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Combined assessment of material and energy supply risks in the energy transition: A multi-objective energy system optimization approach

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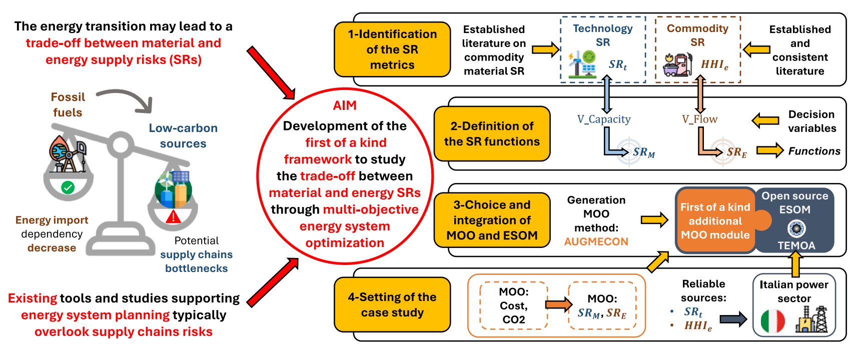
HIGHLIGHTS

- A new framework to study trade-offs between supply risks is presented.
- A multi-objective energy system optimization approach is adopted.
- Two consistent functions measuring materials and energy supply risks are developed.
- Augmented epsilon-constraint method is used within energy system model TEMOA.
- A significant trade-off exists between the two risks in decarbonized power systems.

GRAPHICAL ABSTRACT



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ABSTRACT

This paper proposes a novel framework to study the trade-off between different energy transition supply risks through multi-objective energy system optimization. While the increasing use of clean energy technologies reduces reliance on fossil fuels imports and hence energy supply risks, these technologies depend heavily on critical raw materials, the supply chains of which present high geographical concentration and political instability. Current energy system planning lacks endogenous evaluations (e.g., minimization) of such supply risks. To address this gap, two consistent supply risk functions are derived considering concentration, import reliance, and political stability of supply chains of critical raw materials on the one hand and energy commodities on the other hand. We enhance the open-source energy system modeling framework TEMOA by multi-objective optimization using the AUGMECON method to consider these functions endogenously as objectives and demonstrate the capabilities of this new approach for the Italian power sector decarbonization by 2050. First, total system cost and CO_2 emissions are minimized to establish a baseline. Then, four multi-objective optimizations between material and energy supply risks are conducted, each allowing for increasing total system cost. This approach allows the underlying energy system to adapt to minimize supply risks. Results highlight a significant trade-off between the two risks. Minimizing the material supply risk increases energy supply risk by reducing investments in wind turbines and batteries. These technologies are replaced by solar PV and natural gas plants with CCS, which raises gas imports and energy supply risk. Higher costs lead to wind energy disappearance, replaced

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mainly by natural gas plants, increasing reliance on CCS and imports. These findings emphasize the importance of balancing material and energy supply risks in energy system planning.

Nomenclature

Acronym	*Meaning*
a-Si	Amorphous silicon
AUGMECON	Augmented epsilon-constraint
BEV	Battery electric vehicles
CCUS	Carbon capture utilization and storage
CdTe	Cadmium telluride
CIGS	Copper-indium-gallium-diselenide
CRM	Critical raw material
c-Si	Wafer-based crystalline silicon
DAC	Direct air capture
DD-EESG	Direct-drive electrically excited synchronous generator
DD-PMSG	Direct-drive permanent magnet synchronous generator
ESOM	Energy system optimization model
EU	European Union
GB-DFIG	Gearbox double-fed induction generator
GB-PMSG	Gearbox permanent magnet synchronous generator
HHI	Herfindahl-Hirschman Index
HREE	Heavy rare earth element
IEA	International Energy Agency
IR	Import reliance
IRENA	International Renewable Energy Agency
JRC	Joint Research Center
LCA	Life cycle assessment
Li-ion	Lithium-ion
LREE	Light rare earth element
LWR	Light water reactor
MOO	Multi-objective optimization
MR	Materials requirement
PEMFC	Proton-exchange membrane fuel cell
PV	Photovoltaic
REE	Rare earth element
SR	Supply risk
WGI	World Governance Index

Symbol	*Meaning*
b€	Billions of euros
c	Small constant for AUGMECON
cap	Unit of measure for capacity
cons	Consumption
DomProd	Domestic production of raw materials (energy commodities)
Export	Quantity of exported raw materials (energy commodities)
f	Material intensity or share
$f = (f_1, f_2, \ldots, f_n)$	Objectives of the generic multi-objective optimization problem
g	Generic governance indicator
GW	Unit of measure for Gigawatt
Import	Import
k	Constant
Mt	Millions of tons
N	Number
NetImport	Net import
PJ	Unit of measure for petajoule
S	Market share of countries
s	Slack variable
t	Unit of measure for tons
V_Capacity	Variable for new installed capacity of technologies
V_Flow	Variable for commodities flow
y	Year
ϵ	Constraint

Superscripts	*Meaning*
en	Energy commodity
export	Export
import	Import
mat	Material
MIN	Minimum
st	Sub-technology
T	Transpose
tech	Technology
yref	Reference year

Subscripts	*Meaning*
c	Country (generic)
CO2	Total cumulative net CO2 emissions
cost	Total system cost
countries	Countries (total number)
e	Energy commodity (generic)
E	Energy (supply risk function)
en	Energy commodities (included in the energy system)
end	Ending year
i	i-th constraint
j	j-th objective function
k	k-th sub-technology
m	Material (generic)
M	Material (supply risk function)
mat	Materials (required by a technology)
n	Number of objective functions
p	Time optimize
start	Starting year
sub-tech	Sub-technologies (total number)
t	Technology (generic)
tech	Technologies (total number)

1. Introduction

The energy transition leads to a trade-off between different supply chain risks associated with a shift from fossil fuels to low-carbon energy sources. Renewable energy sources [1] and battery electric vehicles (BEVs) [2] are anticipated to reduce fossil fuel consumption, thereby decreasing the import dependency that many countries have recently experienced. For instance, the 2022 energy import reliance (IR) of the European Union (EU) and Japan was, ~63 % [3] and ~ 85 % [4], respectively. The decrease in IR for a country is expected to reduce its energy supply risk (SR), which is typically defined as the likelihood of a supply disruption due to supply chain bottlenecks [5]. However, technologies for the energy transition (hereinafter clean energy technologies) typically require more minerals and metals than fossil fuels-based technologies The average material requirement (MR) for new power generation capacity increased by ~50 % globally between 2010 and 2020 [6]. Moreover, global demand for several raw materials is projected to increase by several times in the coming decades, with the e-mobility and battery storage sectors accounting for most of the growth [7]. For instance, according to stated policies, the global lithium demand for these sectors is foreseen to rise more than 5 times between 2020 and 2030 [1], and around 13 times by 2040 [6]. Overall, future growth rates for many materials are projected to outreach historical levels, potentially causing a supply-demand imbalance [8,9].

The geographical concentrations in the supply chains of clean energy technologies represent an additional potential bottleneck [7]. China dominates in extracting and processing many materials, such as lithium, silicon metal, and rare earth elements (REEs), currently accounting for 56 %, 76 %, and 90 % of global supply, respectively [10]. The supply of other materials required by clean energy technologies such as cobalt and platinum is more diversified but encompasses countries like the Democratic Republic of the Congo (for cobalt) as well as South Africa and Russia (for platinum), which are not considered politically stable[1] [10]. Moreover, China leads the current and announced manufacturing capacity of several components (e.g., the 2023 and projected 2030 Chinese share for solar PV modules, wind nacelles, and batteries cells lies between 60 % and 80 %) [11]. The geographical concentration is an indicator frequently adopted in materials and technologies criticality assessments to determine their SR [7,12]. In this regard, policymakers start being concerned about the procurement of energy transition materials and technologies [11]. For instance, the EU Net-Zero Industry Act [13] and the Inflation Reduction Act in the United States [14] support the domestic manufacturing along the supply chains of clean energy technologies supply chains. In other countries, similar plans were recently approved (e.g., India, Korea) or proposed (e.g., Canada, Australia) [11]. Furthermore, a growing number of countries are enhancing their comprehension of the SRs by developing and continuously revising critical raw materials (CRMs) lists [15] and by formulating strategies to guarantee a secure and diversified supply, as exemplified by the EU CRMs Act [16].

Potential supply chain bottlenecks could hinder the transition to a low-carbon economy [17] and should therefore be considered in formulating energy policies [18] and studying future energy supply scenarios [19]. Indeed, energy decision makers and other stakeholders are increasingly keen to access more comprehensive insights about impacts and limitations that could affect future energy systems [20], with raw materials among the primary concerns [21]. This increases the complexity of energy system planning and requires more holistic frameworks and methodologies to support decision-making with politically relevant results [21–23]. In this regard, energy system optimization models (ESOMs) are used to test the effectiveness of energy policies, typically by providing the least-cost configuration of an energy system, described through a technology-rich database, over the medium-to-long term [22,24].

Current literature (which is presented in detail in Section 2) highlights that existing tools and studies often overlook supply chain risks. The latter are typically evaluated ex-post[2] through the assessment of MR or SR indicators for preexisting energy scenarios [25]. In particular, the vast majority of the existing research aims to estimate the future materials demand due to the energy transition and usually compares it to current geological availability [17]. Nevertheless, this approach omits supply concentration considerations, which are considered more suited to assess supply chain risks [8]. In this regard, a number of studies include materials supply concentration indicators to evaluate the future SR of energy transition scenarios [20]. Additionally, few works consider both material and energy SR indicators in the same framework [26,27]. These studies provide more comprehensive insights on the potential SRs associated with the energy transition. However, they all adopt an ex-post approach and as a result, the underlying energy systems cannot adapt to minimize supply chain risks.

The existing literature thus reveals a research gap concerning the absence of ESOMs that account for the material and energy SRs ex-ante[3] using dedicated objective functions. This limits the capability of models in supporting a conscious trade-off decision by policymakers, concerning the level of material and energy SRs they are willing to accept along with the corresponding cost implications. In this context, multi-objective optimization (MOO) represents an appropriate means of addressing these shortcomings [25]. MOO is considered very effective when dealing with the multiple and often conflicting interests (leading to trade-offs) in energy systems decision making, as expected for material and energy SRs [22]. Few studies use MOO methods in ESOMs to address criteria related to materials and energy import dependency, such as the depletion of materials and metals in life cycle assessments [28,29], or energy autonomy of small-scaled systems [22,30]. Nevertheless, these studies do not explicitly address SRs with suitable metrics. And indeed, a recent review paper [25] confirms that MOO has not yet been used in an ESOM to approach raw material requirements and SRs of the energy transition.

To address the identified research gap, this paper introduces a novel framework for analyzing the trade-offs between material and energy supply risks in the energy transition using multi-objective energy system optimization. The primary contributions of this framework to advancing the state of the art are:

- The development of comprehensive and consistent metrics for evaluating the supply chain risks associated with the energy transition by considering both material and energy supply risks in energy systems.
- The ex-ante integration of the supply risks as endogenous functions in a multi-objective energy system optimization by implementing the AUGMECON method in TEMOA. The former is based on one of the most widely used MOO frameworks [31], while the latter is considered among the well-established ESOMs in literature [24]. This approach enables to consider the policy interests in minimizing or, more generally, analyzing the trade-offs between the SRs.
- The capability to generate policy-relevant insights on potential effects of supply risks and their trade-offs and management in decarbonized energy systems. In this regard, the decarbonization of the Italian power sector by 2050 is used as a case study. Indeed, the absence of specific supply chain concentration measures in alignment with the energy transition targets [32] makes the Italian case study particularly illustrative, as discussed in Section 3.4.

The paper is structured as follows. The existing literature and its limitations are described in Section 2. Subsequently, Section 3 includes the development of the SR functions and the description of the MOO method, ESOM, and case study that were considered. Additionally, strengths and limitations of the methodology are highlighted. Results are presented and discussed in Section 4, while Section 5 concludes the work and offers future research perspectives.

[1] In the context of raw materials, the political stability of supplier countries is measured through governance indicators, which consider several governance dimensions [12].

[2] The "ex-post" term is used in this paper to identify an approach that combines indicators of materials requirement or supply risks with pre-existing results from energy scenarios. For instance, material intensity indicators are combined with results on new installed capacity of technologies in most of the ex-post assessments.

[3] The "ex-ante" term is used in this paper to identify an approach that endogenously accounts for materials requirement or supply risks within the energy system modeling framework. For instance, the inclusion of materials supply modules within the modelled energy system or the adoption of supply risk objective functions are considered ex-ante approaches.

2. Supply risks in energy system optimization models: state of the art

The existing literature includes several approaches to incorporate supply chain risks in ESOMs. These approaches can be distinguished into three groups, as presented in the next paragraphs.

The first group of studies encompasses a growing number of studies assessing future materials demand due to the energy transition [17]. Most of them apply MR indicators ex-post to energy scenarios from third-party sources. These indicators typically quantify the material intensity of technologies in unit mass of the individual material per unit capacity (e.g., t/GW). For instance, global energy scenarios by the International Energy Agency (IEA) and International Renewable Energy Agency (IRENA) are used to derive materials consumption in decarbonized energy systems in [19,33,34]. More specific analyses are done in [35] for the materials required by offshore wind in the United States and in [36] for the Chinese transport system. The same prospective ex-post approach is adopted in reports by international organizations like IEA [6], IRENA [37], World Bank [38], regional institutions such as European Commission and Joint Research Center (JRC) [7,39,40], and companies like McKinsey [8]. In contrast, a soft link between an ESOM and life cycle inventories is proposed in [41,42], where the requirement of almost 50 raw materials is linked to the outputs of the TIAM-FR model. Conversely, only a few models calculate ex-ante materials consumption within the underlying energy system. This is the case of lithium in the TIAM-IFPEN model [43] and of many raw materials for clean energy technologies in the MEDEAS model [23,44]. The studies in this first group have three main limitations. First, the energy scenarios employed in the ex-post approaches are not influenced by potential unavailability of materials, potentially leading to infeasible results [25]. Second, the models that endogenously calculate materials consumption fail to consider the potential risk of supply chain bottlenecks, nor as a model constraint or objective. Third, both the ex-post and ex-ante approaches consider global geological availability as the only SR proxy, by comparing the projected demands of raw materials to current resources, reserves, and mining [17] and lack regional-oriented insights and overlook supply concentration issues. This approach over-simplifies the actual risks [12,45], as it is widely agreed that scarcity is not as pressing an issue as supply scaling and concentration [8] and it is broadly recognized that supply chain risks have a regional dimension [17,46].

To overcome the latest limitation, a second group of studies estimate future SRs of the energy transition by adopting the most common SR indicators such as measures of supply concentration (e.g., Herfindahl-Hirschman Index (HHI)) and IR [17,45,47]. For instance, the HHI and IR associated with the lithium requirement by the Chinese transport system electrification are studied in [48]. Other analyses, in contrast, apply more comprehensive SR metrics to single materials [49] or technologies such as thin film solar PV [50], cars [51], and wind power [52,53]. Beside the extraction and processing of raw materials only, some studies propose SR metrics for the entire supply chain of technologies, as for instance [7,54], where also the manufacturing and assembly of components is considered. Instead, [55] proposes a technology SR by aggregating the SRs of the raw materials required for the construction and applying this metric to European energy transition scenarios within the ENBIOS modeling framework [20,46]. Note, however that none of the studies in the second group endogenously evaluates supply chain risks within ESOMs. This implies that SRs cannot affect the design and operation of future energy systems and no comprehensive insights into how SRs could be reduced are generated. Second, those studies primarily focus on single raw materials and/or technologies, with few insights on technological (e.g., BEVs and wind turbines both consume REEs) and sub-technological (e.g., different types of solar PV technologies consume different materials) competition in CRMs consumption terms [34]. Moreover, the material SR is evaluated without considering also the energy SR. In this regard, a combined assessment might provide more comprehensive policy-relevant insights on the supply chain risks in the energy transition [18].

The latter two limitations are addressed by a third group of studies, where the SRs of clean energy technologies and energy commodities are integrated into broader energy security metrics, which are ex-post applied to energy scenarios. While most of the energy security metrics account for supply chains risks associated with fossil fuels only, few studies address the effects on the energy transition supply risks of both energy and materials flow changes in the same framework [56]. In this regard, first attempts are presented in [26,27,57], where ex-post assessments are provided for Italian energy scenarios and SR is evaluated both for materials and energy commodities. However, as previously highlighted, the ex-post approach does not allow to study energy scenarios directly affected by potential supply chains bottlenecks.

3. Methodology

The methodology workflow for deriving the supply risk functions and their use in multi-objective energy system optimization encompasses the following steps:

1. **Identification of the supply risk metrics.** To derive the material and energy supply risk functions, coherent metrics were consistently identified to adequately relate the material and energy dimensions. For the former, the supply risk is considered at technological level, while for the latter, it is considered at commodity level (see Section 3.1).
2. **Definition and implementation of the supply risk functions.** To define supply risk functions, the identified metrics was combined with suitable decision variables used in energy system optimization models. The new installed capacity of technologies and the commodities flow were used for the material supply risk and the energy supply risk, respectively. For more details on the definition of such variables in the context of energy system optimization models, see Section 3.2 and [58].
3. **Selection and integration of the multi-objective optimization method and the energy system model.** The augmented epsilon-constraint (AUGMECON) multi-objective optimization method [31] was integrated in the open-source energy system optimization model TEMOA as an additional module, leading to the first multi-objective optimization application for a TEMOA model [59] (see Section 3.3).
4. **Setting of the case study.** The multi-objective optimization framework was applied to a power sector model derived building upon the open-source TEMOA-Italy model [60]. Then, a multi-objective optimization of total system cost and net CO_2 emissions was set as a base case to subsequently define a multi-objective optimization of material and energy supply risks under cost and decarbonization constraints (see Section 3.4).

3.1. Identification of the supply risk metrics

This section presents the development of coherent SR metrics, which consists of a material SR at technological level and an energy SR at commodity level.

Many material SR assessments use the definition in Eq. (1)[4] for a single material m (i.e., a commodity material SR) [45,47], where SR_m is a dimensionless composite index that includes several SR factors. It is typically computed – for a specific region – as a function of indicators of supply concentration and governance – included in HHI_m – and import reliance IR_m. Specifically, high concentration, low governance, and high dependency from abroad are risk increasing factors.

[4] Throughout all equations in the paper, the unit of measures of each quantity is denoted in parentheses, wherein "-" refers to dimensionless quantities.

$$SR_m(-) = f(HHI_m, IR_m) \tag{1}$$

Since clean energy technologies usually require several materials with relevant SRs [7], a material supply risk SR_t of a technology t is the appropriate metric to be included in ESOMs [46]. The only quantitative definition for energy technologies found in literature [55] and adopted in this paper is reported in Eq. (2): for each of the N_{mat}^{tech} materials m required by the technology t, the SR_m (defined in Eq. (1)) is weighted by the material intensity $f_{m,t}$ (measured in unit mass per unit capacity cap, e.g., t/GW for electricity production technologies) and then normalized by the annual consumption level $cons_m^{yref}$ in a reference year $yref$, which is measured in unit mass.

$$SR_t\left(\frac{1}{cap}\right) = \sum_{m=1}^{N_{mat}^{tech}} \frac{f_{m,t}}{cons_m^{yref}} \cdot SR_m \tag{2}$$

A commodity energy SR is widely used in energy security metrics to assess the fossil fuel supply disruption risks. Indeed, the reviews in [5,61,62] of over a hundred ES indicators and indices pointed out a vast use (in 47 studies) of the same supply concentration, governance, and import reliance indicators as for materials, but defined for the single energy commodity e (i.e., HHI_e and IR_e). In particular, they are mainly used as separate indicators, while their combination as in Eq. (1) is adopted less frequently. Nevertheless, a metric consistent with the material SR one was used for the supply risk of an energy commodity.

More details on the definitions described above are provided in the appendices. The definitions of HHI and IR for both materials and energy commodities are provided in Appendix A. Instead, an extensive discussion of the rationale behind the definition of the technology material SR is provided in Appendix B.

3.2. Definition and implementation of the supply risk functions

To derive SR functions to be included within energy system modeling frameworks, the metrics presented in Section 3.1 must be combined with suitable decision variables.

Materials are needed for the manufacturing of technological components and in ESOMs this can be associated with new capacity installations. Hence, looking also at the measurement unit of SR_t (see Eq. (2)) – i.e., in unit capacity 1/cap – the chosen decision variable was the newly installed capacity measured in unit capacity cap. Consider that ESOMs typically incorporate several technologies into their energy systems, and the optimization process is conducted over a time horizon comprising multiple years. Accordingly, the new installed capacity variable $V\_Capacity_{t,p}$ of the technology t is calculated for eachyear p included in the model time horizon. Eq. (3) thus defines the function quantifying the overall material supply risk SR_M over a period from y_{start} to y_{end} for an energy system that incorporates N_{tech} technologies.

$$SR_M(-) = \sum_{p=y_{start}}^{y_{end}} \sum_{t=1}^{N_{tech}} SR_t \cdot V\_Capacity_{t,p} \tag{3}$$

Concerning the energy SR, consider that ESOMs typically incorporate several energy commodities into their energy systems. The related energy flows defining the import reliance IR_e are defined through the decision variable $V\_flow_{e,p}$, measured in unit of energy (e.g., PJ) and computed for each of the modelled energy commodities and model time horizon years. This makes IR_e a derived variable for the optimization problem and the possible commodity energy SR a nonlinear metric if defined as for the materials in Eq. (1). To avoid nonlinearity, Eq. (4) thus defines the function quantifying the energy SR over a period from y_{start} to y_{end} for an energy system that incorporates N_{en} energy commodities. Here, $cons_{energy}^{yref}$ represents a fixed energy consumption level related to the energy system under analysis and is used as a normalization factor to account for the relative importance of energy commodities in the energy supply.

$$SR_E(-) = \sum_{p=y_{start}}^{y_{end}} \sum_{e=1}^{N_{en}} HHI_e \cdot \frac{\left(V\_flow_{e,p}^{import} - V\_flow_{e,p}^{export}\right)}{cons_{energy}^{yref}} \tag{4}$$

3.3. Selection and integration of the multi-objective optimization method and the energy system model

Among the most used MOO are the weighted sum and epsilon-constraint methods [31]. The former provides for the assignment of specific weights to the objective functions involved, whose sum is then optimized. Instead, in the epsilon-constraint method all but one objective are reformulated as inequality constraints, while the remaining one is optimized. The implementation of the epsilon-constraint method is considered the most intuitive approach in ESOMs, since they usually encompass a cost objective function and other potential objectives (e.g., CO2 emissions) as constraints [22]. However, both weighted sum and epsilon-constraint methods do not ensure Pareto optimal solutions, which are those sought in MOO: in this regard, a solution to a MOO is called Pareto-optimal if, improving one objective, necessarily deteriorates another one [31].

Instead, Pareto-optimality is ensured by the AUGMECON method [31], which was used in this paper. It is a reformulation of the epsilon-constraint method, where all objectives but one are reformulated into equality constraints. The main steps involved are the following. First, each objective of the MOO problem is minimized individually to estimate the Pareto front boundaries. Second, a desired number and distribution of caps within the Pareto front boundaries are chosen: the caps represent the right-hand side of the equality constraints that are derived by reformulating all objectives but one. Third, the problem is solved for all the caps, providing Pareto-optimal solutions of the initial MOO problem.

The MOO framework described above was included as an optional module in the open-source ESOM TEMOA [59], leading to a new version of this modeling framework [64]. An overview of the formalization of the MOO problem by the AUGMECON method is provided in Appendix C. Additionally, a more comprehensive description is available in [31], while for ESOM applications, see e.g., [22,65,66]. Moreover, its implementation in TEMOA is detailed in the Supplementary Material.

3.4. Setting of the case study: the TEMOA-Italy power sector

The new TEMOA-MOO module was applied in a case study encompassing a simplified version of the power sector of the TEMOA-Italy model [57], an open-source multi-sectorial ESOM of the Italian energy system, modelled as a single region [60,67].

The Italian energy system was used as case study, since trade-offs might strongly affect its SRs. Fossil fuels accounted for almost 80 % of Italian final energy consumption in 2022, with a net IR of approximately 84 %, making Italy among the largest energy importers in EU [68]. In this regard, the Italian energy security targets provide for a diversification and a progressive decrease of energy imports, in favor of domestic and clean energy sources [69]. For instance, the latest announced policies aim to increase renewables share in electricity mix up to 60 % in 2030 [69], providing for maximum 5 % of natural gas-based generation in 2050 [70]. Additionally, the current BEV fleet of ~0.2 million is projected to exceed 4 million vehicles by 2030 [69]. The enhancement of power grid stability is the only security measure undertaken in association with the vast penetration of clean energy technologies, while potential supply chain bottlenecks are inadequately addressed: The recently approved Italian first legislation on CRMs offers a more preliminary framework than the ones in other countries [11]. Furthermore, it does not incorporate specific measures in alignment with the energy transition targets [32], which makes the Italian case study particularly illustrative.

The case study was limited to a single energy sector to be tractable but, at the same time, sufficiently detailed to facilitate the framework application and results analysis. Among the sectors affected by energy and material supply chains risks, the power sector was chosen for two reasons. First, it allows for a comprehensive assessment involving many technologies and their mutual substitutions, also leveraging the technological richness and explicitness of ESOMs [71]. Second, there is high availability and reliability of MR in literature for that sector. A scheme of the adopted power sector model is depicted in Fig. 1. Both fossil and low-carbon power generation were considered for a total of eleven technology types: solar PV, onshore and offshore wind, hydropower, geothermal, a generic biofuels-based production (hereinafter bioenergy), hydrogen (H2) proton-exchange membrane fuel cell (PEMFC), nuclear (light water reactor (LWR)), coal steam cycle and natural gas combined cycle with and without CO_2 sequestration. These technologies generate electricity, for which a fixed overall demand must be satisfied, and potentially consume commodities that can be imported and/or domestically produced, with constraints on resource availability. Moreover, lithium-ion (Li-ion) batteries and carbon capture, utilization, and storage (CCUS) are modelled (the latter also includes direct air capture (DAC)). The case study time horizon only includes the year 2050[5], for which the total annual electricity demand was set to 1589 PJ based on TEMOA-Italy decarbonization scenarios [72], aligning with other Italian electrification projections [22]. Although electricity imports are modelled in TEMOA-Italy, they were excluded in this case study to focus on the competition between domestic technologies in terms of SRs. Moreover, the energy SR metric discussed in Section 3.1 is not used for electricity in the current literature. Finally, a simplified materials supply chain was also modelled for an endogenous computation of the materials consumption. The details of its implementation in TEMOA are provided in the Supplementary Material.

The new version of TEMOA developed for and adopted in this work, including the database and the MOO module, is openly available at [64]. The techno-economic characterization of the power sector reference energy system, the MOO and materials supply modules, and the TEMOA-Italy model are further detailed in the Supplementary Material. The following sub-sections provide details on data and assumptions adopted to evaluate the material and energy SR metrics in Section 3.4.1 and Section 3.4.2, respectively. Additionally, the studied MOO problems are described in Section 3.4.3.

3.4.1. Evaluation of the material supply risk metric: data and assumptions

To compute SR_t in Eq. (2) for each power generation technology, three parameters were needed: SR_m, $cons_m^{yref}$, and $f_{m,t}$. Values and sources are reported in Table 1. The lack of Italian specific analyses on material SR led us to consider the EU geographical scope, which is nevertheless suitable given the proven marginal role of EU countries in global materials supply chains [7]. Eq. (1) was used to derive SR_m from the latest EU CRMs list [10]. Only CRMs for the EU economy were included in the data gathering. The definition adopted in [10] also includes material recycling and substitution. However, they were neglected for consistency reasons with the energy SR metric without affecting the SR_m ranking. REEs show the highest SR due to the extremely high geographical concentration in China concerning the processing phase. Then, a more diversified supply characterizes other relevant transition materials such as cobalt and platinum, but they still have a high SR due to the high geopolitical instability of the main supplier countries. In this regard, such instability is measured through the well-established World Governance Index (WGI) [73]. Examples are the Democratic Republic of the Congo for cobalt as well as South Africa and Russia for platinum. Instead, the SR of copper and nickel is lower than the criticality threshold used in [10], but they are included in the EU CRMs list because of their consumption anticipated in EU strategic sectors [7]. Concerning the normalization factor $cons_m^{yref}$, the 2016-2020 average EU consumption [74] was used, since the same time scope approach is adopted in [10]. The consumption levels tend to be lower for the materials with higher SR and vice versa, in accordance with [75]: this is especially true for REEs, gallium, and platinum (for higher SR_m) and for copper, nickel, silicon, and manganese (for lower SR_m), while aluminum is the most consumed, despite a commodity SR in between. The high aluminum consumption is also due to its use as structural materials for many technologies.

Concerning the parameter $f_{m,t}$, the power sector technologies mostly addressed in MR studies are solar PV and wind turbines, mainly due to a wide sub-technological diversification. In particular, the very comprehensive JRC report on MR scenarios [39] was used as a data source since it is widely used in literature [76] and belongs to the same EU CRMs analyses framework [77] such as [10] (for SR_m) and [74] (for $cons_m^{yref}$). The main solar PV technologies identified by [39] are wafer-based crystalline silicon (c-Si), cadmium telluride (CdTe), copper-indium-gallium-diselenide (CIGS), and amorphous silicon (a-Si), with the latter three also referred to as thin film technologies. While structural materials like aluminum and copper are similarly required, the sub-technologies differ concerning solar cells specific materials. Silicon is consumed by c-Si (with a much lower amount required by a-Si), while some thin-films consume Gallium, which has a higher SR. However, since such sub-technological distinction is not present in the TEMOA-Italy power sector [57], it was decided to compute an average solar PV SR_t^{st} by weighting the MR of the different sub-technologies $f_{m,t}^{st}$ by their market shares f_j^{tech}, according to Eq. (5). Projections for 2050 were considered, namely intermediate MRs from [39] and IEA market shares in a base scenario (i.e., projecting the 2020 situation) [6]. The latter are reported in Table 2: c-Si are expected to keep market dominance, with thin film technologies remaining niche. A similar approach was used for onshore and offshore wind. The sub-technological assessment in [39] included gearbox double-fed induction generator (GB-DFIG), gearbox permanent magnet synchronous generator (GB-PMSG), direct-drive permanent magnet synchronous generator (DD-PMSG), and direct-drive electrically excited synchronous generator (DD-EESG). Differences in CRM consumption mainly concern REEs[6], more used in PMSG systems. Then, due to weight and efficiency reasons DD-PMSG turbines are mainly used for offshore applications requiring much more copper than the onshore case. Market shares taken from [6] are reported in Table 2.

$$SR_t^{st}\left(\frac{1}{cap}\right) = \sum_{m=1}^{N_{mat}^{tech}} \frac{\left(\sum_{j=1}^{N_{sub-tech}^{tech}} f_{m,t}^{st} \cdot f_j^{tech}\right)}{cons_m^{yref}} \cdot SR_m \tag{5}$$

Data availability and reliability were lower for the other technologies. Their 2050 MRs were estimated as averages between different sources. Among renewables, hydropower and bioenergy have the lowest MR (excluding the cement and concrete needed by the former [6], that are out of the scope of this analysis). Instead, geothermal is considered a key driver in future growing demand of nickel and titanium, used in steel alloys against corrosion [6]. Concerning the other low-carbon sources, LWRs plants have very low MR, while the available literature on

[5] The TEMOA-Italy model includes an exogenous technology learning, considering possible future variations along the time horizon of the techno-economic parameters characterizing the technologies modelled (e.g., reduction of costs and efficiency improvements).

[6] The neodymium consumption is given here as an example of calculating the corresponding average neodymium requirement of onshore wind turbines. Consider the material intensities in Supplementary Material and the market shares in Table 2, which are: 5.2 t/GW for GB-PMSG (10 % of market share), 1.2 t/GW for GB-DFIG (70 % of market share), 18.3 t/GW for DD-PMSG (14 % of market share), and 2.8 t/GW for DD-EESG (6 % of market share). The average neodymium requirement is calculated multiplying the material intensities by the market shares, obtaining a value of around 4.1 t/GW.

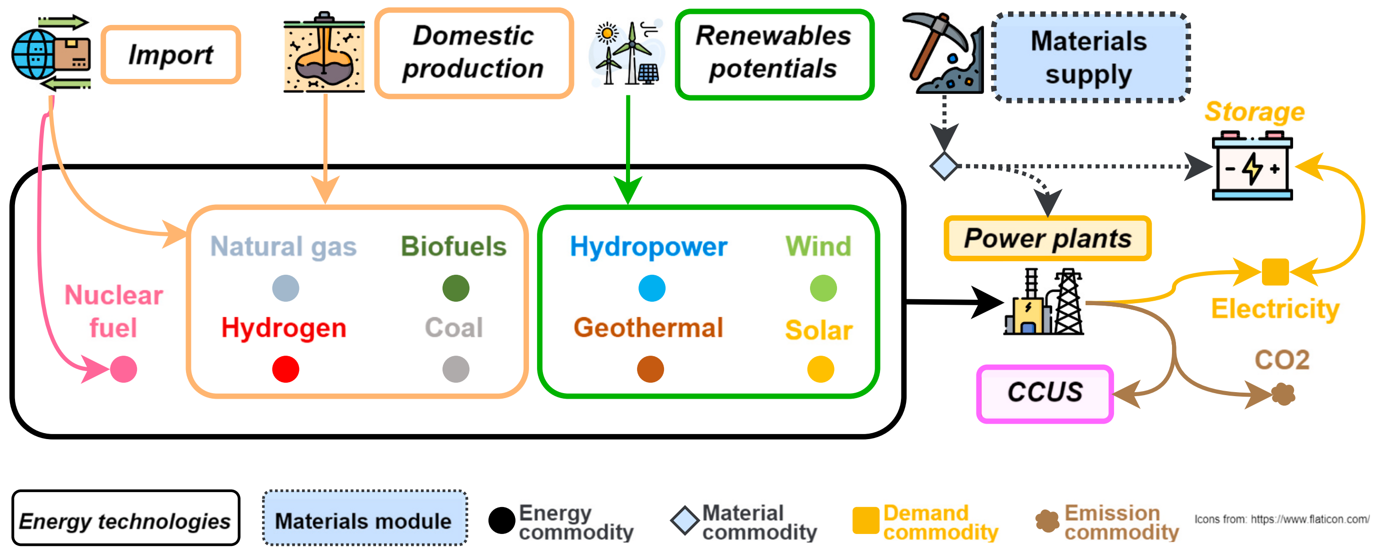

Fig. 1. Reference energy system of the Italian power sector adopted in this paper. The arrows refer to commodity (energy, materials, and emissions) flows. Energy technologies boxes refer both to groups of technologies (Import, Domestic production, Renewables potentials) and single technologies (Storage). Italics is used to distinguish between the energy technologies modules and the novel materials supply module implemented in this paper. The latter is depicted using dotted box and lines.

hydrogen fuel cells focuses on PEMFCs and platinum. Despite a poor literature on fossil fuels [78], MR for coal and natural gas were also considered since they consume some important CRMs such as cobalt, copper, and nickel. Moreover, CCUS is considered for natural gas (w/ CCS in Table 1): the additional materials compared to the traditional plants (w/o CCS in Table 1) concerns the CO_2 capture and pipeline infrastructures. Finally, the material consumption of the generic Li-ion battery technology modelled in TEMOA-Italy [72] was considered from the only 2050 projections found in literature [76], without distinguishing between the different cathode and anode chemistries on which the MR strongly depends.

The resulting SR_t for the power technologies reported in Table 1 are also shown in Fig. 2 on a logarithmic scale for better visualization and comparison. The lowest risk is associated with hydrogen PEMFC, hydropower, and solar PV, with an order of magnitude that is between 10^{-3} and 10^{-2}. This can be expected for the first two technologies due the amount and SR_m of the required CRMs. Instead, for the solar PV it contrasts the great concern about its supply chain. However, the reasons behind this result are twofold: first, the assumption on the market shares (see Table 2) limits the effects of the riskier materials consumed by thin films technologies; second, the material SR metric excludes the supply concentration for building and assembly of components, which is very high for solar PV (see Section 3.1) [7]. Bioenergy, nuclear, and fossil-based power generation present a SR_t about an order of magnitude higher than the previous technologies. Moreover, they have similar values due to the similar SR and intensity of the required materials. Then, Li-ion batteries and geothermal have higher but similar associated risks: the latter presents comparable values with the most debated transition technologies because due to significant nickel consumption, as also pointed out by [46]. Lastly, wind turbines have the highest SR_t with an order of magnitude between 1 and 10. This is due to REEs requirement, which have a very high SR_m and a lower $f_{m,t}$ than other CRMs. This points out the importance of defining Eq. (2) to avoid the dominance of $f_{m,t}$ over SR_m in the contribution to SR_t. See the Supplementary Material for the complete set of data and sources.

3.4.2. *Evaluation of the energy supply risk metric: data and assumptions*

To compute HHI_e (see Eq. (A10)) for each importable commodity considered in the case study, two parameters were needed: $S_{c,e}$ and g_c. Values and sources, along with the resulting HHI_e, also depicted in Fig. 2, are reported in Table 3. The shares $S_{c,e}$ were assessed considering the import markets instead of global supply chains, as is customarily done in the energy SR literature. The latest complete data, mostly from 2022, were used for all commodities except hydrogen, for which 2030 projections were used. Although only the top three supplier countries are listed in Table 3, all supplier countries were included in the calculations. Moreover, the geographical scope changes across the energy commodities depending on the availability of data. The geopolitical stability was measured through the same governance index as for the materials [10,73]. It is worth mentioning that the energy SR metric is to be applied solely to the fraction of energy commodities that is imported in the energy system under analysis. Indeed, energy commodities might also be supplied domestically (e.g., fossil fuels domestic fields, local biofuels supply chain), but the SR indicators discussed in Section 3.1 do not affect the domestic sourcing.

Italy is a major energy importer in the EU, with a high fossil fuels IR [79]. When looking at the origin countries, the combination of very high supply concentration and very low geopolitical stability made natural gas the commodity with highest HHI_e. Indeed, the top three suppliers (out of a total of 9), namely Algeria, Russia, and Azerbaijan, accounted for over 70 % of 2022 imports [80] and have the highest geopolitical instability among the supplier countries [73]. Instead, a more diversified and stable supply chain characterized the coal imports, with around 14 supplier countries [81]. Nuclear fuel ranks between natural gas and coal. However, since Italy does not use nuclear energy, EU imports of natural uranium were considered the most appropriate data to be used. In 2022, almost 75 % was supplied by three countries, among which Kazakhstan and Niger have a very high geopolitical instability [82]. Hydrogen is not yet imported in Italy. In this regard, while devoted national strategies are still under development, a global hydrogen trade is still in its early stages, with few hydrogen pipelines in EU and pilot projects on shipping [83]. Moreover, a common EU strategy is envisaged for hydrogen imports [84]. For these reasons, memoranda of understanding between EU and countries worldwide were considered to estimate the potential hydrogen imports to EU in 2030 [85]: the corresponding HHI_e resulted very close to the coal one. Finally, biofuels are characterized by the lowest HHI_e due to a the highly diversified global supply chain, which was used as a reference due to the lack of specific national and EU data on biomass imports by origin countries [86]. The use of global statistics introduces a greater uncertainty level than the EU data: however, the

Table 1
Data and sources of the parameters needed to define the material SR metric. Concerning SR_m, two values for each material are reported. The one adopted in the manuscript is reported in the column "Eq. (1)". It was derived from the EU CRMs list [10], the value of which is reported in the column "EU", by omitting the recycling and substitution factors. Indeed, they were neglected for consistency reasons with the energy SR metric.

Material	$\mathbf{SR_m}(-)$ [10]		$\mathbf{cons_m^{yref}}$ (**Mt**) [74]	$\mathbf{f_{m,t}}\left(\frac{\mathbf{t}}{\mathbf{GW}}\right)$											
	EU	*Eq. (1)*		*Solar PV* [6,39]	*Wind* [6,39]		*Geothermal* [6,78]	*Hydropower* [6,56]	*Bioenergy* [6,56]	*Nuclear (LWR)* [6,78]	*Hydrogen PEMFC* [34,95–99]	*Coal* [6,78]	*Natural gas* [78,99]		*Li-ion batteries* [76]
					Onshore	Offshore							w/o CCS	w/ CCS	
Aluminum	1.2	2.1	$1.6\cdot10^{1}$	6750.0	901.4	478.8		3400.0	3900.0				4.8	4.8	5796.0
Boron	3.6	3.7	$1.9\cdot10^{-2}$		0.1	0.5									
Cobalt	2.8	3.7	$1.1\cdot10^{-2}$						2.0			201.5	71.1	78.6	720.0
Copper	0.1	0.3	2.1	4150.1	1292.4	1938.6	3605.0	1050.0	2270.0	764.8	14.3	1150.0	355.4	1047.4	2616.0
Dysprosium (HREE)	5.6	5.7	$1.1\cdot10^{-6}$		0.5	1.6									
Gallium	3.9	4.0	$3.3\cdot10^{-5}$	$1.5\cdot10^{-2}$											
Hafnium	1.5	1.6	$1.1\cdot10^{-5}$							0.5					
Lithium	1.9	2.0	$1.8\cdot10^{-3}$												438.0
Manganese	1.2	1.3	$2.7\cdot10^{-1}$		564.5	569.9	4325.0	200.0				4.6	24.1	3785.1	660.0
Neodymium (LREE)	4.5	4.6	$1.2\cdot10^{-4}$		4.1	16.3									
Nickel	0.5	0.6	$2.6\cdot10^{-1}$		287.3	194.4	120,155.0	215.0	20.0	778.0		721.5	29.2	1174.2	2160.0
Niobium	4.4	4.6	$2.8\cdot10^{-3}$										5.3	5.3	
Phosphorus	3.3	3.4	$7.4\cdot10^{-2}$										0.9	0.9	
Platinum	2.1	2.5	$7.2\cdot10^{-5}$								$4.0\cdot10^{-2}$				
Praseodymium (LREE)	3.2	3.3	$1.1\cdot10^{-4}$		0.6	3.1									
Silicon	1.4	1.4	$4.2\cdot10^{-1}$	1900.0									17.3	17.3	
Terbium (HREE)	4.9	5.4	$5.9\cdot10^{-6}$		0.1	0.6									
Titanium	1.6	1.6	$1.4\cdot10^{-2}$				1634.0		400.0	1.5		23.0	4.8	4.8	
Vanadium	2.3	2.7	$4.4\cdot10^{-3}$							0.6			8.2	8.2	
Yttrium (HREE)	3.5	3.9	$2.2\cdot10^{-4}$							0.5					
			$\mathbf{SR_t}\left(\frac{\mathbf{1}}{\mathbf{GW}}\right)$	$9.7\cdot10^{-3}$	2.7	9.2	0.5	$2.1\cdot10^{-3}$	$4.7\cdot10^{-2}$	$8.1\cdot10^{-2}$	$1.4\cdot10^{-3}$	$7.2\cdot10^{-2}$	$3.3\cdot10^{-2}$	$5.7\cdot10^{-2}$	0.7

Table 2
Sub-technological shares adopted to derive a generic SR_t^{st} for solar PV and onshore and offshore wind (the latter shares are in parenthesis).

Technology	Sub-technology	2050 share [6]
Solar PV	*c-Si*	95 %
	CdTe	4 %
	CIGS	1 %
Wind-onshore (offshore)	*GB-PMSG*	10 % (15 %)
	GB-DFIG	70 % (15 %)
	DD-EESG	6 % (0 %)
	DD-PMSG	14 % (85 %)

impact of this uncertainty is partially mitigated by the marginal and diminishing role of biofuels in the Italian power sector [68,87]. See the Supplementary Material for the complete set of data and sources.

3.4.3. Setting of the multi-objective optimization problems

Two types of MOO were conducted in this study, as sketched in Fig. 3. Firstly, the total system cost f_{cost} and the total cumulative net CO_2 emissions f_{CO2} were minimized (hereinafter $min(f_{cost}, f_{CO2})$). The total system cost is the traditional objective function of ESOMs and sums up the capital, fixed, and variable discounted[7] costs incurred in the system under analysis over the model time horizon [58]. The total cumulative net CO_2 emissions correspond to the net CO_2 emissions from all the technologies included in the reference energy system under analysis throughout the model time horizon (see the Supplementary Material for more details about f_{cost} and f_{CO2} definitions in TEMOA).

Instead, the SRs as defined in Eq. (3) and Eq. (4) were only evaluated ex-post in this first MOO. Therefore, the first MOO problem can be seen as a proxy of the state of the art discussed in Section 2. It served to determine the extent to which the existing literature can assess the potential trade-off between the SRs and provided a basis to set the second MOO problem. Specifically, the minimum total cumulative net CO_2 emissions f_{CO2}^{MIN} and the corresponding least-cost f_{cost}^{MIN} were used as constraints in the second type of MOO, the minimization of SR_M and SR_E (hereinafter $min(SR_E, SR_M)$), to examine how much and how the SRs of a decarbonized power system can be improved. For the second MOO, four Pareto fronts were generated by constraining the emissions to f_{CO2}^{MIN} and the total system cost to f_{cost}^{MIN} plus 5 %, 10 %, 15 %, and 20 % increase (see Eq. (6)). The latter constraint allows the model to consider a greater range of possibilities regarding the system configuration.

$$min(SR_E, SR_M) \text{ s.t.} f_{CO2} = f_{CO2}^{MIN} \text{ and } f_{cost} = s_{cost} \cdot f_{cost}^{MIN} \forall s_{cost} \in \{1.05, 1.10, 1.15, 1.20\} \tag{6}$$

Concerning the selection of the caps – during the second step of the AUGMECON method described in Section 3.3 – they were arbitrarily chosen in such a way to obtain ten equal intervals spanning the entire range between the front boundaries.

3.5. Discussion of methodology

The SR functions defined in Section 3.2 were consistently developed based on established methodologies. Concerning the material SR, two additional advantages were identified in defining it as in Eq. (3). First, the metric is flexible: as recognized in [55], Eq. (2) allows for the use of alternative material intensity measures, depending on available data (e.g., per unit of energy). Second, the definition in Eq. (3) remains linear as long as the technology SR is exogenously computed as an input parameter for the ESOM: that is consistent with the linear programming problem typically solved in ESOMs like TEMOA [67]. On the other side, some limitations affect the metric completeness. The SR, as defined in Eq. (1), is usually combined with other indicators in more comprehensive materials criticality assessments, such as economic importance and environmental impacts [12,43]. However, these were considered beyond the paper scope, also because a consistent definition for the energy dimension was only found for SR. Additionally, SR_m (see Eq. (1)) only refers to the raw materials extraction and processing, while SRs can occur along the entire supply chain for most transition technologies, impacting technologies risk ranking (e.g., solar PV) [7]. Such simplification was deemed appropriate and necessary, due to a lack of data and established methodologies. Indeed, only [7,54] evaluate the SR across all supply chain steps: however, while the former uses a semi-quantitative methodology without providing data, the latter employs a SR definition based on lead time to scale up deployment, inconsistent with the most common ones adopted in literature. In this regard, the impacts on the results of the SR metrics adopted can be assessed by comparing definitions other than the ones used in this work. This might be the case for the number of supply chain steps to be included and the SR of technologies (see Eq. (2)), or different aggregation of SR_m than the mass-based one. In this regard, few studies are available in literature and such a comparison would improve the state of the art.

Concerning the energy SR, its definition as in Eq. (4) aligns with well-established methodologies which are consistent with the material dimension. Nevertheless, certain simplifications with respect to these methodologies were implemented. If the supply concentration index $HHI_{g,e}$ is exogenously computed as an input parameter for the ESOM, linearity is guaranteed. In this regard, energy SR metrics typically aggregate SR_e at a system level by considering energy commodities shares in the energy supply or consumption: however, the latter are a direct result of ESOMs and if used would introduce nonlinearity as with IR_e. Furthermore, linearity is guaranteed also by the modeling strategy of the supply chains of materials and energy commodities. The former includes a generic supply process for each material, while the latter do not differentiate between supplier countries, resulting in exogenous assessment of SR_m and HHI_e, still helpful for verifying the applicability and usefulness of the methodology. However, the endogenous and explicit modeling of materials and energy commodities supply chains by country would expand the scope of application for decision-making (e.g., optimization of market shares), at the expense of the problem linearity.

The SR functions were employed in a multi-objective energy system optimization based on the AUGMECON method implemented in TEMOA: the former is based on one of the most widely used MOO frameworks [31], while the latter is considered among the well-established ESOMs in literature [24]. These aspects might be considered positive in terms of credibility and rationality of the methodology development and application. Moreover, it is worth pointing out that the SR functions were developed independently of the adopted MOO method and ESOM. This means that these functions can be employed in methods and tools other than AUGMECON and TEMOA. Additionally, the SR functions definition, and the use of AUGMECON and TEMOA, are not limited to the Italian power sector case study but can be applied to countries or sectors (e.g., transport sector, multi-sectorial systems). Lastly, two MOO problems with two objectives were studied instead of a single MOO with four objectives. On the one hand, the latter approach can provide more comprehensive insights. On the other hand, it increases the complexity and computational burden. In addition, scenarios with low policy relevance could also be included, such as system configuration with high emissions or high costs. To avoid this, the net-zero emission target was chosen as the most policy-relevant, according to latest stated and announced energy policies [88]. The cost range was then arbitrarily considered, and four values were used to reduce complexity. In this regard, the resulting four 2d Pareto fronts are – to a certain extent – a subset of the entire 3d f_{cost}-SR_E- SR_M front. In line with this argument, the trade-offs were studied in all the three “directions” in Section 4.2: along slices, between slices horizontally, and between slices

[7] All the costs are discounted to the initial year of the model time horizon using the global discount rate of 5 %. Moreover, the capital costs are amortized using a technology-specific discount rate. For more details, see e.g., [100,101].

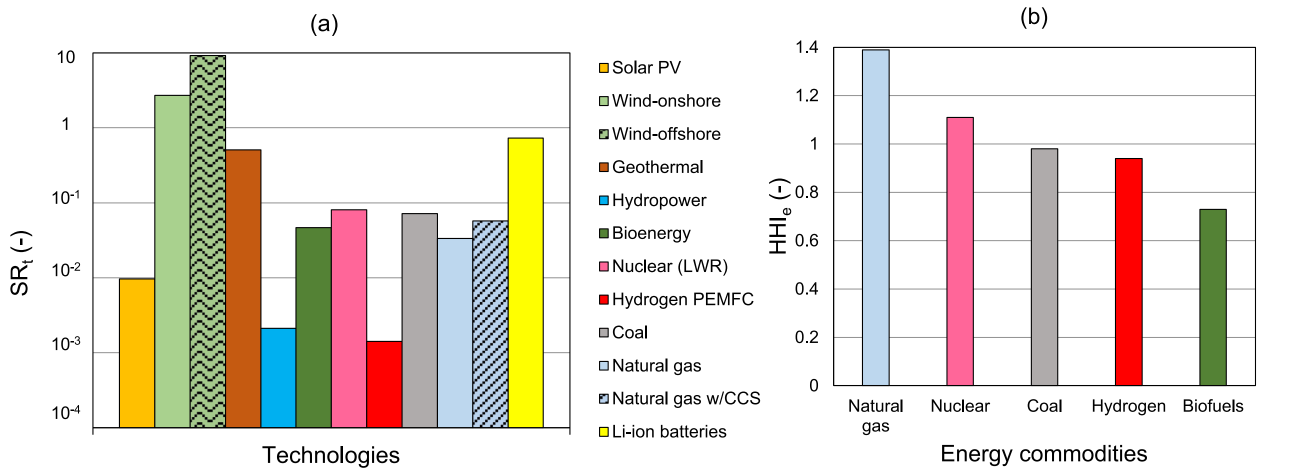

Fig. 2. Material SR metric SR_t by technology (a) and energy SR metric HHI_e by energy commodity (b). Note that the scale for SR_t is logarithmic, while for HHI_e it is linear. The values shown in the figure are calculated using the data of Table 1, Table 2, and Table 3.

vertically.

Concerning the case study, all data and assumptions were made openly available. These aspects might improve the reproducibility and transparency of both the methodology and the case study. However, some limitations are acknowledged, starting with the use of a single-sector model. Despite the simplified TEMOA-Italy power sector enabled a comprehensive analysis, the absence of other relevant sectors such as power grid infrastructure and transportation [6] limits the scope and the insights of the results. Regarding the adopted dataset, present values of parameters needed to define the SR metrics (except future $f_{m,t}$) were assumed for 2050, as there is a lack of projections of these parameters in the existing literature. This assumption is strong for both materials and energy commodities. Indeed, although materials supply concentration is expected to remain relatively constant in the next

Table 3
Data and sources of the parameters needed to define the energy SR metric. Although only the top three supplier countries are shown, all supplier countries are used to derive the HHI_e. Moreover, note that a high value for g_c refers to a low stability while a low g_c value refers to a high stability.

Energy commodities	Geographical scope	Top three supplier countries	$S_{c,e}$	g_c (−) [73]	HHI_e (−)
Natural gas	Italy [80]	Algeria	37.0 %	6.72	1.39
		Russia	20.2 %	6.29	
		Azerbaijan	14.6 %	6.39	
Coal	Italy [81]	Russia	32.8 %	6.29	0.98
		South Africa	18.2 %	4.69	
		United States	13.0 %	2.68	
Nuclear	EU [82]	Kazakhstan	27.0 %	5.72	1.11
		Niger	25.4 %	6.50	
		Canada	22.0 %	1.79	
Hydrogen	EU [84]	Australia	59.7 %	1.92	0.94
		Brazil	15.0 %	5.40	
		Chile	15.0 %	3.08	
Biofuels	Global [86]	United States	38.1 %	2.68	0.73
		Brazil	21.8 %	5.40	
		Indonesia	10.5 %	5.32	

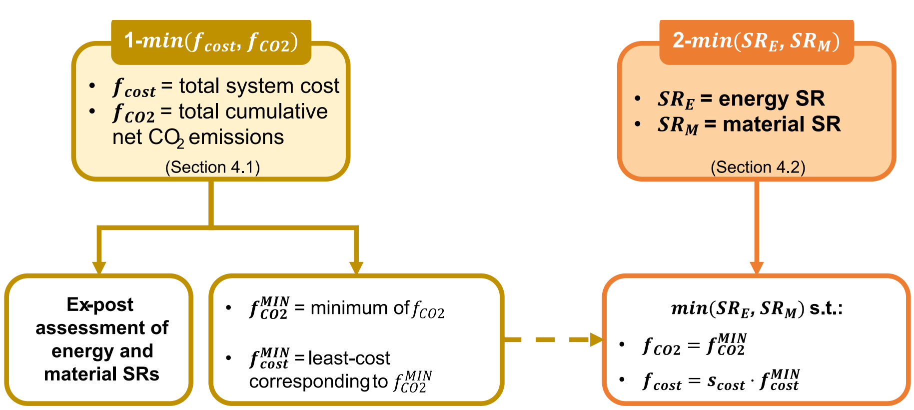

Fig. 3. Scheme of the different MOO problems solved in this study. The scheme also specifies the order of the resolution of the problems and the corresponding results sections. The first MOO problem is presented on the left and referred to as 1-$min(f_{cost}, f_{CO2})$ and its results are presented in Section 4.1. The second MOO problem is presented on the right and referred to as 2-$min(SR_E, SR_M)$ and its results are presented in Section 4.2.

decade [89], it is likely that the increasing devoted policies (see Section 1) will change the current market shares and dimensions affecting SR_m and $cons_{m,yref}$. Concerning energy commodities, recent policies following the Russian-Ukrainian conflict are reshaping fossil fuels supply chains, especially concerning Russian supplies, prompting strategic planning in hydrogen and biofuels markets [85]. Finally, the absence of harmonized and comprehensive datasets providing MR of technologies, and a consistent geographical coverage concerning energy imports, introduce further uncertainty into material and energy SRs calculations. In order to consider the variation of the SR metrics along the model time horizon, uncertainty analysis can be useful to evaluate the variability of the multi-objective optimization outputs due to the variability of the many input data and assumptions that are needed. This might be the case of the current and projected values of the parameters involved in the calculations of the material and energy SR metrics calculations, such as material intensities of technologies, and market shares and political stability of the supplier countries of raw materials and energy commodities. Alternatively, structural uncertainties, e.g. in the form of interests and criteria that cannot or are not captured by the model equations and data, can be addressed by Modeling to Generate Alternatives [90]. The latter can also be combined with MOO to generate alternative solutions that are slightly sub-Pareto-optimal but differ strongly in terms of system design [91].

4. Results

The outcomes of the MOOs formulated in Section 3.4.3 are described, respectively, in Section 4.1 and Section 4.2, looking both at Pareto fronts in the objectives space and at the system design and operation in the variables space. Then, results are discussed in Section 4.3 by highlighting the effectiveness and advantages of using the proposed framework compared to the existing approaches.

4.1. Minimization of total system cost and emissions

The Pareto front from $min(f_{cost}, f_{CO2})$ is shown in Fig. 4a. As expected, reducing emissions increases the total system[8] cost. Specifically, lowering net CO_2 emissions from the maximum of ~86 Mt to zero results in a cost rise from the global minimum of ~117 b€ to ~138 b€. Pareto-optimal solutions represent emissions reduction scenarios, and the computed electricity production by technology is shown in Fig. 4b. In the least-cost system, the power mix is equally composed of solar PV and natural gas generation, with the latter being reduced for lower emissions mainly in favor of onshore wind penetration. Geothermal plants make a minor contribution from f_{CO2}~17 Mt, while CCUS technologies (i.e., natural gas w/CCS and DAC) enable net-zero emissions by capturing nearly 4 Mt of CO_2 from residual natural gas combustion. Full results are available in the Supplementary Material. Further analyses are beyond the scope of this work, but more insights from a $min(f_{cost}, f_{CO2})$-like problem can be found in [22].

Instead, insights on material and energy SRs can be evaluated by applying the definitions in Eqs. (3) and (4) to the capacity and activity results ex-post. The ratio between SRs values in each scenario and the maximum of all scenarios is shown in Fig. 4b, showing that the lower the emissions are, the lower becomes the SR_E, with its linear decline reflecting the gradual reduction in natural gas-based generation. Indeed, the corresponding lower natural gas requirement implies the phasing out of imports until all the natural gas consumed in the net-zero scenario produced domestically, which is more cost-effective than imports. This ultimately results in zero SR_E at zero emissions. Conversely, SR_M increases with decreasing emissions, mainly due to the penetration of onshore wind, which is among the technologies with highest material SR. The maximum SR_M across emissions reduction scenarios occurs at the peak of onshore wind-based generation.

The trade-off between SR_M and SR_E is therefore clear. Decarbonizing the Italian power sector cost-efficiently without constraining or minimizing SRs and given the current CRMs and natural gas supply concentration, reduces SR_E while simultaneously increasing the level of SR_M. In particular, the least-cost net-zero scenario (hereinafter base case) presents zero energy imports, thus zero SR_E. Conversely, SR_M is around 450, which is about thirty-seven times the level in the least-cost scenario. However, this analysis can be extended by studying a MOO of the two SRs as presented in Section 4.2.

4.2. Minimization of energy and material supply risks

The Pareto fronts derived from the four MOOs involved in the problem $min(SR_E, SR_M)$ under varying cost constraints and a strict net-zero emission limit as given in Eq. (6) are shown in the objectives space in Fig. 5. The latter provides insights into the extent to which energy and material SRs can be enhanced in comparison to the base case, which is the least-cost net-zero scenario discussed in Section 4.1, while allowing for a higher total system cost. Moreover, the variables spaces in Fig. 6 and Fig. 7 allows for the assessment of how these objectives are achieved, by illustrating the impact of minimizing the two risks on system design and operation.

The shape of the fronts in Fig. 5 reveals a trade-off between SR_M and SR_E. Indeed, the reduction of the former comes at the expense of an increase of the latter, by reducing the renewable electricity production from onshore wind and solar PV, as depicted in Fig. 6. This is due to the high technology SR of wind and battery storage systems. Although solar PV has a lower SR_t than other renewable energy sources, the reduction in Li-ion battery use (blue line in Fig. 6) limits the variable solar PV production. Solar PV and onshore wind are replaced by natural gas-based generation, mainly with CO_2 sequestration, due to the net-zero emissions target. This, in turn, results in an increase in natural gas consumption and imports, which consequently increases the SR_E (see Fig. 5). A similar behavior can be found in Fig. 4b from the problem $min(f_{cost}, f_{CO2})$, where the reduction of SR_M is driven by a decrease in wind energy, up to a full replacement by solar PV and, mainly, natural gas power plants. However, unlike the problem $min(SR_E, SR_M)$, this is associated with increasing emissions and decreasing costs. Indeed, natural gas-based generation does not involve the expansive CO2 sequestration in the first MOO problem, which is instead needed when minimizing both the SRs in order to ensure net-zero emissions in the second MOO problem.

The trade-offs between the SRs and total system cost are evaluated at fixed SR_E and SR_M. For a fixed energy SR of ~0.7 (dashed black boxes in Fig. 5, Fig. 6, and Fig. 7-top), an increase in extra cost from 5 % to 10 % results in reduction of SR_M from ~198.3 (yellow line) to ~105.2 (gold line). This corresponds to a reduction potential of ~13.5 units per b€ increase in total system cost. Then, higher cost increases further reduce SR_M to ~32.8 (orange line) and ~ 28.2 (red line), with reduction potentials of ~10.5 units and ~ 0.7 units, respectively, per b€ increase in total system cost. This suggests that marginal utility of increasing the allowed total system cost to decrease the material SR is diminishing. Indeed, the higher the cost increase, the lower the SR_M reduction per extra cost at fixed SR_E. The higher cost increase is associated with the substitution of wind energy with less risky technologies in materials terms, such as solar PV and natural gas plants to allow for reductions of material SR without increasing both net emissions and energy SR (see Fig. 6). Particularly, when fixing the SR_E ~0.7, increasing the total system costs leads to higher overall installed capacity (e.g., ~25 % increase from 5 % to 20 % cost increase, cf. dashed black boxes in Fig. 7-top). This increase is mainly driven by solar PV for two reasons. Firstly, a constant SR_E limits import possibilities as per Eq. (4), limiting also

[8] The term "system" refers to the case study energy system, which is limited to the power sector and the related supply-side.

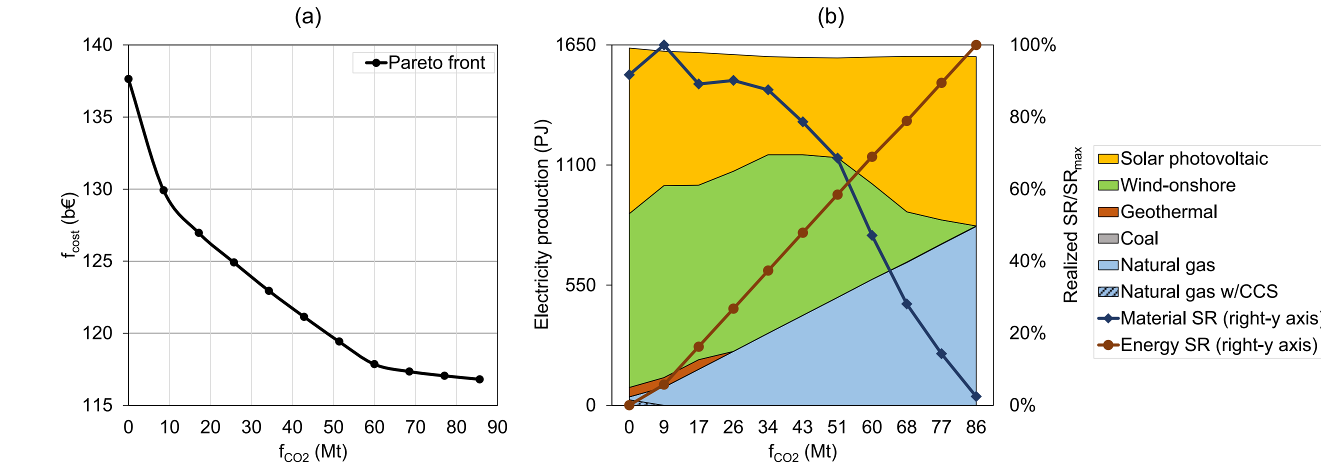

Fig. 4. Pareto front (a) and electricity production by technology across the Pareto front (b), of the MOO problem $min(f_{cost}, f_{CO2})$. The ratio between the realized and maximum values for the material and energy SRs are also depicted on the right-y axis through continuous blue (for material SR) and brown (for energy SR) lines (b). The SRs are neither constrained, nor optimized in this case, but evaluated purely ex-post.

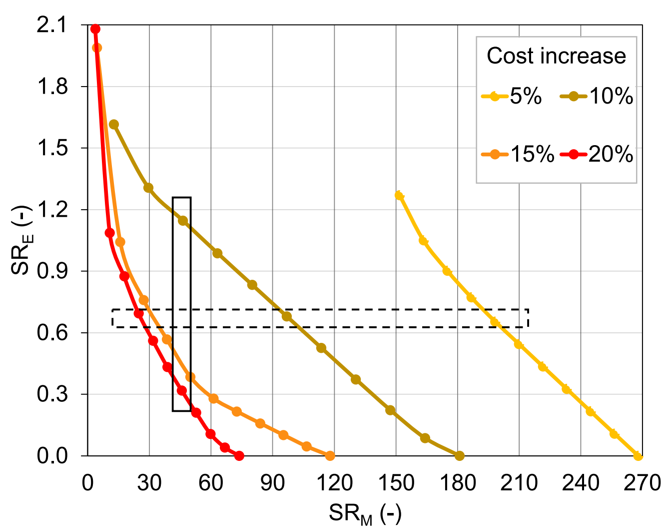

Fig. 5. Pareto fronts of the MOO problem $min(SR_E, SR_M)$ for net-zero emissions and the following total system cost levels: f_{cost}^{MIN} plus 5 % (yellow line), 10 % (gold line), 15 % (orange line), and 20 % (red line) increase. Black boxes highlight solutions at fixed SR_E of ~0.7 (dashed box) and SR_M of ~46 (solid box).

natural gas plants investments due to a small domestic production[9]. Secondly, reducing SR_M limits investments in technologies like onshore wind and Li-ion batteries, which have among the highest technology SR. This necessitates higher PV capacities to replace wind and to compensate for lower PV utilization rates due to decreased storage. Moving to trade-offs between cost and SR_E at a fixed SR_M of around 46 (solid black boxes in Fig. 5, Fig. 6, and Fig. 7-top), an increase in extra cost from 10 % to 15 % reduces SR_E from ~1.2 to ~0.5, with a reduction potential of ~0.10 units per b€ increase in total system cost. A further total system cost increase of 5 % implies an additional decrease to ~0.3, with a SR_E reduction potential of ~0.02 units per b€ increase in total system cost. This also reveals diminishing marginal utility as for SR_M. The higher cost increase is associated with the substitution of natural gas generation (and hence captured CO_2) with solar PV (see Fig. 7). Particularly, at SR_M around 46, moving from 10 % to 20 % increases saves ~5 % of consumed (and imported) natural gas per b€ in total system cost.

Now consider how the Pareto front boundaries, i.e. the lowest energy and material SRs feasible at net-zero emissions, vary with the cost limits. With increasing costs, zero SR_E (i.e., zero energy imports, right boundaries in Fig. 5, Fig. 6, and Fig. 7) can be achieved at a progressively lower SR_M compared to the base case (i.e., ~450). For instance, the highest reduction compared to the base case (~85 %) occurs for a 20 % cost increase (red line in Fig. 5). This is achieved by gradually reducing wind energy in the electricity mix to zero (see Fig. 6, left edges of subfigures) from a share of almost 50 % in the base case (see Fig. 4b, left edge). Moreover, the lowest SR_M at zero SR_E, occurring for a 20 % cost increase, provides for the highest solar PV production (see Fig. 6, rightmost edge of the 20 % cost increase). This also comes with the maximum curtailment of ~605 PJ (dark green line in Fig. 6), which is around 35 % of the electricity produced. Unlike the other cost increases, the curtailment in the 20 % case equals the battery storage utilization (blue line in Fig. 6), which is constrained by its high material-related technology SR. Moving towards the leftmost boundaries of the Pareto fronts in Fig. 5, allowing for higher costs results into a lower SR_M minimum but at a higher SR_E maximum. This is reflected in a shift from a renewables-based to natural gas-based power mix, as shown in Fig. 6. Particularly, the highest material SR reduction compared to the base case (almost 99 %) occurs for 15 % and 20 % cost increases (see Fig. 5). The latter corresponds to the highest natural gas imports ~2380 PJ, with captured CO_2 reaching its maximum value of ~137 Mt.

The electricity production mix in Fig. 6 is reflected in the invested capacities shown in Fig. 7-top. The reduction in SR_M is associated with a decline in total installed capacity, which is mainly due to lower investments in onshore wind and solar PV. Conversely, there is an increase in the capacity and utilization rate of natural gas plants: moving from the rightmost to the leftmost SR_M, these plants shift from serving peak loads to baseload generation. Furthermore, a greater material SR reduction and a higher maximum achievable energy SR are associated with higher total system cost, as illustrated in Fig. 5. This is due to the replacement of wind energy by solar PV and natural gas plants, as depicted in Fig. 7-top. Indeed, the latter are characterized by lower technology SR than wind turbines. Additionally, allowing for higher costs leads to investments in highly expansive CCUS technologies, which are essential for offsetting the residual CO_2 emissions from the combustion of natural gas. The latter, when imported, involves in turn a higher energy SR.

Finally, the CRMs consumption is depicted in Fig. 7-bottom. General trends follow installed capacities, as materials consumption is directly

[9] See the Supplementary Material for more details on domestic production potential.

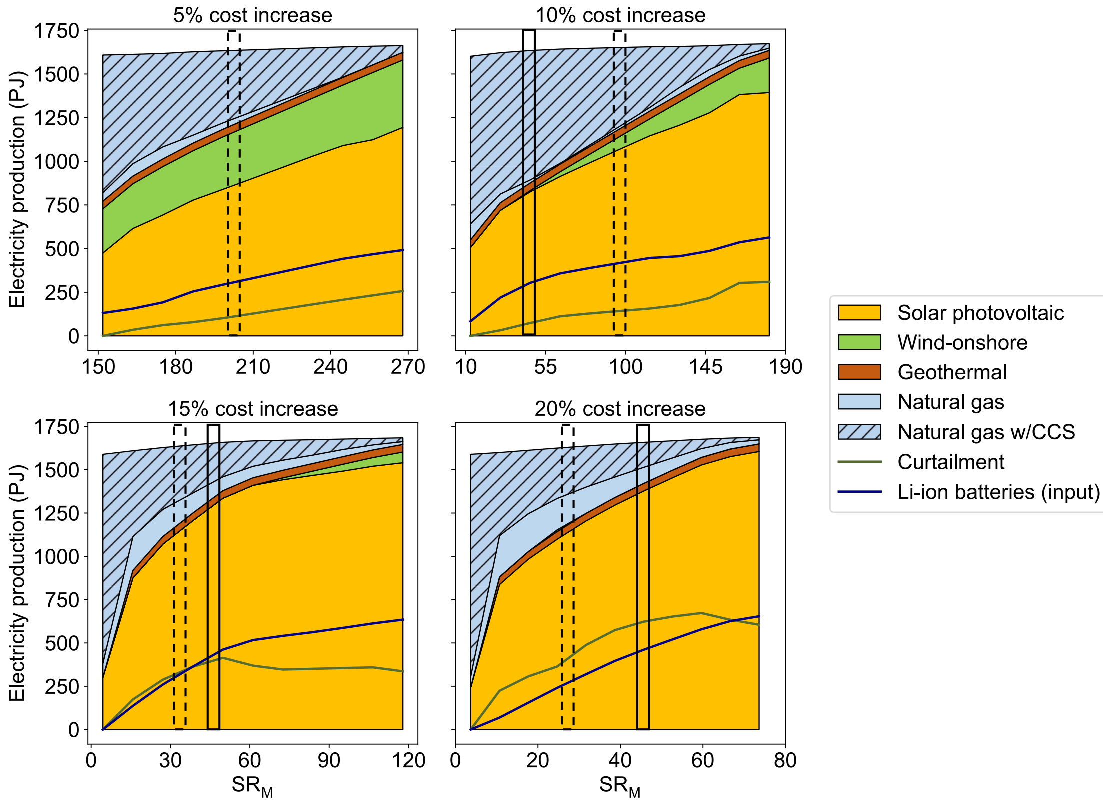

Fig. 6. Electricity generation by technology along the Pareto fronts from Fig. 6 for all analyzed cost constraints. Input electricity to Li-ion batteries (blue line) and curtailed energy (dark green line) are also depicted. Consider that results on DAC are not represented here. Black boxes highlight solutions at fixed SR_E of ∼0.7 (dashed box) and SR_M of ∼46 (solid box). Note that all four x-axes have different boundaries and scales to reflect the different Pareto front boundaries.

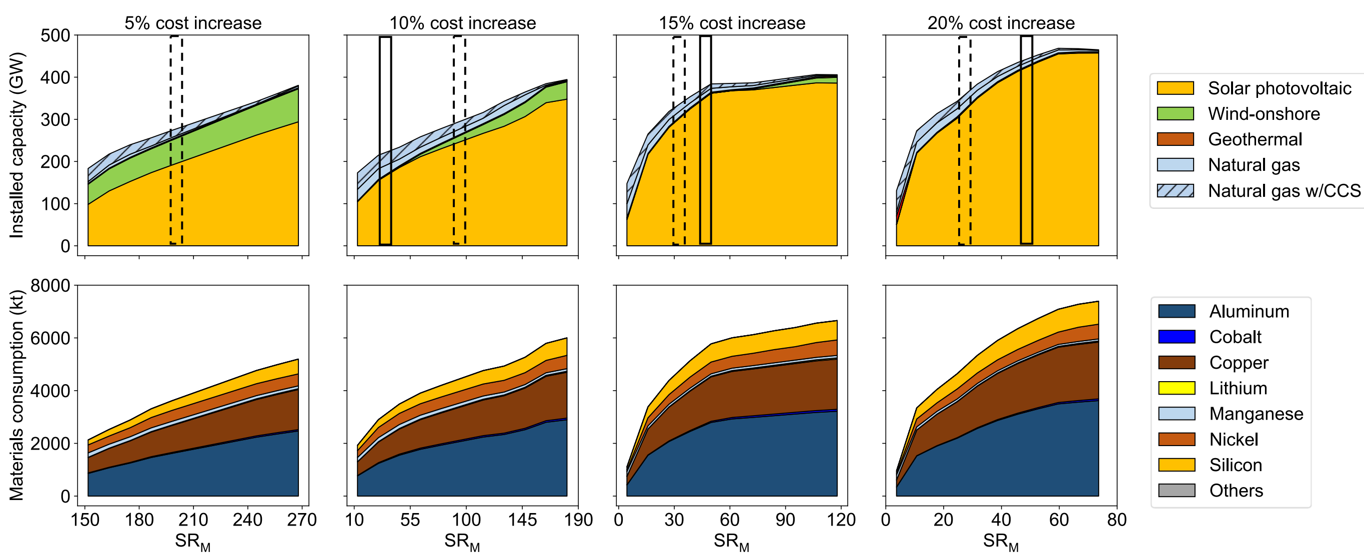

Fig. 7. Installed capacity by technology (top) and materials consumption by material (bottom), along the Pareto fronts for all the analyzed cost increase. Consider that results on DAC are not represented here. Black boxes highlight solutions at fixed SR_E of ∼0.7 (dashed box) and SR_M of ∼46 (solid box). Note that the x-axes have different boundaries and scales across the columns (i.e., cost increase cases).

proportional to it (see the Supplementary Material). Consumed materials qualitatively and quantitatively reflect the MR data of Table 1. For instance, solar PV and natural gas plants drive the consumption of aluminum, copper, and silicon, while geothermal mainly drives nickel demand despite its low installed capacity (i.e., ∼2 GW on average). Other materials with consumption below 5 kt are aggregated into "Others" for graphical reasons. Among these, the most relevant in terms of SR are REEs, peaking at ∼393 t at the rightmost SR_M for a 5 % cost increase, that is much lower than other materials consumption. However, REEs strongly impact the material SR. Indeed, wind energy disappearance from 5 % to 20 % cost increase is associated with a SR_M decrease of about one order of magnitude. Lastly, the overall minimum ∼0.9 Mt and maximum ∼7.4 Mt consumptions across all the scenarios occur, respectively, at the leftmost and rightmost SR_M for the 20 % slack:

the overall MR of ~3.4 Mt in the base case falls in between.

The complete set of results presented in Section 4.1 and Section 4.2 is available in the Supplementary Material.

4.3. Discussion of results

The trade-off between the two analyzed SRs is suggested already by evaluating ex-post the results of the minimization of total system cost and CO_2 emissions in Section 4.1, which represents a proxy of the state of the art discussed in Section 2. Shifting from natural gas-based to renewable-based electricity generation leads to a higher material SR and a lower energy SR. Concerning the former, the highest contribution to the system risk comes from wind turbines, due to the requirement of REEs. This is in accordance with the outcomes of the ex-post assessment in [27], where the authors find an increase of the material SR when studying the decarbonization of the Italian power sector. Similar approach and results, but at European level, are found in [20,46], where the authors point out how the future material SR of the European power sector mainly increases due to wind energy deployment. However, these findings are based on a pure ex-post assessment, meaning that energy system design and operations are not influenced by supply chain risks. Consequently, existing tools and studies can inform policymakers about potential SRs in the energy transition but can only offer limited guidance on efficient means and costs of reducing both these risks in energy planning.

Conversely, minimizing both material and energy SRs under cost and emission constraints (see Section 4.2), as it is possible with the novel framework proposed in this work, provides actionable insights for managing these risks. From a policy perspective, achieving full decarbonization of the Italian power sector while reducing material SR requires accepting higher energy SR and total system costs. These results are associated with reduced investments in wind energy and batteries, increased solar PV investments and curtailment, and higher investments in natural gas plants and CCUS, leading to greater natural gas imports. Three main factors contribute to these outcomes. First, a system without SRs is not possible, since Italy must always import either energy commodities or materials. Moreover, Italy's current supply chains of materials and natural gas are highly concentrated in regions that are politically unstable, at least partially. Second, Italian domestic sourcing of low-carbon fuels like biofuels and hydrogen, the technologies of which are characterized by lower CRMs consumption, is not cost-effective and limited overall. Third, clean energy technologies currently on the market consume many CRMs.

The lack of previous studies employing an ex-ante approach makes a quantitative results comparison difficult. However, the general trends and measures mentioned above can provide insights on making balanced and conscious trade-off decisions in energy system planning. To manage material and energy SRs, strategies should include diversifying supply chains and technology mixes, reducing import dependency, and supporting investments in domestic supply chains. These strategies might be effectively assessed using the novel framework introduced in this work. The risks associated with the supply of materials and energy commodities from specific countries can be minimized, or to some extent controlled, to support decision-making on trade agreements with possible partner countries. Then, studying the effects on SRs of different technological mixes can drive the related investments. This can concern the choices between different types of the same technology (e.g., the traditional c-Si and the emerging thin film PV panels such as the Perovskite technology [6]) or the evaluation of optimal incentives to domestic sourcing of biofuels and hydrogen, the use of which requires less CRMs than other clean energy technologies. However, more exhaustive trade-offs results might be obtained by simultaneously minimizing supply risks and other objectives such as costs and emissions, especially if a techno-economic characterization of material supply chains is included in the energy system optimization model. This approach may be necessary to extend the developed supply risk metric to other critical aspects of energy supply chains, such as social and environmental factors.

Concerning the policy-relevance of the results for the Italian case study, energy system design and operation for the net-zero base case and for the rightmost regions of $min(SR_E, SR_M)$ comply with stated and announced Italian energy policies, which advocate for a marginal role for natural gas-based generation of up to maximum 5 % in the electricity mix [70,87]. This is not the case when aiming to further reduce SR_M, which leads to an increasing demand for natural gas and CCUS up to a maximum of around 2400 PJ of imported natural gas and 140 Mt of captured CO_2. The former is close to 2022 imports [68] and nearly double the latest targets [87], while the latter is almost twice the 2050 target of equivalent CO_2 emissions to be compensated through CCUS [70]. Also, the absence of nuclear power in the results contrasts with the latest debates at the EU [92] and national [93] level, offering insights into its apparent limited economic and SR competitiveness in achieving net-zero emissions. However, more policy-relevant findings for both natural gas with CCUS and nuclear power could be achieved by using, respectively: a multi-sectorial model capable of capturing sector coupling possibilities that strongly affect the CCUS adoption [94] and a more detailed time resolution better suited to model power sector operations [72]. Lastly, overall CRMs demand increase from leftmost natural-gas based mixes to rightmost renewables-driven systems ranges from two to almost eight times, which is consistent with other studies estimating the potential future MR in decarbonized power sectors [6,7]. This might be indicative for the decarbonization of the Italian power sector by 2050, also considering that there is a lack of studies concerning the future MR for the Italian energy transition.

5. Conclusions

This paper introduced a novel multi-objective energy system optimization framework to endogenously assess the trade-off between material and energy supply risks in the energy transition. Unlike existing studies supporting energy system planning, which typically overlook policy interests regarding the minimization of supply chains risks, this framework incorporates the latter ex-ante and endogenously, allowing to generate more comprehensive policy-relevant insights.

Two functions measuring the material and energy supply risks were consistently derived based on well-established literature that leave the optimization problem linear. These functions encompass concentration, import reliance, and political stability of supply chains of critical raw materials and energy commodities. Then, the functions were employed in a multi-objective energy system optimization with AUGMECON applied to TEMOA, which are widely consolidated multi-objective and energy system optimization frameworks. However, it is worth pointing out that the proposed framework was developed independently of the adopted multi-objective optimization method, energy system optimization model, and case study, while all data and assumptions were made completely available. These aspects improve the reproducibility and transparency of the analysis.

The decarbonization of the Italian power sector by 2050 was used as a case study. First, material and energy supply risks were evaluated ex-post in a multi-objective optimization of total system cost and CO_2 emissions, revealing that while decarbonizing the electricity production reduces the energy supply risk, it increases the material supply risk. Building on this, four Pareto fronts were generated in multi-objective optimization problems that included ex-ante material and energy supply risks as objective functions. These problems involved a net-zero emission constraint and varying upper limits on total system cost. The results highlighted a significant trade-off between the two risks, revealing that minimizing the material supply risk leads to higher energy supply risk. Specifically, reducing investments in wind turbines and batteries leads to greater reliance on natural gas generation with carbon capture, which increases both natural gas imports and energy supply risk. Then, higher total system costs resulted in the substitution of wind energy by solar PV and natural gas plants, further increasing reliance on expansive CCUS technologies and natural gas imports. The results also indicated diminishing marginal utility in reducing supply risks as total system costs rise. An additional cost of up to 15 % results in substantial further reductions in supply risk, but beyond this point, significant gains can only be realized in the very low energy supply risk range. Finally, the consumption of critical raw materials aligns with the installation of new capacity. Despite their considerably lower consumption compared to other materials, rare earth elements, which are necessary for wind turbines, had the most significant impact on material supply risk.

Although it might be difficult to derive general trends and insights from a simplified case study, these results align with the increasing number of studies and policies on critical raw materials for the energy transition. Moreover, unlike the existing literature, the ex-ante approach characterizing the proposed framework allows the underlying energy system to adapt to minimize supply chain risks, thus highlighting the need for a balanced approach in energy transition strategies to manage trade-offs between material and energy supply risks, total system cost, and CO_2 emissions.

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CRediT authorship contribution statement

Gianvito Colucci: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jonas Finke:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Conceptualization. **Valentin Bertsch:** Writing – review & editing, Supervision, Conceptualization. **Valeria Di Cosmo:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Laura Savoldi:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

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.

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Appendix A. Appendix A

In Eq. (1), HHI_m is a modified version of the supply concentration index HHI [63], which weighs the market share[10] $S_{c,m}$ of the country c in supplying the material m by a dimensionless governance indicator g_c, to account for the political and economic instability of $N_{countries}^{mat}$ supplier countries (see Eq. (A7)). The risk increasing factors are then: low number of supplier countries; presence of few countries with very high market shares; and high political and economic instability presence of supplier countries. The parameter IR_m is in turn the IR for the material m computed as in Eq. (A8) (with all the flows measured in e.g., tons t), where $Import_m - Export_m$ represents the net imported quantity $NetImport_m$, while $DomProd_m$ is the domestic production. The higher the net import, the higher the import dependency and the associated SR.

$$HHI_m\,(-) = \sum_{c=1}^{N_{countries}^{mat}} g_c \cdot S_{c,m}^2 \tag{A7}$$

$$IR_m\,(-) = \frac{Import_m - Export_m}{DomProd_m + Import_m - Export_m} = \frac{NetImport_m}{DomProd_m + NetImport_m} \tag{A8}$$

A consistent energy SR metric was developed based on established literature. It involves the definition of the supply risk SR_e of an energy commodity e as a function of: a supply concentration index HHI_e as defined in Eq. (A7), and an import reliance indicator IR_e as defined in Eq. (A8), where the flows of commodities are measured in unit energy, e.g., PJ. The same risk increasing factors as material SR exist, since the two metrics were developed consistently.

$$SR_e\,(-) = HHI_e \cdot IR_e \tag{A9}$$

$$HHI_e\,(-) = \sum_{c=1}^{N_{countries}^{en}} g_c \cdot S_{c,e}^2 \tag{A10}$$

$$IR_e\,(-) = \frac{Import_e - Export_e}{DomProd_e + Import_e - Export_e} \tag{A11}$$

Appendix B. Appendix B

The normalization in Eq. (2) allows to reflect more closely the relative differences in SR_m. Indeed, $cons_m^{yref}$ is used as a proxy for the materials market size (e.g., EU or global consumption in a reference year), giving more importance to materials used in smaller amounts, but usually associated with smaller markets and higher SR_m, than bulk materials. This aligns with [75], which integrates material SR aspects in LCAs.

By comparing the normalized SR_t in Eq. (2) with the non-normalized definition in Eq. (A12) – measured in unit mass per unit capacity – the authors

[10] The market share is the only term used in the traditional definition of HHI [63].

of [75] verified that in case of $cons_m^{yref}$ absence, the single material contribution to the technology SR would mainly come from the material intensity magnitude (i.e., as if technology SR was defined as in Eq. (A13)). This is due to the fact that SR_m typically lies within one or two orders of magnitude, while $f_{m,t}$ can vary by many orders of magnitude. Therefore, its contribution would dominate the one from SR_m.

$$SR_t'\left(\frac{t}{cap}\right) = \sum_{m=1}^{N_{mat}^{tech}} f_{m,t} \cdot SR_m \tag{A12}$$

$$SR_t''\left(\frac{t}{cap}\right) = \sum_{m=1}^{N_{mat}^{tech}} f_{m,t} \tag{A13}$$

A similar comparison was carried out for the power sector technologies involved in the paper case study (for data sources and assumptions, see Section 3.4), finding the same conclusions as [75]. The comparison consisted of calculating the contribution in percentage terms of the single raw materials to the above-discussed technology SR definitions, highlighting how the contributions are very similar for SR_t' (see Eq. (A12)) and SR_t'' (see Eq. (A13)). This outcome is shown for selected technologies in Fig. B8. Aluminum and copper are bulk materials for solar PV (Fig. B8b), onshore wind (Fig. B8c), and hydropower (Fig. B8d), and mostly contribute to the technology SR despite the low SR_m (Fig. B8a). Instead, the use of the normalization factor increases the contribution of materials with higher SR_m, such as silicon and gallium for solar PV, heavy REEs (HREEs) for onshore wind, and manganese and nickel for hydropower.

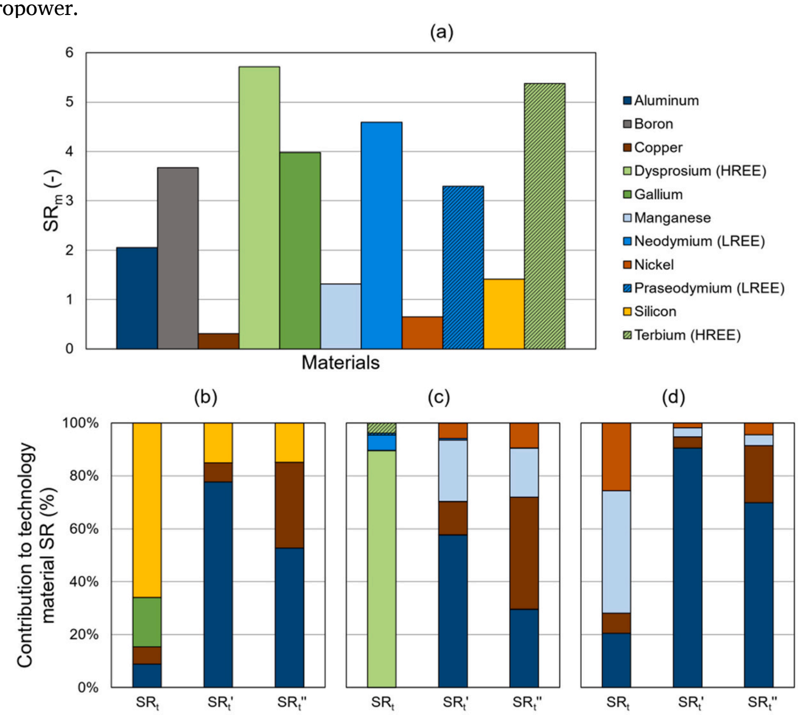

Fig. B8. Single material SR_m (a) and comparison between several types of technology SR (SR_t, SR_t', and SR_t'' as defined by Eq. (4), Eq. (A12) and Eq. (A13), respectively) for solar PV (b), onshore wind (c), and hydropower (d). The comparison is carried out by looking at the contribution in percentage terms of the single materials to the overall technology SR. Data sources and assumptions are discussed in Section 3.4.

Appendix C. Appendix C

Consider the minimization of multiple objective functions $f = (f_1, f_2, \ldots, f_n)^T$. Then AUGMECON reformulates all objectives but one (with index j) into equality constraints and introduces a positive constant $c \approx 10^{-6} \ldots 10^{-3}$, $n-1$ new, non-negative slack variable $s_i, i = 1, \ldots, n, i \neq j$ for the constraints, and $n-1$ constants $k_i, i = 1, \ldots, n, i \neq j$, which reflect the typical order of magnitude of the reformulated objectives:

$$min\left(f_j - c \cdot \sum_{i=1}^{n} s_i \Big/ k_i\right) \text{ s.t.} f_i + s_i = \epsilon_i \forall i = 1, \ldots, n, i \neq j \tag{C14}$$

The main steps to solve the MOO problem (C14) are the following. First, each objective f_i is minimized individually or a lexicographic optimization is done to estimate the Pareto front boundaries. Second, a desired number and distribution of caps ϵ_i within the Pareto front boundaries are chosen: the caps represent the right-hand side of the equality constraints that are derived by reformulating all objectives but one. Third, the problem (C14) is solved for all the caps, providing Pareto-optimal solutions of the initial MOO problem.

Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2025.125647.

Data availability

The novel TEMOA modeling framework and the power sector database, developed for and adopted in this work, are available at [64]. A high-level description of the novel MOO module for TEMOA and the complete set of input data and results are presented in the Supplementary Material.

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