020}/GW$	0.56 $M\$_{2020}/PJ$			90			
		95% CCS	55	30	1330 $M€_{2010}/GW$	38 $M€_{2010}/GW$	0.34 $M€_{2010}/PJ$			90			
		Steam Cycle	40 ~ 44	30	2240 ~ 3075 $M\$_{2020}/GW$	74 $M\$_{2020}/GW$	2.22 $M\$_{2020}/PJ$			76			
	Coal	79 ~ 84% CCS	41 ~ 48	15 ~ 30	2757 ~ 3758 $M€_{2010}/GW$	69 ~ 88 $M€_{2010}/GW$	0.64 ~ 1.62 $M€_{2010}/PJ$			90			(ENEA, 2022; NREL, 2022; NREL, 2023)
	Oil Products	Steam Cycle	40 ~ 44	30	2240 ~ 3075 $M\$_{2020}/GW$	74 $M\$_{2020}/GW$	2.22 $M\$_{2020}/PJ$			85			
	Biofuels	Biodiesel Plant	35 ~ 39	15	3626 ~ 4416 $M\$_{2020}/GW$	151 $M\$_{2020}/GW$	1.61 $M\$_{2020}/PJ$			70			
		Biomass Plant	25 ~ 28	15	3626 ~ 4416 $M\$_{2020}/GW$	151 $M\$_{2020}/GW$	1.61 $M\$_{2020}/PJ$	10		57	100		
		Agriculture and Farming Biogas Plant			2025 ~ 3500 $M€_{2009}/GW$					58 ~ 65	70		
		Landfill Biogas Plant	32 ~ 40	9	900 ~ 1100 $M€_{2009}/GW$	40 ~ 75 $M€_{2009}/GW$	1.61 $M€_{2009}/PJ$			49 ~ 60	50		(ENEA, 2022)
	Hydroelectric	Micro-hydroelectric			4500 $M€_{2009}/GW$	78 $M€_{2009}/GW$					30		
		Mini-hydroelectric		30	2250 $M€_{2009}/GW$	33 $M€_{2009}/GW$				≈ 0.23	30		(ENEA, 2022)
	Geothermal	High Enthalpy Plant			3200 ~ 4000 $M€_{2009}/GW$					86	100		
		Low Enthalpy Plant	10	15	4480 ~ 6000 $M€_{2009}/GW$	60 ~ 86 $M€_{2009}/GW$				88 ~ 90	100		(ENEA, 2022)
	Solar	Ground Photovoltaic			620 ~ 6000 $M\$_{2020}/GW$	13 ~ 43 $M\$_{2020}/GW$					20		
		Rooftop Photovoltaic			751 ~ 8000 $M\$_{2020}/GW$	10 ~ 48 $M\$_{2020}/GW$					15		
		Thermodynamic Plant		30	3928 ~ 5429 $M\$_{2020}/GW$		0.81 $M\$_{2020}/PJ$			≈ 0.14	70		(ENEA, 2022; NREL, 2022; NREL, 2023
	Wind	Onshore			765 ~ 2532 $M\$_{2020}/GW$	33 ~ 49 $M\$_{2020}/GW$					25		
		Offshore (Fixed)			2343 ~ 5000 $M\$_{2020}/GW$	70 ~ 111 $M\$_{2020}/GW$					30		
		Offshore (Floating)		20	3467 ~ 4049 $M\$_{2020}/GW$	57 ~ 69 $M\$_{2020}/GW$				≈ 0.17	35		(ENEA, 2022; NREL, 2022; NREL, 2023)
Power Plants	Hydrogen	PEM Fuel Cell	45 ~ 47	15	1000 ~ 3000 $M€_{2013}/GW$	56 ~ 61 $M€_{2013}/GW$	8.33 ~ 29.17 $M€_{2013}/PJ$	5	31.536 PJ/GW	90	100		(Sofia et al., 2013a)
CHP Plants	Natural Gas	Gas Cycle	77 ~ 86	25	960 $M€_{2009}/GW$		1.11 ~ 1.67 $M€_{2009}/PJ$	10	31.536 PJ/GW	57	70	≈ 1.3	(ENEA, 2022)

(*continued on next page*)

Table 3 (*continued*)

Category	Resource	Technology	Efficiency (%)	Lifetime	Investment Cost	Fixed O&M Cost	Variable O&M Cost	Discount Rate (%)	Capacity to Activity	Capacity Factor (%)	Capacity Credit (%)	CHPR	Source
		Combined Cycle	90	30	720 M€$_{2009}$/GW		0.33 ~ 0.50 M€$_{2009}$/PJ			34		≈ 0.6	
		Cycle in Counter Pressure	84	35								≈ 4.0	
		Cycle with Steam Tapping	82	35	702 M€$_{2009}$/GW		1.39 M€$_{2009}$/PJ			74		≈ 2.5	
	Municipal Waste	Municipal Waste Cycle	38	20	2059 ~ 4000 M€$_{2009}$/GW		9.50 ~ 12.50 M€$_{2009}$/PJ			70 ~ 80		≈ 0.5	
		Internal Combustion Engine (Commercial)	80 ~ 88	15	900 ~ 1100 M€$_{2009}$/GW		4.17 M€$_{2009}$/PJ			34		≈ 1.1	
		Microturbine (Commercial)	80 ~ 88	12 ~ 20	1000 ~ 1500 M€$_{2009}$/GW		2.78 M€$_{2009}$/PJ			34		≈ 0.4	
		Combined Cycle (Commercial)	80	15 ~ 20	1300 M€$_{2009}$/GW		5.00 M€$_{2009}$/PJ			34		≈ 0.4	(ENEA, 2022)
	Natural Gas	Solid Oxide Fuel Cell (Commercial)	90 ~ 96	20	2250 ~ 10000 M€$_{2020}$/GW		4.86 ~ 30.56 M€$_{2020}$/PJ			90		≈ 0.4	(Sofia et al., 2013a)
	Biofuels	Internal Combustion Engine (Commercial)	80	15	1350 ~ 1870 M€$_{2009}$/GW		4.17 M€$_{2009}$/PJ			34		≈ 0.4	(ENEA, 2022)
	Hydrogen	PEM Fuel Cell (Commercial)	94 ~ 96	20	1050 ~ 1500 M€$_{2020}$/GW		6.94 ~ 13.89 M€$_{2020}$/PJ			90	20	≈ 0.8	(Sofia et al., 2013a)
		Internal Combustion Engine (Residential)	80 ~ 88	15	900 ~ 1100 M€$_{2009}$/GW		2.78 ~ 4.17 M€$_{2009}$/PJ			34		≈ 1.1	
		Microturbine (Residential)	80 ~ 92	12 ~ 20	1000 ~ 1500 M€$_{2009}$/GW		1.67 ~ 2.78 M€$_{2009}$/PJ			34		≈ 1.5	
		Combined Cycle (Residential)	80	15 ~ 20	1300 M€$_{2009}$/GW		0.42 ~ 0.50 M€$_{2009}$/PJ			34		≈ 0.4	
		Stirling Engine (Residential)	80 ~ 90	15	2100 ~ 2180 M€$_{2009}$/GW		2.78 ~ 5.00 M€$_{2009}$/PJ			34		≈ 0.2	(ENEA, 2022)
	Natural Gas	Solid Oxide Fuel Cell (Residential)	90	20	3500 ~ 10000 M€$_{2020}$/GW		6.97 ~ 27.78 M€$_{2020}$/PJ			90		≈ 0.5	
	Hydrogen	PEM Fuel Cell (Residential)	92 ~ 96	20	4000 ~ 6000 M€$_{2020}$/GW		6.94 ~ 20.89 M€$_{2020}$/PJ			90	20	≈ 0.5	(Sofia et al., 2013a)
		Internal Combustion Engine (Industry)	80 ~ 91	15	1030 ~ 1100 M€$_{2009}$/GW		2.78 ~ 4.17 M€$_{2009}$/PJ			57		≈ 1.1	
		Gas Turbine (Industry)	74 ~ 80	20 ~ 25	800 M€$_{2009}$/GW		1.39 ~ 1.67 M€$_{2009}$/PJ			74		≈ 1.2	
	Natural Gas	Steam Turbine (Industry)	75 ~ 79	30	1500 M€$_{2009}$/GW					63		≈ 0.3	
Micro-CHP Plants	Biofuels	Internal Combustion Engine (Industry)	85 ~ 93	15	1800 ~ 2100 M€$_{2009}$/GW		2.50 ~ 3.75 M€$_{2009}$/PJ	10	31.536 PJ/GW	57	100	≈ 0.2	(ENEA, 2022)
	Natural Gas	Natural Gas Plant			4 M€$_{2009}$/PJ	2.4 M€$_{2009}$/PJ							
	Coal	Coal Plant			6 M€$_{2009}$/PJ	2.8 M€$_{2009}$/PJ							
	Oil Products	Oil Products Plant			5 M€$_{2009}$/PJ	2.5 M€$_{2009}$/PJ							
	Biofuels	Biofuels Plant	80		6 M€$_{2009}$/PJ	2.8 M€$_{2009}$/PJ							
		High Enthalpy Plant			12 M€$_{2009}$/PJ	2.5 M€$_{2009}$/PJ							
Heat Plants	Geothermal	Low Enthalpy Plant	10	60	12 M€$_{2009}$/PJ	2.5 M€$_{2009}$/PJ		10	1.00 PJ/PJ	60	100		(ENEA, 2022)

Table 4
Description of sustainability dimensions and indicators.

Sustainability Dimension	Sustainability indicator	Measure	Normalization
	Global Warming Potential (GWP)*	$\frac{Kg_{CO_2,EQ}}{MWh}$	
	Acidification Potential (AP)	$\frac{g_{SO_2,EQ}}{MWh}$	
	Eutrophication Potential (EP)	$\frac{g_{PO_4,EQ}}{MWh}$	
	Land Use	$\frac{m^2}{MWh}$	
Environmental	Water Use	$\frac{m^3}{MWh}$	TLTB
	Reliability	Capacity factor (%)	THTB
	Import Dependence	% of imported commodity	TLTB
	Volume shortage Risk	N-1 residual supply (%)	THTB
Security	Political Stability Index	Political Stability Index [-]	THTB
	Human Health Damage	$\frac{DALY}{MWh}$	TLTB
	Fatalities	$\frac{Deaths}{MWh}$	TLTB
Social	Quality of Labor	Human Development Index	THTB

cause a reduction in overall LCA impacts. This process is called harmonization and adds a dynamic component to the LCA dataset. If the life cycle-based impacts are primarily due to the operation of the plants (as in the case of fossil power plants or biomass power plants), then a change in efficiency has a significant impact. On the other hand, if the impact is primarily due to the construction of the plants (as in the case of PV and wind and non-emitting technologies), then capacity factor and lifetime are the most influential parameters. To account for this temporal variation, the LCA parameters vary according to the average growth rate of the technological drivers as in Equation (3a) for the fossil and biomass efficiency, in Equation (3b) for CF and lifetime for the other technologies.

$$\overline{GR}_{t,j} = \begin{cases} \dfrac{\eta_{t,j} - \eta_{t,BY}}{\eta_{t,BY}} \\ \dfrac{CF_{t,j} - CF_{t,BY}}{CF_{t,BY}} + \dfrac{LT_{t,j} - LT_{t,BY}}{LT_{t,BY}} \end{cases} \tag{3a,b}$$

For each technology, the average variation of the three technical parameters at year j with respect to the base year ($j = BY$) is used to reduce the LCA Impacts according to Eq. (4).

$$LCA \quad Footprint \quad indicator_{t,j} = LCA \quad Footprint \quad indicator_{t,BY} \bullet \left(1 - \overline{GR}_{t,j}\right) \tag{4}$$

As shown in Fig. 6, the final dataset is composed of a set of parameters $I_{t,j,i}$ of twelve indicators, where both activity and parameters are defined for each technology and year.

2.3.2. Normalization and weighting

The second step involve converting the different technology indicators ($I_{i,t,j}$) to a single value. Each indicator i in year j is first normalized for each technology t using a common scale of [0,1] with reference to the best and the worst indicator for the same indicator category, as in Eq. (5).

$$I^{NORM}_{i,t,j} = \frac{I_{i,t,j} - \mathrm{worst}(\quad I_{i,t,j})}{\mathrm{best}(I_{i,t,j}) - \mathrm{worst}(\quad I_{i,t,j})} \tag{5}$$

For each indicator, the technology with the most sustainable value takes 1 and the worst 0, while the others are interpolated between this range. As explained in Table 4, we utilize two distinct normalization approaches for our indicators: traditional normalization, where the highest value is assigned a score of 1, and the lowest receives 0, and reverse normalization. Several normalization techniques are available (OECD, 2008), but we have found (not shown) that the min-max scaling is the one causing less distortion on data distribution. Moreover, some indicators already in a 0–100% scale (import dependency, volume shortage, reliability) do not require this process, but just a translation in the range 0–1. After this step a new dataset of indicators I^{NORM} for each sustainability indicator (i) is obtained for each milestone year in the model. The overall yearly sustainability performance of a technology ($TSS_{t,j}$) is obtained by hierarchical weighted sum of its qualitative set of

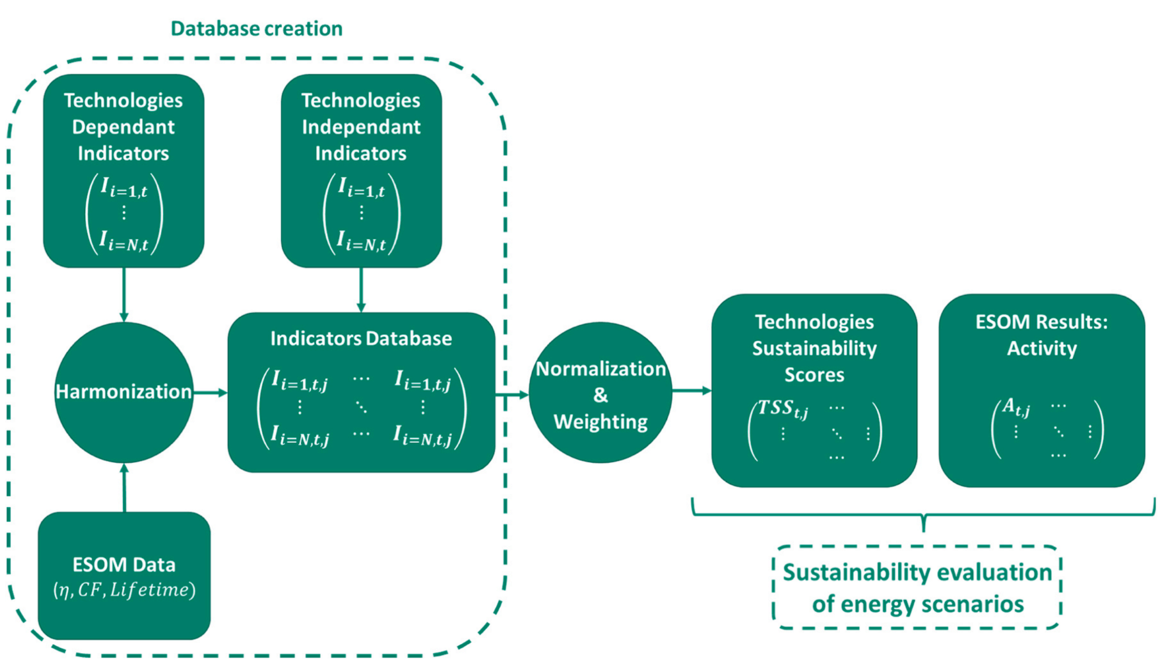

Fig. 6. Data flows of the developed MCDA process.

indicators, that allows moving to a single SI value. Since there may be different configurations according to how different indicators are relevant for the scope of the analysis, each indicator must be associated to a weight (the sum of all the weights always has to be equal to one). Weights are identified by the term w_i in Eq. (6), and assigned to each indicator (i). Technology sustainability score (TSS) is the weighted sum of all the indicators.

$$TSS_{t,j} = \sum_{i=1}^{12} I_{i,j}^{NORM} \bullet w_i, where \quad \sum_{i=1}^{11} w_i = 1 \tag{6}$$

2.3.3. Sustainability evaluation of energy scenarios

When all the power sector technologies are characterized by a yearly overall sustainability evaluation, it is possible to compute a global score (SS_j) evaluating the sustainability of the technology miv under analysis. This is done by allowing each technology to influence the final score according to its contribution to the electricity production share used in Eq. (7), where the electricity production share (activity share AS) is identified by the term $AS_{t,j}$ and represents, as an outcome of the scenario, the contribution of the produced electricity by the technology t (or process) in the final electricity mix for the year j. AS is an output of the ESOM, computed according to a specific scenario.

$$SS_j = \sum_{t=1}^{N_{tech}} TSS_{t,j} * AS_{t,j} \tag{7}$$

This framework allows the direct visualization of the power system performance in terms of sustainability through a trendline. One sustainability profile, associated to a specific set of weights, is obtained as output for each analyzed scenario.

2.4. Post-mining analysis

To assess the impact that different sets of weights have on the SI profile in a specific scenario, a sensitivity analysis is performed. In this regard, for each scenario, the weights of the twelve indicators used for the evaluation of the SI are sampled generating 10.000 combinations with the only constraint that their sum should be always equal to 1. As expected, each set of weights produces a unique SI profile that, over the reference time horizon of the scenario, is characterized by its own magnitude (e.g., low, medium, high) and trend (e.g., increasing, decreasing, stable). The main objective of this analysis is then to extract from the considered scenarios recurring patterns that describe the relationship between indicator weighs and the characteristics (trend and magnitude) of 10.000 SI profiles obtained after the weight sampling. To do so, magnitude and trend are treated separately according to the following methodological steps:

a. **Clustering analysis of the SI profiles**: In a selected scenario, this analysis aims at identifying reference groups of SI profiles among the 10.000 ones obtained after the sampling of indicator weights. At the end of this analysis each SI profile is tagged with the label of the cluster in which it has been grouped in using a hierarchical clustering algorithm with the Euclidean distance used as a similarity metric and the Ward.D2 as linkage method (Capozzoli et al., 2017). The optimal number of clusters is determined by means of well-known quality metrics such as Davis-Bouldin (Davies and Bouldin, 1979) and Silhouette index (Rousseeuw, 1987);
b. **Development of a classification model**: At this stage an estimation model based on a machine learning decision-tree algorithm is developed to classify a SI profile in one of the pre-determined classes evaluated through the clustering analysis. The considered model inputs are the weights of the 12 indicators used to calculate the sustainability index while the estimated output variable is the cluster label. The developed model is a random forest based on the ensemble of 500 decision trees trained on different parts of the available dataset imposing a minimum size of terminal nodes equal to 10. The classification accuracy of the model is assessed training the classifier on the randomly sampled 70% of the dataset and testing it on the remaining 30%.
c. **Analysis of the feature importance**: This step exploits an explainable artificial intelligence (XAI) technique to explain and interpret the developed classification model to infer which indicators have the highest influence on a specific feature of the SI profile (i.e., magnitude or trend). Specifically, the importance of an input variable (i.e., one of the 12 indicators used to evaluate the SI) is assessed according to the increase in the model classification error after permuting the variable. A variable is than considered as “important” if the shuffling of its values significantly increases the model error, because in this case the model relied on that variable for the classification. On the other hand, a variable is considered “unimportant” if shuffling its values, the model error is not remarkably affected, because in this case the model did not exploit that variable for the classification. In this study the increasing of the model classification error is measured in terms of Cross-Entropy, as reported in (Law Biecek, 2023).

To separately analyze the SI profile properties, the above-described process is applied to not normalized profiles to characterize the magnitude of the profiles and to normalized profiles to better highlight differences in terms of their trends. To analyze the trend, all the considered 10.000 SI profiles of a scenario are normalized with respect to their maximum value then emphasizing the shape attributes of the profiles more than the magnitude ones. Eventually, the sensitivity analysis for both magnitude and trend of the SI profiles is carried out for different scenarios to understand if the discovered relations are or are not characterized by traits of generalizability.

3. Results

The outcomes resulting from the application of the methodology are here presented. The section is structured as follows. First, the energy scenarios in terms of electricity production and emissions are discussed in Section 3.1. In particular, the scenarios are explained with a specific focus on the technological change in the power sector required by the decarbonization policy and its implications in terms of sustainability. Next, the outcomes for the SI calculation are presented: Section 3.2 provides the mere sustainability evolution, highlighting the role of the SI as a tool to compare energy scenario and providing an example of readability and interpretation. In Section 2.1, the post-mining analysis is performed, gaining a deeper understanding on the effect and impact of alternative selection of the weight values.

3.1. Electricity mix and CO2 emissions

Constraints discussed in Section 2.1 result in different electricity production and carbon emission trajectories between scenarios. Thanks to Fig. 7a is possible to appreciate how the emissions reduction (evaluated with respect to the period 2007–2010) performed by the Reference scenario (thanks to efficiency improvements) is incomplete if compared to net-zero targets. Indeed, the reduction of carbon emissions only reaches around 30% in 2050.

Differently, the Decarbonization scenario (Fig. 7b) puts in place a transition to an almost carbon-neutral condition: in 2050, with a ~94% emissions reduction with respect to base year. It is also evident how the main emission sources are the transport and the power sector (in the Reference 2050). In absence of constraints (Fig. 7a) the emissions from the two sectors are quite constant. On the contrary, in the Decarbonization (Fig. 7b), the final emissions reach negative values (-24,5 Mt CO_2) thanks to the direct air capture and the biomass with CCS. Moreover, both the transport and the power sector experience a deep emission reduction driven by the constraints. This means a higher electrification of transports and renewable share in the power sector.

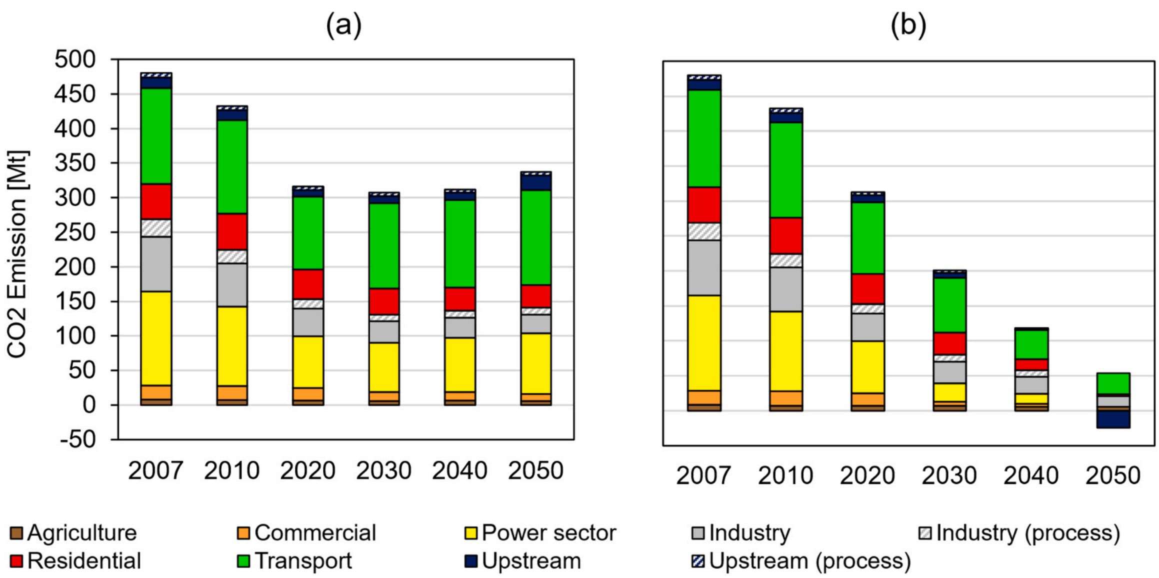

Fig. 7. CO2 emissions reduction for TEMOA-Italy Reference and Decarbonization scenarios (a) and Electricity consumption increase (b).

The higher decarbonization effort in the Decarbonization scenario requires a 30% increase in electricity consumption with respect to the base year (see Fig. 8), while the Reference one presents an almost stationary trend. Considering the electricity production sources, the Reference scenario (Fig. 8a) does not significantly change its energy mix across the time, relying mainly on natural gas, import and renewables, respectively. Differently, the strong Decarbonization targets mainly leads to a transition towards solar and wind (Fig. 8b).

Diving into details, Fig. 8 shows that after 2030 the differences between the two scenarios start being sharper. If in the Reference the gas dominates the electricity production with a significant increase (around 30% from 2030 to 2050), in the Decarbonization renewables take the scene. From 2030–2050, photovoltaic and wind experience a sharp rise in production, around 120% and 300% respectively.

3.2. Evaluation of the sustainability score

Once all the necessary data are acquired, the sustainability index calculation discussed in Section 2.3 is applied, combining technology production by source from ESOM and the sustainability indicator dataset of Section 2.2. Since the sustainability index calculation is affected by the assigned sets of weights, 10000 combinations of indicator weights are tested, by making all the weights vary between minimum and maximum values of 0 and 1, respectively, and keeping their overall sum equal to 1. The implications of using different sets of weights are reflected in the technology sustainability evaluations that, applied to scenarios activity, define 10000 different SI profiles. To preserve interpretability, only the case with an equal weight configuration is shown, with the other profiles laying in the background of the plot. In Fig. 9 the SI for both Reference and Decarbonization scenarios is plotted.

This visualization highlights the role of the sustainability index as a tool to quantitively compare scenarios across a user-specified indicator ranking. With the specific weight configurations applied, the Decarbonization scenario demonstrates a slightly superior performance when compared to the Reference scenario. Notably, the former exhibits a progressively increasing trend in contrast to the relatively flat to slightly decreasing trajectory of the latter, resulting in an approximately 10% relative difference by the year 2050. Despite the case-specific outcome, what must be noticed is the wide spectrum of profiles (grey lines) covered by the SI when changing the set of weights. Indeed, according to

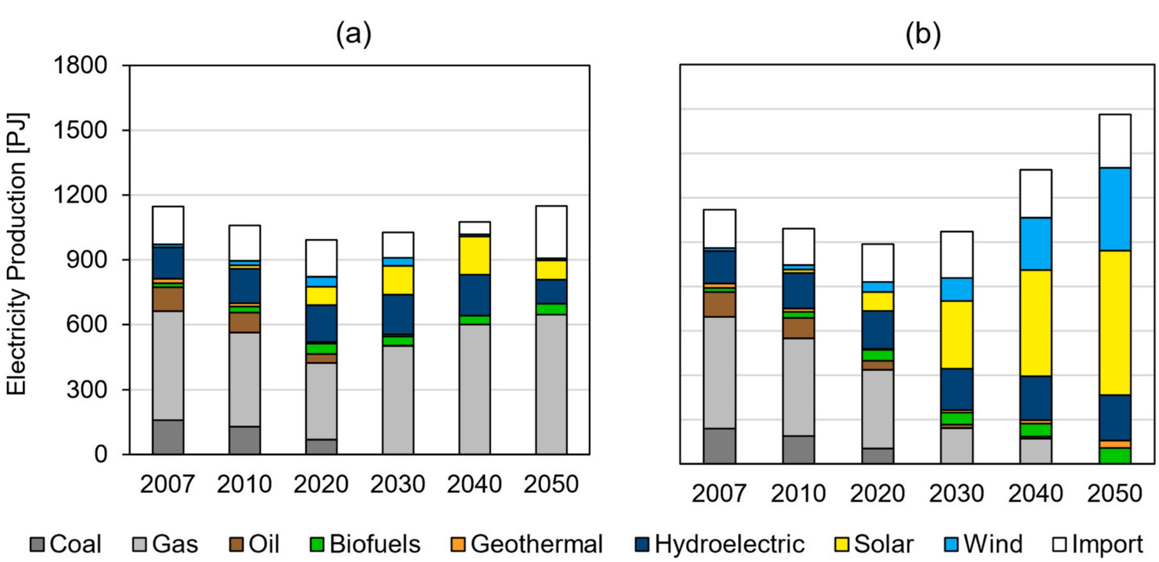

Fig. 8. Evolution of the electricity production by source obtained in the TEMOA-Italy a) Reference scenario and b) Decarbonization scenarios.

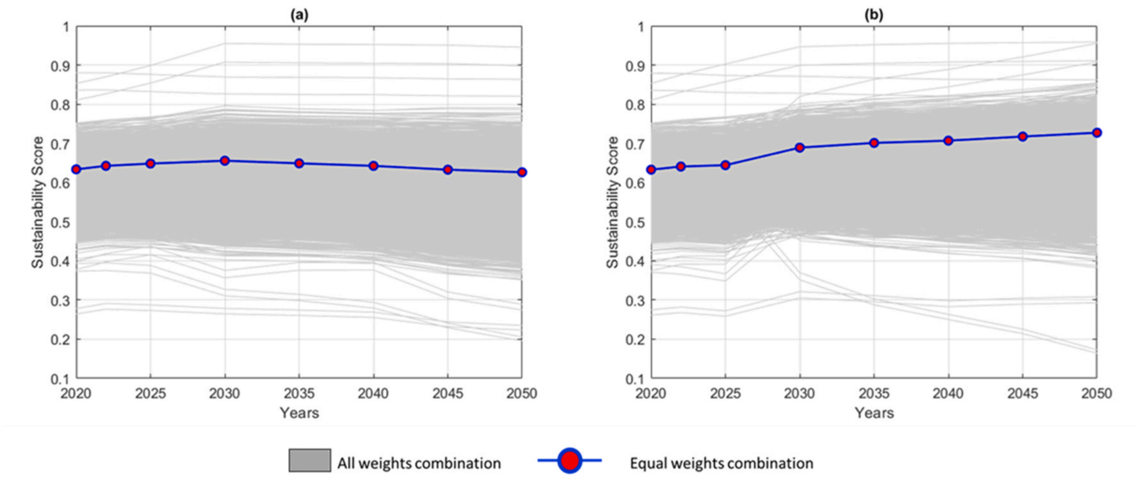

Fig. 9. Sustainability score profiles for Reference (a) and Decarbonization (b) scenarios considering all the 10'000 combinations (grey lines) with evidence of the SI profile associated to an equal weight of the indicators (blue dashed line).

the assigned set of weights, the SI can range from 0.1 to 1 in magnitude while assuming different trends. A level of explanation based on artificial intelligence techniques is used to determine whether and how the magnitude and trend of SI are affected by the single indicators, trying to find patterns allowing for extraction of general knowledge.

3.3. Post-mining analysis

The aim of the post mining analysis is the assessment of the influence that indicator weights have on the sustainability index. After having obtained 10,000 SI profile samples, they are analyzed considering their magnitude and their trend separately but repeating the same steps in analyzing both. The first step of the post-mining analysis is clustering the SI profiles (Section 3.3.1), which makes possible to extract reference qualitative groups for magnitude (e.g., Low, Medium, High) and trend (e.g., increasing or decreasing over time). The clustering phase results are not to be intended as final outcomes, but functional to the generation of them. Indeed, after the identification of the reference clusters of SI profiles, the classification models are developed with the aim to extract the relationships between the indicator weights and the features of the SI profile itself (Section 3.3.2). This last step facilitates the identification of patterns that substantially influence the variations of the SI.

3.3.1. Clustering analysis

Cluster profiles obtained following the methodology of Section 2.4 are reported in Fig. 10, showing the clustering results obtained for both the Reference and Decarbonization scenarios. In particular Fig. 10 (a) and Fig. 10 (c) show the obtained reference clusters of SI profiles if not normalized (to characterise the magnitude) and when normalized (to characterize the trend), respectively, for the Reference scenario.

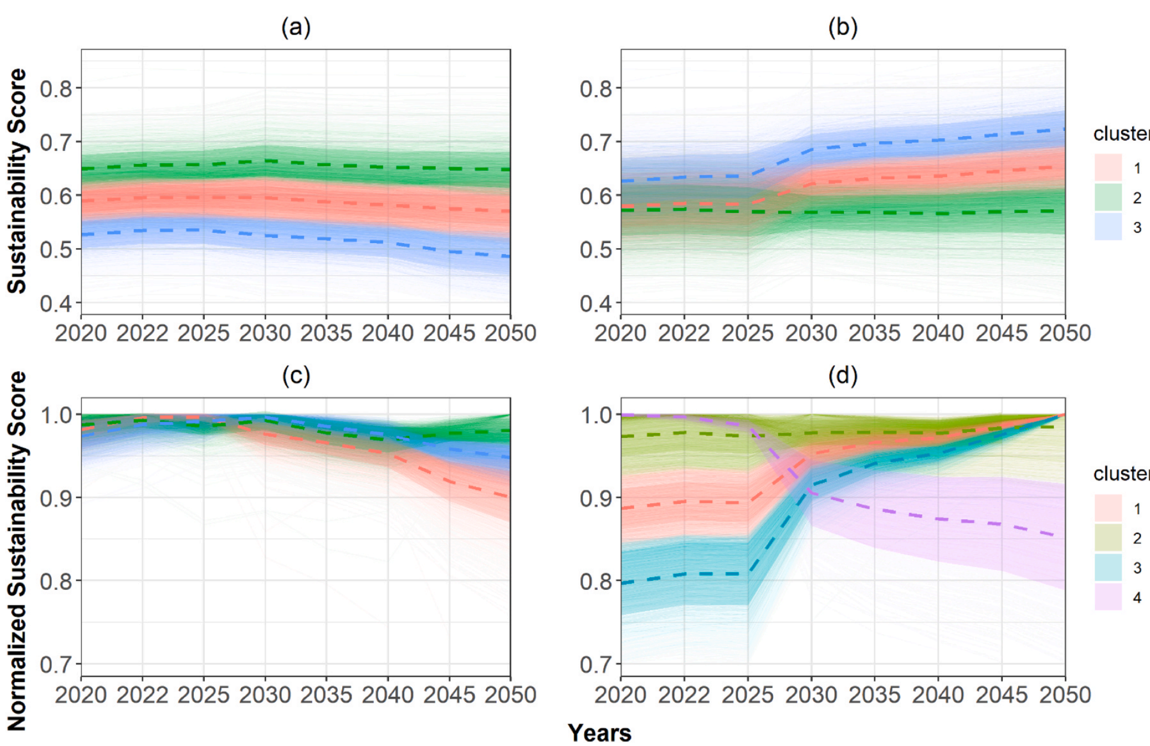

Fig. 10. Analysis of the SI profile magnitude (a, b) and of the profile trend (c, d) for the Reference (a, c) and Decarbonization (b, d) scenarios, respectively. Dashed lines represent the centroid of the three identified profiles and the red green -blue areas around them are the associated standard deviations.

Similarly in Fig. 10 (b) and Fig. 10 (d) the clustering results pertaining the Decarbonization scenario are shown. It is possible to notice that the four indipendent clustering analyses converged on a optimal number of SI profile groups equal to three, with the only exception of Fig. 10(d), with four optimal groups. The SI magnitude of both scenarios is generally included in the range between 0.4 and 0.8, with slightly higher values for the Decarbonization scenario. For what concerns the trend patterns extracted from both scenarios, it is possible to identify three main behaviors for the Reference scenario and four for the Decarbonization one. Specifically, regardless to the magnitude level, the SI profiles can decrease over time (as for the Reference scenario), can be stable on the first period of the scenario and then decrease (cluster 4 in Fig. 10 (d)), or can increase (during the first part of the scenario and then remain stable, as cluster 1 in Fig. 10 (d), or increase like cluster 2 in Fig. 10(d)).

3.3.2. Classification models and feature importance

To extract the relationships that exist between the indicator weights and the features of the SI profile itself (i.e., magnitude and trend), two classification models for each scenario are applied. The four models achieved very good accuracy values (85 ∼ 90%) demonstrating their capability in capturing all the important dependencies between a certain level of magnitude or trend of an SI profile and the associated indicator weights. Table 5 reports the results obtained for each classifier in terms of accuracy achieved in the testing phase, calculated as defined in (Powers, 2023).

The final step of the analysis aims at describing what the classification model learnt from the data generated with the sampling of indicator weights. To this purpose an explanation layer is defined on top of the classification model to assess the importance of each input variable in the characterization of SI profile magnitude and trend. As reported in Section 2.4, the importance of an input variable is measured according to the increase of the model prediction error when its values are shuffled. Table 5 Each bar chart included in Fig. 11 reports the input variables in descending order according to their importance. The bar height is associated to the average increase of the model Cross-Entropy among 10 permutations, while the vertical dashed lines represent the baseline Cross-Entropy value for each model. The higher the Cross-Entropy loss after permutations, the higher is the importance of the input variable.

The first interesting result is that in both analyses (magnitude and trend), the most important features are the same across scenarios. For magnitude these are Import Dependence, EP, and quality of labor, while for trend Reliability the Land Use, Fatalities, and AP ones. This fact can be read as a general validity of the most important indicators among the scenarios, at least for those analyzed in this work.

Delving into the details of the magnitude plots, the Reference scenario results appears to be strongly influenced by environmental indicators related to plants operations (AP, EP) and geopolitical issues related to fossil fuels (quality of labor and Import dependence). For the Decarbonization scenario results, the model predicts reliability as a pivotal issue due to a strong renewable penetration. Furthermore, the Eutrophication fostered by solar panels construction (Lechón et al., 2018) and the Import dependency issues previously discussed also gain their relative importance.

The second noteworthy finding pertains to the role of Reliability and the Land Use indicators in predicting the trend of the Sustainability Index. Indeed, Reliability and Land Use weights assume a primary role in affecting the model accuracy, with a dominant role of the former in both scenarios. This second consideration suggests that Reliability and Land Use have a high impact on its increasing or decreasing trend over time. With the Reliability playing a pivotal role in both magnitude and trend of the Decarbonization. The importance attributed to these features highlights two major technological challenges, already mentioned in actual literature, associated with the energy transition (Child et al., 2018).

Table 5
Accuracy, Recall and Precision of the four classifiers developed for the Reference and Decarbonization scenarios.

Scenario	SI Profile Feature	Accuracy
Reference	Magnitude	87.6%
Reference	Trend	85.3%
Decarbonization	Magnitude	86.9%
Decarbonization	Trend	83.8%

4. Discussion

In this section, each phase of the sustainability metric for the evaluation of the evolution of the power sector technology through energy scenarios is examined, highlighting potential challenges and opportunities for improvements within the context of these four critical areas: data uncertainties, assumptions, limitations, and reproducibility of the study. All these areas are analyzed following the chronological construction of the paper.

The first phase of the work involves data acquisition. Data essentially falls into two categories: Model-derived data and data obtained from external sources. The former can be categorized into two types pertaining to the techno-economic characterization of technologies and energy commodities: those that remain consistent across scenarios, namely the data for the reference energy system (RES), and those who varies (scenario-specific data). Uncertainty regarding these data has been addressed in the case-study presented here by using national data for both technical and economic parameters. As a rule, data precision tends to increase as the geographic scale decreases (Kotzur et al., 2021). However, this poses a challenge in terms of the study reproducibility beyond the Italian context: replicating the study for another country, the adopted data for this analysis would no longer be valid. The set of technologies considered is extensive, and the technological discretization aligns as closely as possible with data from official sources (see the dedicated section) and existing models. Concerning data that vary among the scenarios, a first limitation is encountered, namely the use of only two scenarios. The generalizability of the results discussed in the previous section is as robust as the number of scenarios confirming those results: however, exact (published) data were only available for the two analyzed scenarios, as per Italy's long-term strategy. Therefore, any other scenario would have been a modeler's hypothesis without a basis to be found in stated policies. The selected scenarios promote the reproducibility and accuracy of this study. The latter consideration generally holds true for the entire model, which has been extensively discussed, and for which all relevant data have been presented. The main limitation of the model, which will be discussed later, is the absence of data on import by country for energy commodities and critical materials used in the scenario. This required the use of external sources, assumptions, and simplifying hypotheses, significantly increasing the uncertainty of this study. As a first suggestion for future research direction, modelling frameworks providing a better representation of the different supply options will be beneficial for the scientific community.

Regarding data from external sources, they primarily pertain to the sustainability indicator calculations. The foremost source of uncertainty undoubtedly lies in the selection of the entity that should encapsulate the sustainability phenomenon. This uncertainty is less pronounced concerning environmental indicators, as they are quantifiable through physical quantities (e.g., GHG emissions for global warming). However, for safety and social indicators, it was necessary to assume a quantitative measure to represent a qualitative phenomenon (e.g., the Human Development Index for labor quality): these assumptions thus constitute a significant source of uncertainty. Nevertheless, by employing well-referenced data sources, logical assumptions in alignment with the scientific literature, we ensure comparability with existing studies.

Delving into the individual indicator definition, they can be

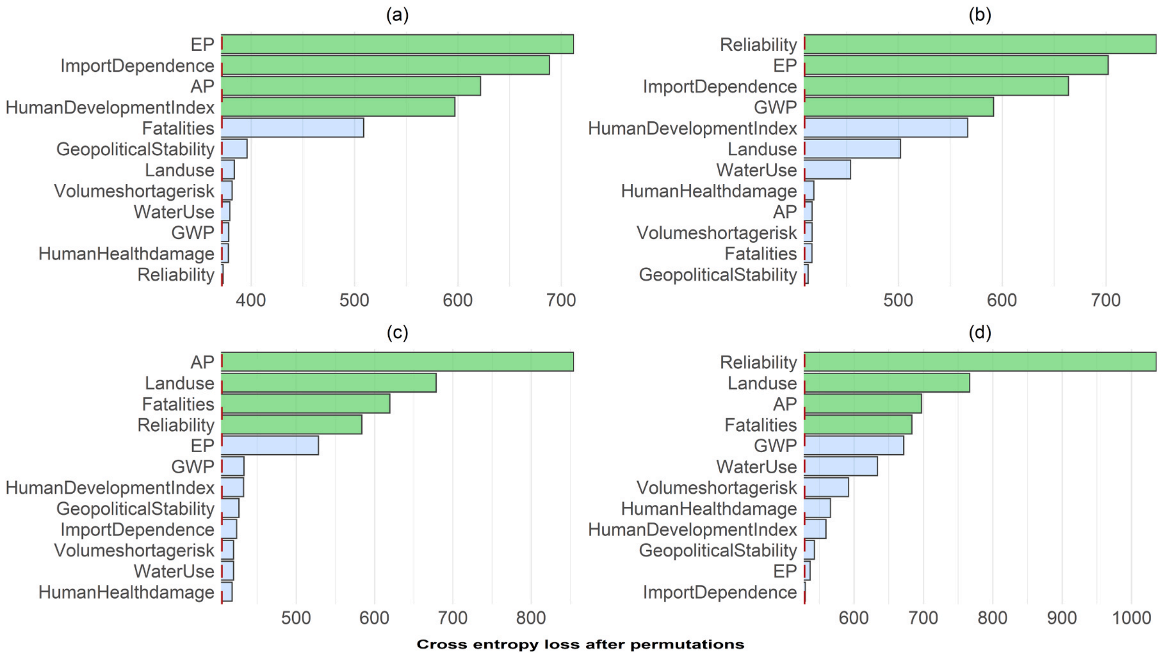

Fig. 11. Feature importance for Magnitude (a, b) and Trend (c, d) classification analysis in both Reference (a, c) and Decarbonization (b, d) scenarios.

categorized into three distinct groups: environmental ones, social ones, and energy security ones. All environmental indicators are derived from LCA frameworks, a scientifically validated and reproducible procedure. A potential issue concerns to the geographical extension of these data, which is not always available for the Italian territory and, sometimes, even for the European region. Furthermore, the technological discretization of the LCA database in comparison to the TEMOA-Italy technological database is significantly limited, necessitating associative assumptions. These assumptions, especially in the case of biomass, but generally applicable to all technologies, further exacerbate data uncertainty. Lastly, the LCA database undergoes a harmonization process to estimate values for future years. Although the assumption of keeping data as constant is incorrect from a technological point of view (technologies typically improved as time goes by), projecting future data accounts for the key impact driver\s for various technologies (e.g., lifetime and capacity factor for renewables, lifetime, and efficiency for fossil fuels). However, introducing such an assumption of variation infuses uncertainty concerning the actual extent of change, which remains unknown a priori.

Regarding security data, several aspects need to be discussed, with the most critical aspect being simplifying assumptions. In the technologies data gathering phase, simplifications were introduced also during the metric calculation. Linking security to individual technologies introduces significant uncertainties. As energy systems are complex, their behavior cannot be explained solely by understanding their individual components. Thus, system security is not a function of individual components but rather their dynamic interactions (Deane et al., 2015). The technology-centric approach of this paper has two main limitations. First, security indicators for power plants (e.g., PV) and energy carriers (natural gas) are underestimated in this study, even though the consequences of an import disruption differ significantly. Sustainability scores are assigned to each technology, and the overall score is weighted proportionally to activity. Theoretically, the renewable supply chain aspect should be evaluated in proportion to the new capacity installed, while commodity imports should relate to upstream sector activity. This approach was not adopted because the goal is to derive a single score rather than one for each model layer. Future research directions should focus on implementing more comprehensive metrics capable of accounting for these intricacies.

Delving into the mathematical aspects of the sustainability metric, the most intricate aspect arises when technology sustainability scores are multiplied by their respective activity shares to yield the final sustainability score. The underlying hypothesis is that all the indicators included in the sustainability score are proportional to the activity even if, as discussed above, this involves limitations particularly for the security indicators. Future research must address this issue by improving the mathematical formulation of the metric and the way it accounts upstream import, capacity installed, and overall electricity production (and not only its production share).

Concerning the result section, a major observation must be done regarding the power sector focus of this analysis. The sustainability comparison of the two scenarios is based solely on the shares of the different technologies in the electricity generation mix. If the sustainability comparison had been carried out based on the absolute values of power generation per technology instead of based on the shares, the impacts of the decarbonisation scenario would be significantly higher than those of the reference scenario.

Finally, regarding the post-mining phase, this analysis allows trend and magnitude analysis to be conducted independently. Where no trend is observed, this process provides an opportunity to identify a pattern and explain it. Where profiles with a marked upward or downward trend with different magnitudes are present, it is possible to understand both the factors driving the change and the ones influencing the magnitude value. That provides the possibility of maintaining a neutral approach. In similar situations, with stable profiles over time, both low-magnitude and high-magnitude effects occur, but s considerations can still be made (Reliability in cluster 4 of the Decarbonization trend).

Concerning the use of AI, ML techniques allow the evaluation of many iterations identifying typological group inside them. In this regard, a very accurate model was developed, from which the analyses between input and output were subsequently extracted. This allows to extract general pattern able to explain the particular situation rather than developing particular knowledge from case-specific results.

5. Conclusion and perspectives

In this study, a comprehensive sustainability metric for the evaluation of the sustainability of the power sector has been developed and applied to alternative scenarios. The analysis has been performed to cope with the necessity to produce insights that traditional energy system optimization models are not able to deal with, attempting to answer to a crucial question in the actual energy modeling field: how much can we exploit carbon emissions as an indicator of sustainability? The comprehensive and hierarchical framework for evaluating sustainability developed in this work allowed for the incorporation of preferred dimensions of sustainability while accounting for their relative importance. Since different stakeholders may rank sustainability aspects differently according to their preference, the role of the weight has been assessed through a post-mining analysis, to understand which weights mostly affect the SI profile trend and magnitude. These considerations have led to the development of a novel tool (the comprehensive Sustainability Index) for decision-making in energy planning, especially crucial for identifying and addressing potential negative impacts within the decarbonization strategies. The innovative aspect of the post-mining analysis has been used to identify the most challenging features of a decarbonization strategy, as this approach is capable to directly extract information on the role of individual indicators, without imposing limitations on the potential indicators that can be included or the number of weight combinations that can be tested.

The utilization of the SI methodology in the context of the Italian decarbonization strategy has served as an illustrative example of the proper interpretation of results. Specifically, it has been demonstrated a significant impact of factors like Import Dependence, Environmental Production, and Quality of Labor on the magnitude of sustainability in the power sector, especially under the Reference scenario. The Decarbonization scenario shifts the focus towards Reliability due to increased renewable energy penetration, with additional emphasis on issues such as Eutrophication from solar panel construction and Import Dependence. The analysis also reveals that Reliability and Land Use are key aspects for the Sustainability Index trend, indicating their high impact over time. In answering the question which originated the study, this analysis confirms the limitation of carbon emission as the only indicator of sustainable energy policy. Indeed, GWP does not turn out to be the most influencing indicator in predicting sustainability, highlighting the necessity of going deeply in exploring energy transition impact, and providing a tool for it.

Future improvements can follow in two directions: the use of post-processing techniques to analyze energy scenarios, and the direct integration of sustainability paradigms in energy models. The second line of future research is based on the development of frameworks able to account for both decarbonization and other sustainability aspects. One option could be extending the traditional economic optimization paradigm including this metric directly in the objective function formulations. These advanced models should contain an environmental and a security layers other than economic one: all these elements need to be coupled with objective functions that account for the three components.

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CRediT authorship contribution statement

Gianvito Colucci: Writing – review & editing, Investigation, Conceptualization. **Daniele Mosso:** Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marco Savino Piscitelli:** Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Matteo Nicoli:** Writing – review & editing, Methodology, Formal analysis. **Laura Savoldi:** Writing – review & editing, Supervision, Resources, Methodology, Funding acquisition, Conceptualization. **Daniele Lerede:** Writing – review & editing, Methodology, Formal analysis.

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 are shared and made available by Mendeley link

Appendix. A. : Sustainability data inventory

Environmental data

In LCA analyses, the primary goal is to assess and quantify the environmental impact associated with a specific technological process, encompassing its entire life cycle from extraction of raw materials to disposal. This entails establishing a comprehensive linkage between the overall impact of the production process and expressing the analysis as a ratio between the total impact and the output quantity of the process. By doing so, it becomes possible to derive impact factors for each indicator identified by f_I^{LCA}. Each factor represents the impact (I) associated to the production of an electricity unit (MWh) ReCiPe (2022).

The overall impact values of the different phases (I_n) for a reference power technology are summed creating the overall Life Cycle Impact (each impact is characterized by a different Unit of Measurement (UoM_I). Then, the overall impact is divided by the total electricity produced by the reference power plant (MWh) creating an average impact for each unit of produced electricity $\left[\frac{UoM_I}{MWh}\right]$. By considering an electricity production technology characterized by N life cycle stages, the LCA unitary impact factor f_I^{LCA} for a generic impact I is calculated as in the Eq. (8).

$$f_I^{LCA}\left[\frac{UoM_I}{MWh}\right] = \frac{\sum_{n=1}^{N} I_n \quad [UoM_I]}{Life \quad cycle \quad electricity \quad production \quad [MWh]} \tag{8}$$

However, there is an issue related to the regional variability of the LCA impacts parameters. UNECE (UNECE, 2021) analyzed the vast majority of LCA impact from power plants, dividing the values for 12 world regions. Considering the relative difference between the European data and the rest of the world region (computed for each impact and for each technology included in the study), is possible to observe a delta around 50%, with peaks reaching 200%. Therefore, data must be selected as local as possible when performing an LCA Analysis, otherwise the introduced uncertainty is very high. In this work, the European data of the UNECE report has been assumed valid for the Italian case study due the absence of more detailed sources. Moreover, due to the lack of biomass and geothermal in the main source, data are completed with the NEEDS database, elaborated with the ReCiPe (ReCiPe, 2022) method in the OpenLCA (OpenLCA Nexus, 2022) software. Unfortunately, spatial aggregation for the biomass and geothermal was present only at global level, introducing further uncertainties in the analysis. Beyond the spatial aggregation, there is an issue of technological aggregation when performing LCA analysis. The discretization for the type of power plants usually presents in ESOMs, and in TEMOA-Italy, is not always reproducible in the LCA database, where the discretization is generally lower. Therefore, simplifying assumptions are needed to group plants together. The way technologies are matched to LCA database ones, specifying the spatial and technological aggregation, is shown in Table A1.

Table A1. LCA data sources (categorized by reference power plant and origin database) for the technologies involved in this study.

Technology	Reference Power Plant	Source	Reference Zone
Coal steam turbine	Hard coal, IGCC, without CCS	UNECE	EU
Oil steam turbine	Generic, oil-fired power plant	UNECE	EU
Gas turbine < 300 MW	Natural gas CC, without CCS	UNECE	EU
Gas turbine < 80 MW with steam	Natural gas CC, without CCS	UNECE	EU
Gas Combined cycle< 3000 MW	Natural gas CC, without CCS	UNECE	EU
Biogas Agro-Zoo	Biofuel CHP	NEEDS+ReCiPe	Global
Biogas Waste	Biofuel CHP	NEEDS+ReCiPe	Global
Bioliquid plant	Biofuel CHP	NEEDS+ReCiPe	Global
Biomass plant	Biofuel CHP	NEEDS+ReCiPe	Global
CSP	CSP, trough	UNECE	EU
PV roof plant	Photovoltaic, polycrystalline silicon, roof-mounted	UNECE	EU
PV ground plant	Photovoltaic, polycrystalline silicon, ground-mounted	UNECE	EU
On-shore wind farm	Wind, onshore	UNECE	EU
Off-shore wind farm	Wind, offshore, gravity-based foundation	UNECE	EU
Off-shore deep water wind farm	Wind, offshore, steel foundation	UNECE	EU
Mini hydro	Hydro, 660 MW	UNECE	EU
Mini hydro >1 MW	Hydro, 660 MW	UNECE	EU
Geothermal plant – high enthalpy	Flash steam power plant	NEEDS+ReCiPe	Global
Geothermal plant – low enthalpy	Flash steam power plant	NEEDS+ReCiPe	Global

As it can be observed from Table A1, the most significant case is the one of biomass, where a single plant is used to describe four different technologies- in TEMOA-Italy. Concerning the regionality, European data coming from UNECE are the majority, even if global data are found for biomass plants and geothermal plants. In conclusion, biomass plants constitute the highest source of uncertainty, also due to the complexity of modelling the various feedstock-agricultural practices-conversion-technology combinations (UNECE, 2021).

An overview of the indicators of the LCA Environmental Footprint dimension for power sector processes is provided in Table A2. The table summarizes the environmental impacts of various energy generation technologies using five indicators: Global Warming Potential (GWP), Acidification Potential (AP), Eutrophication Potential (EP), Land Use, and Water Use. Conventional sources like coal and oil steam turbines have the highest environmental impact, emitting significant GHGs and pollutants while requiring relatively less land and water. Gas turbines perform better in terms of emissions and resource use. Biogas, bioliquid, and biomass plants offer sustainable alternatives by utilizing organic materials, resulting in lower environmental impacts compared to coal and oil steam turbines. Renewable energy technologies, including solar, wind, and hydro, exhibit favorable environmental indicators. In particular, solar power has low emissions and water use, while wind farms perform well in terms of emissions and land and water use. Hydroelectric power has higher emissions due to reservoir methane, but minimal acidification and eutrophication potential if compared with the other technologies. Finally geothermal plants show low emissions and land use, but higher acidification and eutrophication potential.

Table A2. Power sector technologies characterization for LCA Environmental Footprint indicators at the base year.

LCA Footprint indicator	GWP[a] $\left[\frac{kg_{CO_2,EQ}}{MWh}\right]$	AP[b] $\left[\frac{g_{SO_2,EQ}}{MWh}\right]$	EP[c] $\left[\frac{g_{PO_4,EQ}}{MWh}\right]$	Land Use $\left[\frac{m^2}{MWh}\right]$	Water Use $\left[\frac{m^3}{MWh}\right]$
Coal steam turbine	849.0	430.2	424.0	0.3	1.7
Oil steam turbine	693.6	627.5	128.7	0.3	1.9
Gas turbine < 80 MW	433.7	966.7	19.7	0.2	1.2
Gas turbine < 300 MW	433.7	966.7	19.7	0.2	1.2
Gas Combined cycle< 3000 MW	433.7	966.7	19.7	0.2	1.2
Biogas Agro-Zoo	212.0	853.1	138.5	0.1	1.5
Biogas Waste	212.0	853.1	138.5	0.1	1.5
Bioliquid plant	212.0	853.1	138.5	0.1	1.5
Biomass plant	212.0	853.1	138.5	0.1	1.5
CSP	42.0	528.4	13.8	10.1	0.34
PV roof plant	34.8	528.4	39.3	5.6	0.63
PV ground plant	36.7	528.4	28.4	10.1	0.58
On-shore wind farm	12.4	60.9	6.7	1.4	0.18
Off-shore wind farm	13.3	50.1	6.9	1.4	0.16
Off-shore deep water wind farm	14.2	50.1	6.8	1.4	0.16
Mini hydro	147.0	0.2	12.6	10.1	0.37
Hydro >1 MW	147.0	0.2	12.6	10.1	0.37
Geothermal plant – high enthalpy	41.0	189.7	25.1	2.5	1.4
Geothermal plant – low enthalpy	41.0	189.7	25.1	2.5	1.4

[a]Global Warming Potential (GWP) factor for equivalent carbon dioxide emissions each MWh of electricity produced
[b]Acidification Potential (AP) factor for equivalent sulfur dioxide emissions each MWh of electricity produced
[c]Eutrophication Potential (EP) factor for equivalent sulfur phosphate emissions each MWh of electricity produced

Security data

Security indicators are derived from both external sources and model data. The reliability indicator is directly obtained from the capacity factor values available in the TEMOA-Italy database: hence, there are not concerns regarding spatial and technological aggregation when considering this indicator. The model includes capacity factor data for all the modelled years and for all the technologies. Unlike environmental data, it is not necessary to assume future variation for the capacity factor: indeed, in TEMOA-Italy a certain capacity factor variation throughout the time horizon is already considered, accounting for technology improvement.

Instead, the remaining security indicators are obtained from external sources, since TEMOA-Italy only provides, among the results, the total amount of imported energy commodities. The fuels considered in the analysis are oil, coal, and natural gas, while it is worth pointing out that their import is not solely related to the power sector consumption, since other sectors (chemical in particular) strongly rely on these fuels. Moreover, in the model version used for this study there is no explicit distinction between import countries. Data for fuel import by country are taken from the Italian fossil fuels national statistics ((Ministry of Environment and Energy Security, 2023a), 2023b) and reported in Table A3. For each fossil fuel, its import dependence is the sum over all the supplier countries.

Table A3. Italian primary fossil fuel supply in 2021 distinguishing between supplier country and national production (Ministry of Environment and Energy Security, 2023a, 2023b).

Country	Coal	Oil	Natural Gas
Africa	2%	31%	30%
Asia	2%	25%	10%
Europa	10%	6%	3%
Middle East	22%	24%	16%
North America	5%	3%	2%
Russia	52%	10%	39%
Latin America	3%	1%	0%
National Production	0%	0%	5%

Table A3 shows that Africa is the largest supplier of oil, followed by Asia and the Middle East. Russia supplies to Italy most of the coal and natural gas. For natural gas, Russia is followed by Africa and the Middle East. Latin America is the smallest exporter of all three commodities. Among the major exporters, the Middle East has an almost constant presence in all the three fossil fuels, while Russia and Africa are unbalanced with respect to oil and coal, respectively. For the materials, the current version of the model does not account for the required amount in the case of technology installation. Moreover, concerns about security of supply arise along the whole clean energy technology supply chain, as described in the JRC report (JRC, 2020), that distinguishes the following steps: raw material extraction, material processing, manufacturing of the technology components, and system assembly. The indicators related to the security of supply are formulated for all these steps, considering only solar photovoltaic systems (i.e., solar PV) and wind turbines, since they are the only technologies included in the TEMOA-Italy power sector (indeed, batteries are not modelled) for which the JRC report has highlighted relevant potential bottlenecks. The global supply share in 2020 by country and supply chain step from (JRC, 2020) is summarized in Table A4.

Table A4. Global supply chain share in 2020 by country and by supply chain step for solar PV and wind turbines (JRC, 2020).

Technology	Country	Raw Materials	Processed Materials	Components	Assemblies
	EU27	6%	5%	0%	1%
	Rest of Europe	3%	0%	0%	0%
	China	53%	50%	89%	70%
	Japan	4%	0%	0%	0%
	Russia	5%	0%	0%	0%
	US	7%	0%	0%	0%
	Africa	13%	0%	0%	0%
	Rest of Asia	3%	0%	1%	8%
	Latin America	4%	0%	0%	0%
Solar PV	Others	3%	38%	9%	21%
	EU27	0%	12%	20%	58%
	Rest of Europe	1%	0%	0%	0%
	China	54%	41%	56%	23%
	Japan	1%	6%	0%	0%
	Russia	0%	0%	0%	0%
	US	3%	9%	11%	0%
	Africa	2%	0%	0%	0%
	Rest of Asia	6%	0%	2%	0%
	Latin America	29%	0%	0%	0%
Wind turbines	Others	3%	32%	11%	19%

In Table A4 the diversification of the wind and photovoltaic supply chain is reported. It is imperative to acknowledge that the dataset under consideration pertains to the comprehensive global supply dynamics, as opposed to being exclusive to the supply specifically destined for the European region. Notably, there exists a current dearth of available data pertaining to the supply directed towards Europe (JRC, 2023). Underlying this analysis is the assumption that the global supply data can reasonably serve as a surrogate for European imports, predicated upon the notion that if Europe engages in importation, the aggregate composition of its imports will inherently mirror the broader landscape of global supply patterns. This hypothesis is very relevant because it constitutes the basis for the calculation of three security indicators: Import dependence, Political Stability Index and Volume shortage. Moreover, it the next section, also the Human Development Index is calculated under this assumption.

In Table A4 is possible to observe a higher diversification in the wind turbine supply chain than in the solar PV one. Wind turbine raw material extraction mainly happens in China and Latin America. Then, the next processing steps are mainly owned again by China, then Europe and Other countries (plus a little in the US), respectively. For the photovoltaic systems, despite a small diversification for the raw material phase, all the other steps are mainly concentrated in China. It must be remarked that, in absence of analysis conducted at an Italian level, European data are assumed to be valid for Italy also considering the small role played by all the EU27 countries in this market.

Data of Table A3 and Table A4 represent the present situation and, since the model does not account for changes on supplier countries, all the assumptions about the future evolution of these data must be exogenous. Therefore, it is assumed to keep these values constant for all the time horizons. – For fossil fuel extraction the situation is not expected to change dramatically (due to the physical location of the natural resources), while for the solar PV and wind technology supply chain, no possible evolution was found in literature (even if some mitigation solution to the diversification problem has started being discussed (JRC, 2023)).

Once the geographical concentration data above discussed are collected, the Import dependence and the Volume shortage indicators are computed. For each fossil fuel, the import dependence value from Table A3 (summing up over all the importer countries) is directly associated to the technology consuming it (e.g., import dependence of natural gas is associated to all the natural gas-based power production technologies). For the renewable technologies where 4 values are present (one for each supply chain phase), the worst one is chosen to account for possible bottlenecks risks. Concerning the Volume shortage indicator (see Eq. (1)), it is obtained by considering all the suppliers (import and domestic supply) and subtracting the maximum value, obtaining as a final amount the percentage of fuel or renewable technology available if there is a shortage from the largest supplier. Concerning renewable technologies, the worst values of Table A4 are taken. Final technology values for both the indicators are reported in Table A6. The security of supply depends also on geopolitical factors (Ang et al., 2015): in this perspective, the supplier countries can be characterized in terms of reliability as a trading partner. This have been already done both for fuels (Ang et al., 2015) and raw materials (JRC, 2023; Helbig et al., 2021b), considering geopolitical stability indexes that account for several governance dimensions. The one chosen for the analysis is the Political Stability Index (PSI) (Kaufmann and Kraay, 2010), which measures perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including politically motivated violence and terrorism. Its measure is usually performed at a country level, while commodities are supplied by a mix of countries. Therefore, is necessary to pass from a country-defined to a commodity-defined PSI value. This step is obtained through a weighted sum approach. By multiplying a country's PSI with its supply share for a specific commodity, a weighted average is calculated to determine the overall supply quality of its supply. The PSI for the different regions involved in Table A3 and Table A4 are reported in Table A5.

Table A5. Political Stability Index (PSI) by country.

Country	Political Stability Index (PSI)
EU27	0.76
Rest of Europe	0.21
China	-0.48
Japan	1.03
Russia	-0.65
USA	0.42
Africa	-0.69
Rest of Asia	-0.39
Latin America	-0.23
Others	0.86

As it is possible to notice in Table A5 the highest PSI occur for the western countries such as Japan, Europe 27 and USA. The tier 2 countries are the other European nations, the Latin America, and the Rest of Asia. Finally, the less trustable countries in terms of political stability are Africa, Russia, and China, that also plays a major role in the international trade as confirmed by Table A3. Conclusively, Table A6 reports all the supply chain indicators.

Table A6. Power sector technologies characterization for security indicators at the base year.

Security indicator **Descriptive parameter**	**Import Dependence** ***Imported supply (%)***	**Volume shortage risk** ***N-1 residual supply (%)***	**Geopolitical Stability** ***Political Stability Index [-]***
Coal steam turbine	100.0%	47.2%	-0.20
Oil steam turbine	100.0%	77.0%	-1.10
Gas turbine < 300 MW	95.0%	60.0%	-0.59
Gas turbine < 80 MW with steam	95.0%	60.0%	-0.59
Gas Combined cycle < 3000 MW	95.0%	60.0%	-0.59
Biogas Agro-Zoo	0.0%	100.0%	0.76
Biogas Waste	0.0%	100.0%	0.76
Bioliquid plant	0.0%	100.0%	0.76
Biomass plant	0.0%	100.0%	0.76
CSP	0.0%	100.0%	0.76
PV roof plant	96.0%	34.5%	-0.16
PV ground plant	96.0%	34.5%	-0.16
On-shore wind farm	76.5%	56.5%	0.12
Off-shore wind farm	76.5%	56.5%	0.12
Off-shore deep water wind farm	76.5%	56.5%	0.12
Mini hydro	0.0%	100.0%	0.76
Mini hydro >1 MW	0.0%	100.0%	0.76
Geothermal plant – high enthalpy	0.0%	100.0%	0.76
Geothermal plant – low enthalpy	0.0%	100.0%	0.76

The fossil fuel supply chain security refers to the imported fuels: then, security issues can be reflected at the technology level since technologies consume these fuels to produce their outputs, referred to as technology activity (e.g., the activity of a power plant is the produced electric energy). On the contrary, the technology supply chain security directly refers to the installation phase of the technologies. In both cases, these indicators are associated with the activity of the technologies, leading to two limitations. First, for the fuels, the indicators measured for the imported, and then consumed fuels, are directly associated to the technology, without passing through its efficiency, as specified in Eq. (7) of Section 2.3. Indeed, mixing upstream data (fuel import) and production (activity) is not possible, because the scenario evaluation must be performed on a normalized basis, in this case obtained by the activity share (which values are always between 0 and 1). Second, the technology supply chain security issues are reflected in the technology operation phase (activity share), instead of the installation phase (capacity share). Theoretically, fossil fuel powered plants involve a security issue if the commodity is consumed, and this is someway proportional to the activity. For renewable plants, the security issue related to materials happens only in the installation phase, quantified in the model by the new installed capacity. Again, due to the need of evaluating the scenario on a common basis, security issue of renewable plants is assumed proportional to activity. Both these limitations are considered necessary to consistently include the security dimension in the sustainability metric, in which all the indicators are associated to the activity of a technology. Limitations induced by these choices are detailed in the discussion section.

Social data

The Social dimension is characterized by several indicators. Human Health Damage is expressed in DALY, which is the acronym of Disability-Adjusted Life Years, a measure of the overall severity of a disease, expressed as the number of years lost due to the disease, disability, or premature death, commonly used to evaluate the impact of technologies (Murray, 1994). The source for this indicator is the same as other LCA parameters discussed in the environmental dimension (Table A1) and presents the same technological and spatial aggregations issues related to the data source as the environmental indicators. Data are reported in Table A1. Within LCA HHD indicator lies the fatalities one. It represents the complement of the human health damage. If HDD accounts for the predictable deaths or damages to human health linked to normal power plants operations, fatalities account for accidental events (deaths) caused by electricity production. Data for fatalities are derived from the IPCC study on renewable energies and climate change mitigation (Pichs Madruga et al., 2023) and are reported in Table A7. As happens for the LCA parameters the technological discretization of the study is different from the model one, therefore a connection between databases is performed.

Table A7. Accident-related fatality rates/GWh.

Technology	Specifications (Country / Sub-tech)	[Fatalities / GWyr]
	OECD	1.2E-01
	EU 27	1.4E-01
	non-OECD w/o China	5.7E-01
Coal	China	5.9E+00
	OECD	9.3E-02
	EU 27	9.9E-02
Oil	non-OECD	9.3E-01
	OECD	7.2E-02
	EU 27	6.8E-02
Natural Gas	non-OECD	1.2E-01
	OECD	2.7E-03
	EU 27	8.5E-02
	non-OECD	7.0E+00
Hydro	non-OECD	9.4E-01
PV	Cristalline Silicon	2.5E-04
Wind Onshore	DE	1.9E-03
Wind Offshore	UK	6.4E-03
Biomass	CHP Biogas	1.5E-02
Geothermal	EGS	1.7E-03

In Table A7 accident fatality rates for one GWh of electricity are reported for different power sector technologies. The IPCC study provides a statistical analysis conducted on different countries, highlighting for each technology the rate of fatalities, providing, when possible, some specifications about the type of plants used for the study and the countries. Accident-related fatalities range from 2,5E-04 (PV min) to 7,0E+00 (hydro-max. The maximum IPCC hydropower value represents nations out of the Organization for Economic Co-operation and Development, while the minimum values are found for OECD countries and nations of the European Union. This is a general pattern in the table, even if the hydropower case is the most visible, also due to the three order of magnitude variation. The IPCC does not explain the large difference between these values compared to other technologies.

Finally, Quality of labor is expressed through an ad-hoc developed indicator that relates the power sector technologies to the Human Development Index (HDI) of the countries owning their supply chain phases. Data for the technology supply chain phase are already known from Table A3 and Table A4. For the HDI, it is a summary measure of average achievement in key dimensions of human development for a certain country. HDI is generally expressed in a 0–1 scale where the closer the value to 1, the higher the country achievements in terms of human development. For the sake of this study, as it happens for the PSI, the HDI is translated from the one of the supplier countries to the one of energy material/commodities. HDI of supplier countries is reported in Table A8:

Table A8. Human Development Index by country.

Country	Human Development Index (HDI)
EU27	0.94
Italy	0.89
Rest of Europe	0.89
China	0.77

(*continued on next page*)

(*continued*)

Country	Human Development Index (HDI)
Japan	0.93
Russia	0.82
USA	0.92
Africa	0.55
Rest of Asia	0.63
Latin America	0.75
Others	0.71

According to Table A8, Europe, Japan, and USA are the most developed countries according to this index, while Africa and Rest of Asia lie at the bottom of this ranking. The conversion between country values to technology-specific value is done by performing a weighted average of the HDI of countries for their supply chain phase shares (single value for fossil and worst value for PV and Wind, as before). The result is an HDI defined for each material and fossil fuels, that can be subsequently associated to the technologies consuming that specific commodity.

Table A9. Power sector technologies characterization for Equity indicators at the base year.

Equity Indicator	Fatalities $\left[\frac{\text{Deaths}}{\text{MWh}}\right]$	Quality of Labor *Human Development Index*	Human Health Damage[a] $\left[\frac{\text{DALY}}{\text{MWh}}\right]$
Coal steam turbine	0.14	0.85	1.9
Oil steam turbine	0.09	0.83	1.0
Gas turbine < 300 MW	1.08	0.78	0.5
Gas turbine < 80 MW with steam	1.08	0.78	1.1
Gas Combined cycle< 3000 MW	1.12	0.78	0.5
Biogas Agro-Zoo	0.15	0.94	2.0
Biogas Waste	0.15	0.94	2.0
Bioliquid plant	0.15	0.94	2.0
Biomass plant	0.15	0.94	2.0
CSP	0.02	0.94	0.2
PV roof plant	0.02	0.76	1.9
PV ground plant	0.02	0.76	1.9
On-shore wind farm	0.19	0.80	0.0
Off-shore wind farm	1.04	0.80	0.0
Off-shore deep water wind farm	1.04	0.80	0.0
Mini hydro	1.25	0.94	0.0
Mini hydro >1 MW	1.25	0.94	0.0
Geothermal plant – high enthalpy	0.17	0.94	0.0
Geothermal plant – low enthalpy	0.17	0.94	0.0

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