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Integrating Critical Raw Materials into Energy System Optimization Models: Approaches for More Informed Energy System Planning

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Abstract

The energy transition from fossil fuel-based technologies to clean energy ones – such as solar PV, wind turbines, utility scale batteries, and electric vehicles – is expected to substantially increase the consumption of raw materials in the next decades. Future growth rates for many of these materials will overcome historical levels, potentially causing a supply-demand imbalance. Moreover, the current and planned supply chains of clean energy technologies present high supply risk (SR). Indeed, potential bottlenecks can be caused by the high concentration and/or political instability across all the supply chain steps. This concerns the primary supply of many materials required by those technologies, which are then referred to as critical raw materials (CRMs), such as cobalt, graphite, lithium, nickel, platinum, rare earth elements, and silicon metal. Also, the manufacturing and assembly of technology components is affected, such as solar PV modules, wind nacelles, and battery cells. The bottlenecks described above might counterbalance the advantages of reduced fossil fuel consumption and the associated import dependency, which is experienced by many countries worldwide, therefore leading to SR trade-offs.

The transition to a low carbon economy might then be hindered by clean energy technology supply chain bottlenecks. In this regard, stakeholders have recognized the need of incorporating them in energy system planning, especially calling for CRMs to be included in planning tools such as energy system optimization models (ESOMs). The latter have been widely used to assess the effectiveness of energy policies, by identifying cost-effective evolutions of an energy system, described through a technology-rich database, over the medium-to-long term energy scenarios. However, the state of the art reveals a limited capability of existing studies and models to represent policy interests in reducing the material SR of the energy transition. Three main research gaps can be identified: (i) the absence of energy scenarios properly including material supply disruption constraints; (ii) a lack of material SR assessment at the energy system level; (iii) the absence of a framework to analyze the trade-offs between material and energy SRs. To address these gaps, this thesis proposes three approaches, which were developed for implementation in open-source ESOMs and independently of the tool used for their application. In this regard, the case studies were built upon the multi-sectorial TEMOA-Italy model: TEMOA is among the most mature open-source model, while the Italian energy system was considered particularly illustrative.

The first approach focuses on developing material supply disruption constraints for integration into ESOMs. The constraints were modeled as part of a material value chain, which includes the material supply – to which the constraints have to be applied – and requirement for technology manufacturing (i.e., proportional to newly installed capacity). The second approach concerns the ex-post application of a material SR indicator at technology level. The indicator was defined by aggregating measures of supply concentration, import reliance, political stability, and material intensity of the raw materials required by the technology. These two approaches were tested across baseline, decarbonization, and four supply disruption scenarios. The latter include economic, geopolitical, and physical supply disruption causes. Results highlight how the decarbonization requires much more CRMs and accepting a higher SR than a baseline evolution. Then, even in case of partial material unavailability, the net-zero target was achieved at the expense of total system cost increase, by favoring low-CRM-intensive but more expansive alternatives. Electric vehicles emerged as major contributors to material consumption, while materials like cobalt, lithium, and rare earth elements showed the highest impact on system SR. The third approach concerns the first-of-a-kind integration of material and energy SRs as objective functions in energy system models. The material SR is the same as the second approach, while the energy one was consistently derived. The two functions were employed in a multi-objective optimization of the Italian power sector by 2050. Results highlight a significant trade-off between the two risks: achieving full decarbonization of the Italian power sector while reducing material SR requires accepting higher energy SR and total system costs. In particular, investments in wind turbines and batteries reduced in favor of solar PV and natural gas plants with CCS, which raised gas imports and energy SR.

Unlike earlier studies, the three approaches allow the underlying energy system to adapt and mitigate CRM supply chain risks, allowing for more informed energy system planning. The outcomes have provided actionable insights for managing these risks. The strategies that can be derived include the diversification of supply chains and technology, as well as the reduction of import dependency and supporting domestic supply chains. Credibility, reproducibility, and transparency of the approaches are ensured using established and referenced methods and tools, as well as making openly available all data, assumptions, and results.

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Nomenclature

Acronym	Meaning
a-Si	Amorphous silicon
AUGMECON	Augmented epsilon-constraint
BEV	Battery electric vehicle
CCUS (CCS)	Carbon capture utilization and storage (without utilization)
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
EC	Electrolysis cell
ESOM	Energy system optimization model
EU	European Union
EC	European Commission
ES	Energy security
FC	Fuel cell
FCV	Fuel cell vehicle
FHEV	Full hybrid electric vehicle
GB-DFIG	Gearbox double-fed induction generator
GB-PMSG	Gearbox permanent magnet synchronous generator
HHI	Herfindahl-Hirschman Index
HR	Hurdle rate
HREE	Heavy rare earth element
ICE	Internal combustion engine vehicle
IR	Import reliance
LIB	Lithium-ion battery
LREE	Light rare earth element
LWR	Light water reactor
MI	Material intensity
MOO	Multi-objective optimization
MR	Materials requirement
PEM	Proton-exchange membrane
PV	Photovoltaic
REE	Rare earth element

SR	Supply risk
WACC	Weighted Average Cost of Capital
TEMOA	Tools for Energy Model Optimization and Analysis
WGI	Worldwide Governance Indicators

Symbol	**Meaning**
%	Unit of measure for percentage
$b€$	Unit of measure for billions of euros
$bvkm$	Billions vehicle-kilometer
c	Small constant for AUGMECON
cap	Unit of measure for capacity
Cap	Capacity
$cons$	Consumption
d	Material supply disruption factor
Dem	Cumulative material demand
$DomProd$	Domestic production of raw materials (energy commodities)
$Emissions$	Net emissions
EoL	End-of-life recycling rate
$Export$	Quantity of exported raw materials (energy commodities)
F	Objective functions
f	Material intensity or market share
$f = (f_1, f_2, \dots, f_n)$	Objectives of the generic multi-objective optimization problem
f_k^{tech}	Market share of sub-technologies
g	Generic governance indicator
GDP	Global gross domestic product
GW	Unit of measure for Gigawatt
$Import$	Import
k	Constant
km	Kilometer
kt	Unit of measure for kilotons
$M\$$	Unit of measure for millions of dollars
$MaxMaterial$	Maximum material availability
Mt	Unit of measure for millions of tons
Mv	Unit of measure for millions of vehicles
N	Number
$NetImport$	Net import
PJ	Unit of measure for petajoule
$Reserve$	Reserve of raw materials
S	Market share of countries
s	Slack variable
SI	Substitution index
t	Unit of measure for tons

tr	Trade indicator
$V\_Capacity$	Variable for new installed capacity of technologies
V_Flow	Variable for commodities flow
$V\_MatCons$	Variable for total consumption of materials
$V\_MatSupply$	Variable for total production of materials
$vehicle$	Unit of measure for vehicle
X, X'	Feasible solutions of the generic multi-objective optimization problem
y	Year
ϵ	Constraint

Superscripts	**Meaning**
dec	Decarbonization
en	Energy commodity
export	Export
g	Governance
global	Global level
GS	Global supply
import	Import
IT	Italian level
mat	Material
MIN	Minimum
original	Original
RIR	Recycling input rate
st	Sub-technology
t	Trade
T	Transpose
tech	Technology
yref	Reference year

Subscripts	**Meaning**
a	Annual
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)
elcz	Electrolyzer
em	Emission commodity (generic)
emi	Emission commodities (included in the energy system)
en	Energy commodities (included in the energy system)
end	Ending year
f	Share
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	Optimization year
r	Energy system region under analysis
start	Starting year
sub-tech	Sub-technologies (total number)
t	Technology (generic)
tech	Technologies (total number)
v	Installation year of technologies
vint	Vintage (installation year of technologies)

Chapter 1

Introduction

"The energy transition is a materials transition" [1]. Indeed, technologies for the energy transition – hereinafter clean energy technologies – require much more raw materials (RMs) than conventional fossil fuel-based ones [2]. Moreover, the shift from fossil fuels to low-carbon alternatives may result in a trade-off between the supply risk (SR) along their supply chains [3], where SR is typically defined as the likelihood of supply disruption due to supply chain bottlenecks [4]. Renewable energy sources and battery electric vehicles (BEVs) are expected to reduce fossil fuel consumption [5], [6], thereby decreasing the import dependency that many countries have recently experienced. For instance, the 2022 energy import reliance (IR) – i.e., the share of primary energy needs of a country met by imports from other countries [7] – of the European Union (EU) and Japan was ~63% [8] and ~85% [9], respectively. The decrease in IR for a country is expected to reduce its energy SR [10]. Conversely, potential bottlenecks may arise along the supply chain of clean energy technologies. This is due to the high concentration and political instability affecting: (i) the extraction and processing of many RMs required by these technologies and that are referred to as critical raw materials (CRMs) [11]; (ii) the manufacturing and assembly of technology components [1], [12]. In this context, there is a growing concern among stakeholders, who have recognized the necessity of incorporating supply chain bottlenecks in energy system planning [12]. In particular, they call for CRMs to be included in planning tools such as energy system optimization models (ESOMs) [13], as they currently lack them [2]. This thesis aims to address this shortcoming by developing three approaches for integrating CRM aspects into energy system modeling. In particular, the potential bottlenecks along the extraction and processing phases of RMs were considered through SR constraints, indicators, and objective functions.

The research context of the thesis is delineated in Section 1.1, which provides a general overview of the potential supply chain bottlenecks for clean energy technologies. The state of the art on the integration of CRMs in energy system modeling is then examined in Section 1.2, highlighting the main limitations. An overview of the main features of ESOMs is presented in Section 1.3, including the main reasons for choosing an open-source application. Finally, the aim and structure of the thesis are described in Section 1.4.

1.1 Critical raw materials in energy system planning: research context

Clean energy technologies typically require more RMs than fossil fuel-based technologies. The average material (hereinafter "material" is also used to mean "raw material") requirement (MR) for new power generation capacity has increased by ~50% globally between 2010 and 2020 [2]. Moreover, global demand for several RMs 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 [1]. For instance, according to stated energy policies, the global lithium demand for these sectors is foreseen to rise more than 5 times between 2022 and 2030 [5], and around 13 times by 2040 [2]. Consider that a time horizon up to 2040 is often used in prospective analyses of RMs supply side when projects in very early stages of development and with longer time horizon are typically not considered [14]. Instead, global demand for copper, rare earth elements (REEs), and silicon metal is projected to double between 2022 and 2030 [5]. The demand for these materials might further increase when considering the net-zero emissions pledge [2]. The demand for lithium might grow by over 40 times by 2040, while the one for cobalt, graphite, and nickel between 20 and 25 times. Overall, future growth rates for many RMs are projected to overcome historical levels, potentially causing a supply-demand imbalance [15], [16]. A recent IEA[1] analysis in 2024 [14] pointed out high risks of long-term market balance for lithium, copper, cobalt, REEs, graphite, and nickel, considering: (i) RM supply from existing projects, along with projects under construction and at an advanced development stage; (ii) accomplishment of announced energy policies. Lithium and copper turned out to be the most exposed to supply-demand imbalance risks. The expected lithium supply in 2040 might be less than 40% of the primary supply requirement. Instead, a copper primary supply shortfall might start already after 2025, reaching 80% of the primary supply requirement in 2040.

The concentration in the supply chains of clean energy technologies represents an additional potential bottleneck [1]. A few major companies control the mining industry [17]. For instance, more than half of the primary supply of cobalt and lithium is due to the corresponding top five mining companies. Concerning the geographical concentration, China dominates in extracting and

[1] International Energy Agency.

processing many RMs, such as lithium, silicon metal, and REEs, and currently accounts for 56%, 76%, and 90% of global supply, respectively [18]. The supply of other materials relevant to the energy sector such as cobalt and platinum is more diversified. However, it encompasses countries like the Democratic Republic of the Congo (for cobalt) and South Africa and Russia (for platinum), which are not considered politically stable (in the context of RMs, the political stability of supplier countries is measured through governance indicators, which consider several governance dimensions [4]) [18]. Such a high supply concentration is expected to characterize the mining and processing of these RMs also in the next decade [14]. The top three global supplier countries are foreseen to provide around 80% of cobalt, lithium, and REEs in 2030. The concentration issue also affects the manufacturing of clean energy technology components [12]. China, the United States, the EU, and Japan accounted for about 65% of global manufacturing value added in 2023, which is similar to the trend over the past two decades [19]. In this context, China leads the current and announced manufacturing capacity of several components at the global level. For instance, the 2023 and projected 2030 Chinese share for solar PV modules, wind nacelles, and battery cells lies between 60% and 80% [12].

The amount of RMs that clean energy technologies require and the supply concentration along the steps of their supply chains are the primary reasons behind potential supply chain bottlenecks [1]. The latter could hinder the transition to a low-carbon economy [20]. In this regard, policymakers have started being concerned about the procurement of materials and technologies for the energy transition[2] [12]. For instance, the EU Net-Zero Industry Act [21] and the Inflation Reduction Act in the United States [22] support 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) [12]. Furthermore, a growing number of countries are enhancing their comprehension of the SRs by developing and continuously CRMs lists [23] and by formulating strategies to guarantee a secure and diversified supply, as exemplified by the EU CRMs Act [24]. These dedicated measures should be considered when formulating energy policies [25] and studying future energy supply scenarios [26]. 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 [27], with RMs among the primary concerns [13]. This increases the complexity of energy system planning and requires more holistic frameworks and methodologies to support decision-making with politically relevant results [13], [28], [29]. In this regard,

[2] The scale of the problem increases when considering that many of the highly concentrated raw materials required for the energy transition are also demanded by the digital transition and defense and aerospace applications [1].

ESOMs are to assess the effectiveness of energy policies, typically by identifying cost-effective evolutions of an energy system, described through a technology-rich database, over the medium-to-long term energy scenarios [30].

1.2 Critical raw materials in energy system modeling: state of the art

The existing literature on CRM integration in ESOMs can be classified into two groups: (i) studies assessing the energy transition MR; (ii) studies assessing the energy transition SR. These studies are described, respectively, in Section 1.2.1 and Section 1.2.2, while a scheme of their classification and main limitations is depicted in Figure 1.

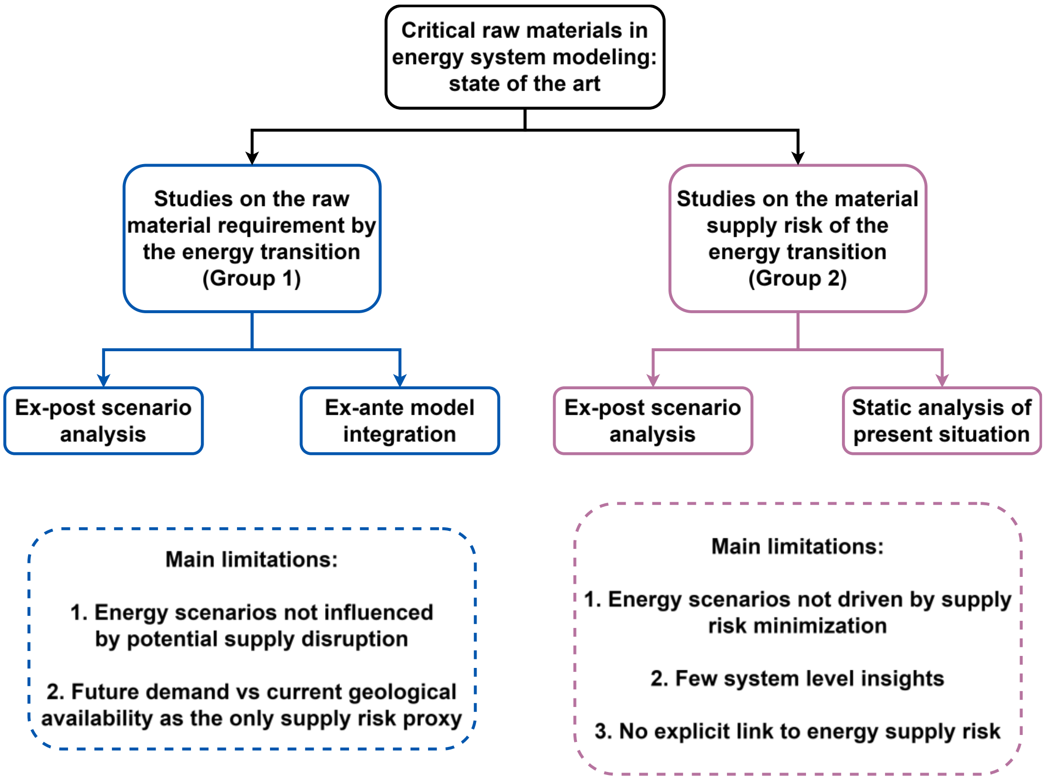

Figure 1. Scheme of the classification and limitations of the existing studies.

1.2.1 Raw material requirement by the energy transition

Recent years have seen an increase in the number of studies assessing the demand of RMs due to the energy transition [20]. Most of them apply MR indicators ex-post to energy scenarios from third-party sources. This was highlighted in a comprehensive review of 132 studies until 2019 on MR for clean energy technologies in [20]: among the 86 scenario analyses included in the review, only one study presented an ex-ante approach. The latter was used in a few recent studies, which evaluated FRM consumption directly within the adopted modeling framework. In both approaches, the capacity installation of technologies is used to quantify the MR.

In the ex-post scenario analyses, the MR indicators typically quantify the material intensity of technologies in unit mass of the individual material per unit capacity (e.g., t/GW). For instance, [26] used global energy scenarios by IEA and IRENA[3] to derive future consumption of cobalt, lithium, and REEs. IEA scenarios were also used to estimate the MR of future low-carbon power generation in [31] and other sectors like battery storage, hydrogen production, and BEVs [32]. More specific analyses were done in [33] for the materials required by offshore wind in the United States and in [34] for the Chinese transport system. The same prospective ex-post approach was adopted in reports by international organizations like IEA [2], [14], IRENA [35], World Bank [36], regional institutions such as the European Commission and JRC[4] [1], [37], [38], and companies like McKinsey [15].

Most of the ex-ante studies coupled at least two different models with a soft-linking approach, i.e., by using the outputs of one model as the inputs of another, running the models separately [39]. In some cases, these studies considered integrated assessment models, which involve other systems besides the energy one, like the climate, land, and water systems [29]. For instance, the MEDEAS framework included a materials model that provides for the RMs required by renewable power generation technologies, the power grid, and BEVs, whose installed capacities result from a dedicated model [29], [40], [41]. Instead, a soft-link between an integrated assessment model and life cycle inventories was proposed in [42] and [43], where the requirement of almost 50 RMs for the construction, operation, and decommissioning of power sector technologies was linked to the outputs of the TIAM-FR model. Five sector-specific models – including transport, buildings, agriculture, electricity generation, and RM supply – were iteratively used in [44]. Then, an energy system model and an RM supply one were linked in [45] and [46], with a focus on renewable electricity generation technologies. The framework in [46] considered the energy-material nexus, i.e., it accounts for RMs requirement by energy technologies and the energy required to supply these RMs. This is also the case in [19], where the IEA linked the energy scenarios results from its Global Energy and Climate model to an optimization model. The latter provided for the optimal manufacturing capacity and trade flows along the supply chains of some key clean energy technologies. Finally, three models were hard-linked in [47] and [48], where the hard-linking approach works by running a single common simulation of the interlinked models [49]. A TIAM-like model was used for the energy system part: then, MR from electricity generation and transmission technologies, as well as electric vehicles, were evaluated.

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[3] International Renewable Energy Agency.
[4] Joint Research Center.

Conversely, only a few models have the capability to evaluate ex-ante RMs within a single model, in an integrated way. The global lithium and copper supply chains are modeled within the integrated assessment model TIAM-IFPEN, alongside the energy required by these supply chains. This model considers lithium requirement from industry and transport sectors [50], and copper requirement from electricity production and network, transport, industry, construction, and good services production sectors [51]. To the author's knowledge, TIMES US Model RES is the only ESOM including ex-ante RM requirement [52]. This model covers the RMs required by fossil-, nuclear-, and renewable-based electricity generation.

The studies of the first group have two main limitations. First, their results are not influenced by the risk of potential supply chain bottlenecks, potentially leading to infeasible outcomes. Indeed, the energy scenarios employed in the ex-post approaches existed before the analysis, potentially leading to infeasible results in terms of RM requirement [39]. Instead, the modeling frameworks capable of endogenously evaluating MR do not consider the risk of supply disruption nor as a model constraint or objective. Second, both the ex-post and ex-ante approaches consider global geological availability as the only SR proxy, by comparing the projected RM demand to current resources, reserves, or mining [20] and lacking regional-oriented insights. This approach oversimplifies the actual risks [4], [53]. Indeed, it is widely agreed that scarcity is not as pressing an issue as supply scaling and concentration [15], and that supply chain risks have a regional dimension [20], [54].

1.2.2 Material supply risk of the energy transition

A second group of studies overcame the SR oversimplification of the studies presented so far. Indeed, these studies estimated future SRs of the energy transition by adopting the most common indicators, such as supply concentration and import dependency ones [20], [53], [55]. In most cases, these indicators were combined ex-post with energy scenario results.

Supply concentration and import dependency associated with the lithium requirement by the Chinese transport electrification were studied in [56]. The indicators were computed based on the results of a material flow analysis[5], which required, among the inputs, scenarios on the BEV penetration worldwide and in China. Then, the IEA employed a more comprehensive metric in [14] to evaluate the SR of key RMs required by: low-emission power generation, power grid, battery storage, hydrogen production, and electric vehicle technologies. Among other indicators, the supply-demand imbalance of RMs in the short- and long-term

[5] Material flow analysis is a method used to quantify the flows of input, processing, and output of materials in a defined system [202].

was used. It is evaluated based on the penetration of the aforementioned technologies in the IEA stated policy scenario [57]. IEA scenarios were also used in other studies that have a single technological focus to project future RM demand. The latter was then compared to the expected level of future supply and combined with other indicators to estimate the SR associated with: thin film solar PV [58],wind power [59], [60], and cars [61]. Instead, the authors in [62] proposed a technology material SR by aggregating the SRs of the RMs required for the technology manufacturing, deriving a SR per unit of capacity or energy produced. This metric was then applied ex-post to European energy transition scenarios within the ENBIOS modeling framework [27], [54]. In particular, the technology material SR indicator was multiplied by the energy produced by technologies, with a focus on the power sector.

All the studies described so far consider the SRs along the extraction and processing of RMs. Conversely, some studies proposed SR metrics for the entire supply chain of technologies, as [1] and [16], where the manufacturing and assembly of components were also considered. In particular, rather than conducting a prospective SR analysis, they evaluated the current concentration along the supply chain steps individually, without deriving a single aggregated value for the analyzed technologies.

The studies of the second group have three main limitations. First, none of them 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, these studies primarily focus on single RMs and/or technologies, with a lack of system-level perspectives and insights on technological competition in CRM consumption terms [32]. Examples of competition are: wind turbines and BEVs, since they both require REEs, or different types of solar PV technologies, which consume different RMs. 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 [25]. In this regard, a first attempt was presented in [63], where an IR indicator was considered alongside other – security, environmental, and social acceptability – indicators to define a sustainability index. The indicators were applied ex-post to decarbonization scenarios of the Italian power sector. In particular, a single power sector IR was measured considering both the fossil fuels and the RMs required by solar PV and wind turbines. However, the absence of separate indicators for material and energy SRs reduces the extent to which policy-relevant insights might be derived. Additionally, as previously highlighted, the ex-post approach does not allow to study energy scenarios directly affected by potential supply chain bottlenecks. In this context, multi-objective optimization (MOO) represents an appropriate means of addressing these shortcomings [39]. MOO is considered very effective when dealing with multiple and often conflicting interests (leading to trade-offs) in energy systems decision-making, as expected for material and energy SRs [28]. Few studies used MOO methods in ESOMs to address criteria related to material and energy import dependency, such as the depletion of materials and metals in life cycle assessments [64], [65], or energy autonomy of national [66] and energy small-scale systems [28], [67]. Nevertheless, these studies do not explicitly address SRs with suitable metrics. Indeed, a recent review paper [39] confirmed that MOO has not yet been used in an ESOM to approach RM requirements and SRs of the energy transition.

1.3 Energy system optimization models: an overview

Energy system models emerged in response to the 1973 oil crisis, as the only reliable tools capable to address the issue of resource dependency as linked to economic growth [30]. These models have evolved over decades, initially focusing on energy-environment interactions and later incorporating the cost of mitigation strategies of climate change and environmental impacts [68].

Bottom-up models are distinguished by their detailed representation of energy sectors and their interconnection, and they are particularly suited to evaluate the impact of different technologies on the evolution of future energy systems [69]. In this regard, ESOMs aim to provide the optimal configuration of an energy system, according to a certain objective function, over the medium-to-long term [70]. The objective is typically to minimize the total system cost over the entire time horizon considered [28]. In particular, the latter envisages a subdivision into time-steps, which represent a subset of hours or times of day within a month or season (for operational decisions) and are modeled as a single or a number of optimization years (for investment decisions) with planning horizons usually ranging from 5 to 30 years in the future [71]. The general structure of an ESOM framework is depicted in Figure 2. The energy system under analysis is characterized by a technology-rich database that covers supply- and demand-side energy sectors. The least-cost match between the two sides is computed during the optimization problem – typically a linear programming problem – where the decision variables include new installed capacity of technologies and the level of their production (also referred to as activity) [30]. The inputs are: the techno-economic parameters characterizing the technologies modeled; the evolution of the energy demands that must be satisfied by the supply-side; constraints that define the energy scenario to be studied (e.g., CO_2 emissions reduction targets) [72]. Results can be then directly analyzed in terms of energy and technology mixes, costs, and emissions, or further elaborated to provide insights on, e.g., environmental impacts, energy security, social acceptability [63].

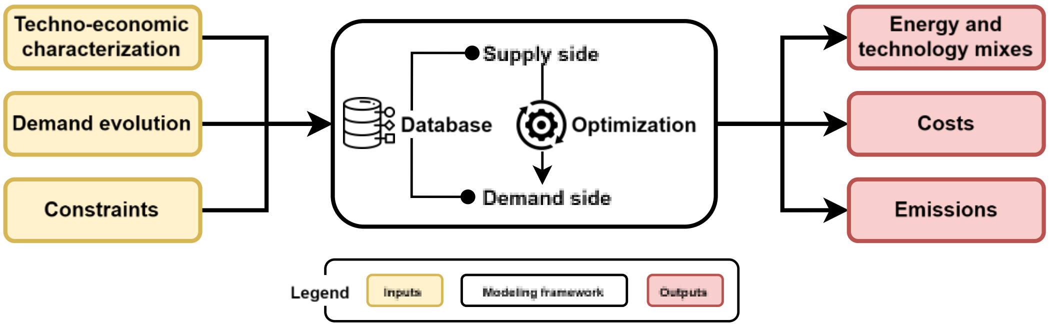

Figure 2. General structure of an energy system optimization modeling framework.

The supply-side typically represents the upstream sector, including the extraction, transformation, and import of primary energy resources, and their use in, e.g., electricity, heat, and hydrogen production [30]. The demand-side typically covers agriculture, residential and commercial buildings, industrial, and transport sectors, referred to as end-use sectors [30]. The interconnection between the supply- and demand-side sectors is modeled through a detailed network description, referred to as reference energy system. Its three basic elements [73] are described below and are depicted in Figure 3:

1) **Technologies (or processes):** they represent systems that transform commodities into other commodities. Some examples are: sources of commodities, such as mining or import processes; transformation technologies such as refineries, power plants, or hydrogen production processes; demand-side technologies such as vehicles or domestic heating systems [30]. Moreover, technologies are characterized by techno-economic parameters like costs, efficiency, capacity factor, lifetime, and emission factors.

2) **Commodities:** they represent physical, demand, and emissions commodities. Physical commodities include: energy sources such as fossil fuels, biofuels, or uranium; energy carriers such as electricity, heat, or hydrogen; materials such as feedstocks for iron and steel and chemical industries. Demand commodities include end-use sector demands: they are modeled as energy consumption or end-use service demands, like kilometers driven by cars. Finally, emission commodities include greenhouse gases or other pollutant emissions.

3) **Commodity flows:** they represent the link between technologies and commodities, like the link between power plants and electricity generation, or boilers and domestic heat production.

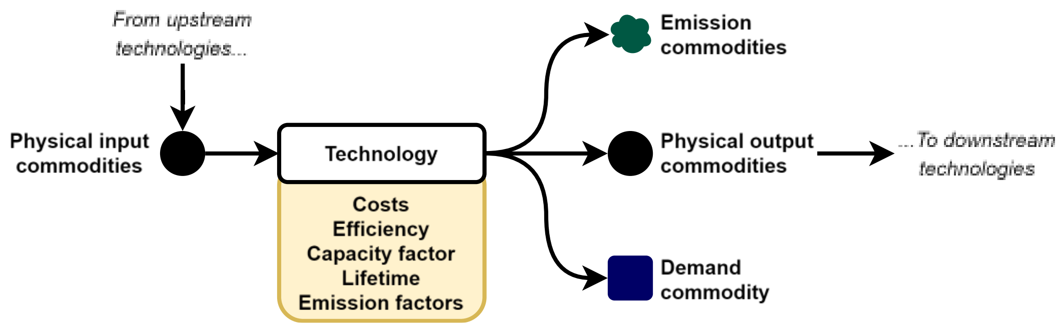

Figure 3. Elements of the typical reference energy system of ESOMs.

The three approaches presented in this thesis were designed for application to open-source ESOMs, which have emerged in recent years in a context of increasing interest in open-source science among scientists [74] and policymakers [75]. The proven benefits of making source code, data, and methodologies publicly available in the energy system modeling community are: increased transparency and credibility; reduction of wasteful double-work; improved overall quality [76], [77]; the possibility of expanding the capabilities of the traditional modeling frameworks [74], which is the high-level contribution of this thesis. The choice of the model for the application of the approaches fell on TEMOA [78], which is among the most mature and well-established open-source ESOMs [76]. It was chosen over other long-term planning open-source tools (e.g., Switch, OSeMOSYS [76]) mainly for the following reasons[6], which were extensively described in [30] and [74]: (i) the possibility to use powerful open-source solvers like CPLEX and Gurobi, which are well suited for large-scale optimization problems; (ii) the full implementation in Python, whose extensive libraries and packages simplifies development and customization; (iii) the possibility to model large-scale sector coupled energy systems.

1.4 Aim and workflow of the thesis

The analysis of the state of the art on the integration of CRMs in energy system modeling – which is detailed in Section 1.2 – highlights that supply chain bottlenecks have been disregarded in energy scenarios results from existing tools and studies [3]. This thus reveals a limited capability of existing energy system models to represent policy interests in reducing the material SR of the energy transition. Three main research gaps can be identified: (i) the absence of energy scenarios properly including RM supply disruption constraints; (ii) a lack of material SR assessment at the energy system level; (iii) the absence of a framework to analyze the trade-offs between material and energy SRs. To address

[6] The choice of TEMOA was made based on the state of the art of open-source ESOMs until 2022. Consequently, any novelties that became publicly available after 2022 were not considered in the choice.

the identified research gaps, this thesis proposes three approaches. They are listed below, alongside their primary contributions to advancing the state of the art:

1) **Approach 1 – Integration of materials supply disruption constraints:** this approach concerns the integration of constraints on the maximum availability of RMs in ESOMs. It is based on [79] and aims to fill the research gap (i). The primary contributions to the state of the art are: the capability to generate energy scenarios influenced by RM supply disruption; the modeling of the value chain of RMs that can be easily implemented in any ESOMs.

2) **Approach 2 – Ex-post application of a material supply risk indicator:** this approach concerns the ex-post application of a technology material SR indicator to ESOM results. It is based on [79] and aims to fill the research gap (ii). The primary contribution to the state of the art is a system-level evaluation of the material SR across multiple energy sectors.

3) **Approach 3 – Multi-objective optimization of material and energy supply risks:** this approach concerns the first-of-a-kind integration of material and energy SR objective functions in ESOMs. It is based on [3] and aims to fill all the research gaps mentioned above. The primary contributions to the state of the art are: the development of a comprehensive and consistent metric to evaluate the material and energy SRs as objective functions in ESOMs; the capability to generate policy-relevant insights on potential effects of SRs and their trade-offs and management in decarbonized energy systems.

The three approaches were conceived for implementation in open-source ESOMs, yet their development occurred independently of the ESOM framework to which they were subsequently applied. Particularly, the choice fell on Tools for Energy Model Optimization and Analysis (TEMOA) [78]. Building upon an extended version [80] that was developed by the MAHTEP Group at the Department of Energy Politecnico di Torino [81], dedicated TEMOA versions were developed, and different energy sectors were involved, as summarized in Table 1. The Italian case study was considered particularly illustrative, due to their ambitious energy transition targets and the preliminary CRMs legislation.

Table 1. List of reference journal papers and TEMOA versions for the three approaches.

Approach	Reference journal paper	Dedicated TEMOA version	Sectorial scope
Approach 1	[79]	TEMOA-Italy-materials [82]	Power sector, Battery storage, Hydrogen production, Transport sector (cars)
Approach 2			
Approach 3	[3]	TEMOA-MOO [83]	Power sector

A scheme of the thesis organization is shown in Figure 4, distinguishing between chapters (white boxes) and sections (light blue boxes). After the introduction presented above, the three approaches are described in Chapter 2. Each of them has its dedicated section, while a common one is devoted to the discussion of the strengths and limitations identified. Then, the case studies used for the application of the approaches are presented in Chapter 3. An overview of the TEMOA-Italy model is provided, before the description of the data and assumptions adopted to build the case studies. In particular, the dedicated TEMOA versions are described: the TEMOA-Italy-materials, which is used for the first and second approaches; the TEAMOA-Italy-moo, which is used for the third approach. As for the methodology, a common discussion section is also included. The results from the application of the three approaches are subsequently presented and discussed in Chapter 4. The results concerning the first and second approaches are grouped together since they share the same case study. In this regard, the effects of CRM supply disruption on the Italian energy transition are evaluated for the whole energy system. Instead, the third approach has a dedicated section, which accounts for the SRs associated with the Italian power sector decarbonization. Finally, Chapter 5 concludes the thesis, also identifying possible future developments.

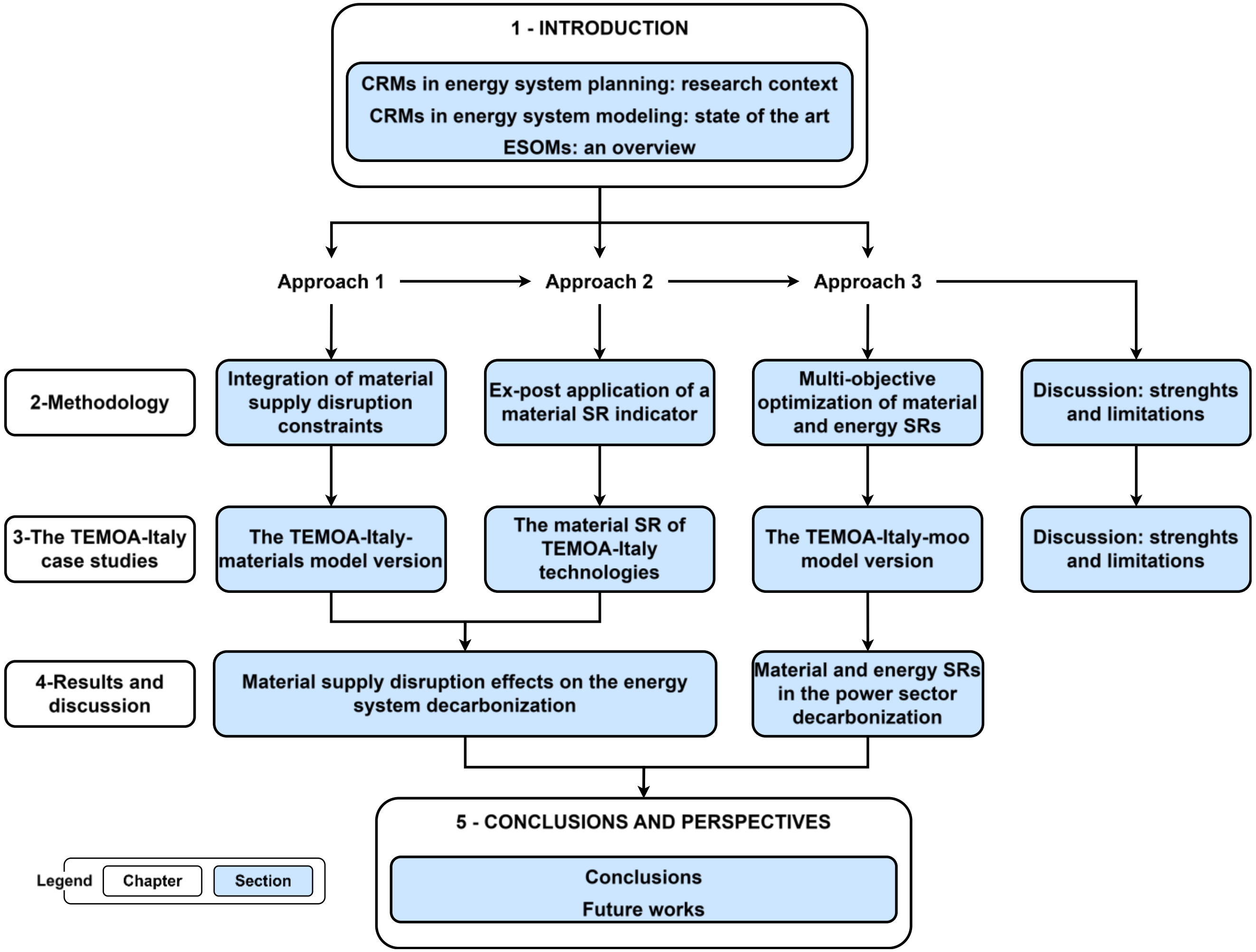

Figure 4. Scheme of the thesis organization.

Chapter 2

Methodology

This chapter includes the description of the three approaches proposed in this thesis, namely:

1) **Approach 1:** its description is presented in Section 2.1 and is based on [79].
2) **Approach 2:** its description is presented in Section 2.2 and is based on [3] and [79]. In particular, the ex-post application was implemented in [79], as pointed out in Table 1, whereas the same indicator was used in the methodology developed in [3].
3) **Approach 3:** its description is presented in Section 2.3 and is based on [3].

After the description of the development and the application of the approaches, their strengths and limitations are discussed in Section 2.4. Consider that the description of the three approaches refers generically to RMs, without specifying their type (e.g., CRMs). In fact, the proposed methods are valid for any type of RM. Instead, the scope of the materials depends on the model instance and case study adopted, which are described in Chapter 3.

2.1 Integration of material supply disruption constraints

Constraints on RM supply disruption consist of applying a maximum availability over the model time horizon to each RM that is to be included in the energy system under analysis. However, to integrate such constraints in ESOMs, the consumption and supply of RMs must be considered, too. In this regard, the modeling of the RM value chain as proposed in this thesis is schematized in Figure 5 for the generic RM *m*, which is required to manufacture the generic energy technology *t*. The RM value chain modeling involved the following novelties compared to the traditional ESOM framework described in Section 1.3, which are also highlighted in the scheme:

- A new type of commodity for RMs, which is supplied by a dedicated supply process.
- Two parameters that measure the material intensity (MI) of technologies and the maximum availability of materials.
- Three equations that encompass the consumption, balance, and maximum availability of RMs. They are identified in the scheme through cross references to the equations in the thesis. Moreover, throughout all equations in the thesis, the unknown terms – i.e., the variables – begin with $V\_$ to distinguish them from the known terms.

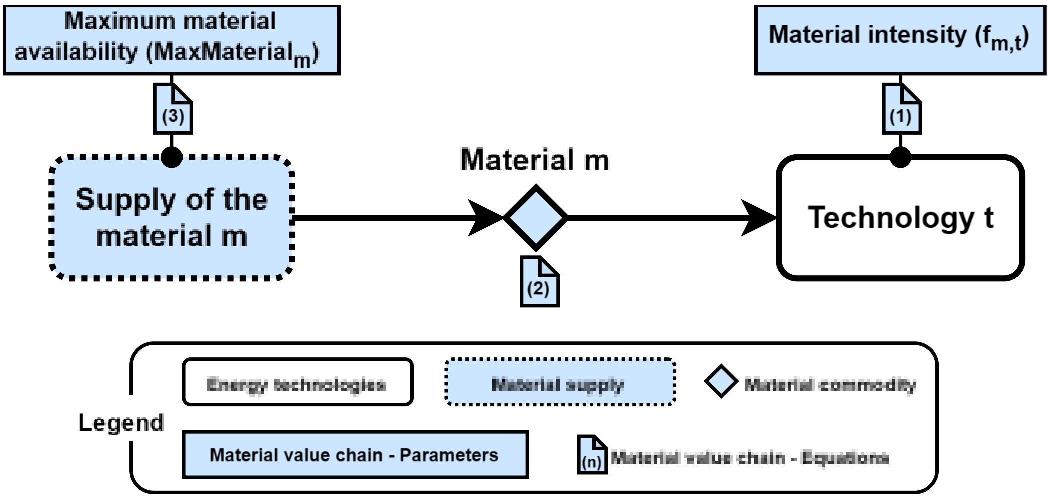

Figure 5. Scheme of the raw material value chain as proposed in this thesis. The light blue elements represent the novelties compared to the traditional ESOM framework (as described in Section 1.3) associated with Approach 1.

The consumption of the RM m was modeled through an MI parameter $f_{m,t}$, which measures the specific material consumption in mass (e.g., tons t) per unit capacity cap of the technology requiring it. In particular, the consumption by a technology occurs when the latter is installed in the installation year v and with a new installed capacity $V\_Capacity_{t,v}$, which is measured in unit capacity cap. Moreover, the material intensity might change over time (e.g., improved material efficiency of technologies): in this regard, the MI parameter can depend on the installation year v (i.e., $f_{m,v,t}$) The consumption $V\_MatCons_{m,t,v}$ of the material m by the technology t is then computed as in Equation (1) [7].

[7] Throughout all equations in the thesis, the unit of measures are denoted in parentheses, where "-" refers to dimensionless quantities.

$$V\_MatCons_{m,t,v}(t) = f_{m,t,v} \cdot V\_Capacity_{t,v} \tag{1}$$

Then, the balance constraint in Equation (2) ensures the balance of RMs at the system level, as it is typically done in ESOMs for energy commodities [84]. The total consumption of the material m is derived summing over all the technologies $N_{tech,m}$ requiring it. Then, the total consumption is set equal to the total production $V\_MatSupply_{m,v}(t)$ from the corresponding supply process.

$$\sum_{t=1}^{N_{tech,m}} f_{m,t,v} \cdot V\_Capacity_{t,v} = V\_MatSupply_{m,v} \tag{2}$$

Lastly, the inequality constraint in Equation (3) is introduced to account for RMs supply disruption causes as in [79]. The parameter $MaxMaterial_m$ is applied to the supply processes of RMs and represents the maximum value that can be reached by the cumulative total supply over the entire model time horizon. This maximum availability might also represent the available reserves or resources of RMs as in [3].

$$\sum_{v=1}^{N_{vint}} V\_MatSupply_{m,v} \le MaxMaterial_m \tag{3}$$

For example, consider in Table 2 the value chains of lithium and REEs in an ESOM that includes, among technologies, Li-ion batteries, BEVs, and wind turbines. Integrating Approach 1 in such ESOM would enable tracking the supply of lithium to Li-ion batteries and BEVs, and the supply of REEs to BEVs and wind-turbines. Data are taken from [82]. More qualitative and quantitative details on the type of RMs required by technologies typically included in ESOMs are provided in Section 3.2.

Table 2. Example of lithium and REE value chains.

Material	**Material supply**	**Maximum material availability (Mt)***	**Energy technology**	**Material intensity**
Lithium	Supply of lithium	2.6×10^1	Li-ion batteries – utility scale	8.7×10^2 t/GW
			BEVs	7.6×10^2 t/bvkm
REEs (e.g., Dysprosium)	Supply of REEs	3.1	BEVs	1.4×10^1 t/bvkm**
			Wind turbines - onshore	4.7 t/GW

* At global level

** billions vehicle-kilometers

2.2 Ex-post application of a material supply risk indicator

The second approach concerns the ex-post application of a SR indicator to ESOM results, as schematized in Figure 6, which also includes the cross reference to the equation describing the application. The indicator – or metric – was developed to account for the supply chain risks associated with technologies, by fulfilling criteria of reliability and consistency with ESOMs. Reliability refers to the use of established SR methodologies. The consistency refers to the associability of the SR indicator to the energy technologies typically included in ESOMs.

First, a SR indicator for the single RM was identified in Section 2.2.1. Then, a SR indicator for technologies was derived in Section 2.2.2 by aggregating the SR of the RMs required for the manufacturing of technologies. Lastly, the technology material SR indicator was properly linked to ESOM results (i.e., new installed capacity) to enable the assessment of the risks linked to the penetration of technologies in future energy systems, as described in Section 2.2.3.

The technology material SR indicator was integrated alongside other indicators in a broader energy security metric in [79]. Beyond material SR, the metric included indicators on diversification of primary energy supply, renewable energy sources, IR, and internal reliability of the energy system. An energy security index was then developed, building upon the ex-post application of these indicators to results from an ESOM.

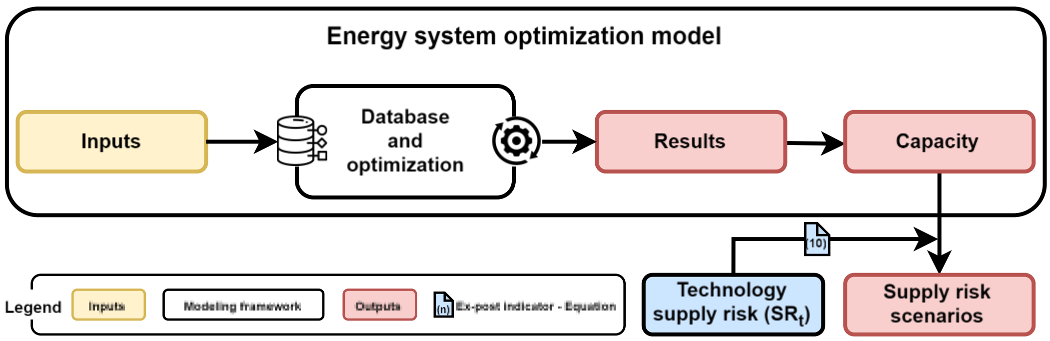

Figure 6. Scheme of the ex-post application of the technology material supply risk indicator to ESOM results. The light blue elements represent the novelties compared to the traditional ESOM framework (as described in Section 1.3) associated with Approach 2.

2.2.1 Supply risk of raw materials

The supply risk SR_m of a RM m is defined as the probability of a disruption occurring along the mining or refining steps of its supply chain [4]. The existing literature provides a number of indicators to measure this probability by considering different SR factors, including geological, geopolitical, economic, technical, social, and environmental factors [85]. Two extensive reviews of SR indicators in [4] and [55] identified indicators of supply concentration (e.g., Herfindahl-Hirschman Index (HHI) [86]), governance (e.g., Worldwide Governance Indicators (WGI) [87]), by-product dependency, and recycling among the most common ones. Moreover, prominent criticality methodologies – which are detailed in Section 2.2.4 – typically aggregate these indicators into composite SR ones [4], [11]. For instance, HHI, WGI, and indicators of by-product dependency, alongside other indicators, are aggregated in the frameworks elaborated by the United States Department of Energy [88], Yale University [89], and EC [90]. The main differences between the type of indicators and aggregation adopted by these frameworks are due to the goal and scope of the SR assessment, as well as data availability [4]. For instance, indicators of physical scarcity are used in [88] and [89], whose methodologies include medium-to-long term time horizon and whose analyses were mainly applied at national (i.e., United States) and global level. Instead, the EC methodology [90] adopts a shorter time scope and aims to assess the SR at EU level. The Italian case studies adopted in this thesis and the lack of Italian specific SR assessments, made the EC framework the most suitable to be used, as detailed in Section 3.3, In this regard, such framework is described in detail below. However, it is important to point out that the methodology developed and adopted for the second approach is also valid for other definitions of SR_m.

The supply risk SR_m^{EC} of the RM m as computed in the EC methodology for the EU [90] is shown in Equation (4).

$$SR_m^{EC}(-) = \left(HHI_m^{GS,g,t} \cdot \frac{IR_m}{2} + HHI_m^{EU,g,t} \cdot \left(1 - \frac{IR_m}{2}\right)\right) \cdot (1 - EoL_m^{RIR}) \cdot SI_m \quad (4)$$

This definition encompasses three risk measures. The first one includes the risks associated with the supply concentration at global and EU level, and the EU IR. The supply concentration is evaluated through an adjusted version of the Herfindahl Hirschman Index $HHI_m^{g,t}$, which is defined in Equation (5) and considers both the global supply ($HHI_m^{GS,g,t}$) and the supply to the EU Member States ($HHI_m^{EU,g,t}$). This adjusted version of HHI weighs the market share $S_{c,m}$ of the $N_{countries}^{mat}$ countries c supplying the RM m by a governance indicator g_c^{mat} and a trade indicator $tr_{c,m}$. The supplier countries and their market shares changes depending on whether $HHI_m^{g,t}$ is evaluated at global or EU level. Then, the governance indicator is considered a proxy of the political and economic stability of the supplier countries, which is measured by averaging between the six governance indicators included in the WGI provided by the World Bank [87]. The six indicators aim to measure the perception of different governance dimensions, such as voice and accountability, political stability and absence of violence/terrorism, government effectiveness, regulatory quality, rule of law, and control of corruption. Instead, the trade indicator considers trade restrictions between the EU Member States and the supplier countries. Consider that the standard HHI_m is computed only by the sum of the squares of $S_{c,m}$ [86].

$$HHI_m^{g,t}(-) = \sum_{c=1}^{N_{countries}^{mat}} S_{c,m}^2 \cdot g_c^{mat} \cdot tr_{c,m} \tag{5}$$

The supply concentration is evaluated both at global and EU level because of differences in data availability and quality. Indeed, EU supply data are more representative of the risk specific to the EU than global supply data. However, the latter can be considered more stable since the global supply mix is likely to change less than the EU one. In addition, global supply data are also more reliable in terms of data quality. In this regard, the import reliance IR_m of the RM m is used to balance between these two measures. It is computed as in Equation (6) (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. In particular, when IR_m is 100%, the overall supply concentration is the average between the global and EU measures; in case EU does not import or is a net exporter (i.e., $IR_m \leq$ 0%), the global supply is neglected.

$$IR_m(-) = \frac{Import_m - Export_m}{DomProd_m + Import_m - Export_m} \tag{6}$$

Finally, two risk-reducing measures are considered to consider alternatives to primary supply of RMs, thereby reducing the risk associated with the primary supply concentration. The end-of-life recycling input rate EoL_m^{RIR} is computed as the ratio (i.e., dimensionless) between the secondary RM amount from post consumption recycling in EU and the overall supply to EU processing and manufacturing activities. For instance, some studied pointed out that with recycling uptake, the mining growth might decrease by 30% on average by 2050 [14], [91]. Then, the substitution index SI_m accounts for the availability of substitutes for the RM m that have been proven to be readily available nowadays. In particular, the index is dimensionless and is calculated by considering the following factors: the global production and criticality of the substitutes compared to the RM m under analysis, and whether the substitutes are produced as a main product or by-/co-product of other RMs.

For example, consider in Table 3 the SR evaluation for lithium and REEs in the latest EU assessment by the EC methodology [18]. EU entirely depends on third countries for both lithium and REE supply. However, the latter SR is almost three times the former one, due to a much higher supply concentration. In particular, China accounts for almost 100% of the REE processing stage. More qualitative and quantitative details on the SR of RMs required by technologies typically included in ESOMs are provided in Section 3.3.

Table 3. Example of lithium and REE material supply risk.

Material	$HHI_{m}^{GS,g,t}(-)$*	$IR_{m}(-)$*	$SR_{m}^{EC}(-)$
Lithium	2.2	100 %	1.9
REEs (e.g., Dysprosium)	5.7	100 %	5.6

* Processing stage

2.2.2 Material supply risk of technologies

Clean energy technologies usually require several RMs, which might have a relevant associated SR [1]. Therefore, the material supply risk SR_t of a technology t is considered as a proper indicator to be linked to ESOM results [54]. The only quantitative definition of SR_t that was found in the existing literature and selected for this second approach is defined in Equation (7). It provides for the aggregation of the SR_m of the RMs needed for technologies manufacturing into a single SR_t. This definition was proposed for life cycle assessments of products [92] and energy technologies modeled in ESOMs [62], and considers the SR only at the level of RM mining or refining.

$$SR_t\left(\frac{1}{cap}\right) = \sum_{m=1}^{N_{mat}^{tech}} SR_m \cdot \frac{f_{m,t}}{cons_m^{yref}} \tag{7}$$

For each of the N_{mat}^{tech} RMs m required by the technology t, the supply risk SR_m of the RM m is weighted by the MI $f_{m,t}$ (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*. The normalization allows to reflect more closely the relative differences in SR_m. Indeed, $cons_m^{yref}$ is used as a proxy for the RM 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, which could be affected by high price volatility, because of a higher probability of producers' dominance and less flexibility to adjust to a demand increase [92]; higher SR_m than bulk materials. This aligns with the outcomes of [92], which integrated material SR aspects in life-cycle assessments. By comparing the normalized SR_t with the non-normalized definition in Equation (8), the authors of [92] verified that in case of $cons_m^{yref}$ absence, the single material contribution to the technology material SR would mainly come from the MI magnitude (i.e., as if the technology material SR was defined as in Equation (9)). This is because 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.

$$SR_t'\left(\frac{t}{cap}\right) = \sum_{m=1}^{N_{mat}^{tech}} SR_m \cdot f_{m,t} \tag{8}$$

$$SR_t''\left(\frac{t}{cap}\right) = \sum_{m=1}^{N_{mat}^{tech}} f_{m,t} \tag{9}$$

A similar comparison was conducted for the power sector technologies in [3], finding the same conclusions as [92]. The comparison consisted of calculating the contribution in percentage terms of the single RMs to the technology material SR definitions discussed above, highlighting how the contributions are very similar for $SR_t{}'$ (see Equation (8)) and $SR_t{}''$ (see Equation (9)). This outcome is shown for selected technologies in Figure 7 (data sources and assumptions are discussed in [3] and Section 3.4). Aluminum and copper are bulk materials for solar PV (Figure 7b), onshore wind (Figure 7c), and hydropower (Figure 7d), and mostly contribute to the technology material SR despite the low SR_m (Figure 7a), when it is calculated as in Equation (8) and see Equation (9). Instead, the use of the normalization factor increases the contribution of RMs with higher SR_m, such as gallium and silicon for solar PV, heavy REEs (HREEs) for onshore wind, and manganese and nickel for hydropower. Consider that REEs are typically classified in two sub-categories, based on the atomic weights [18]. Heavy REEs have higher atomic weights than light REEs. Conversely, the latter are more abundant in the earth crust than heavy REEs.

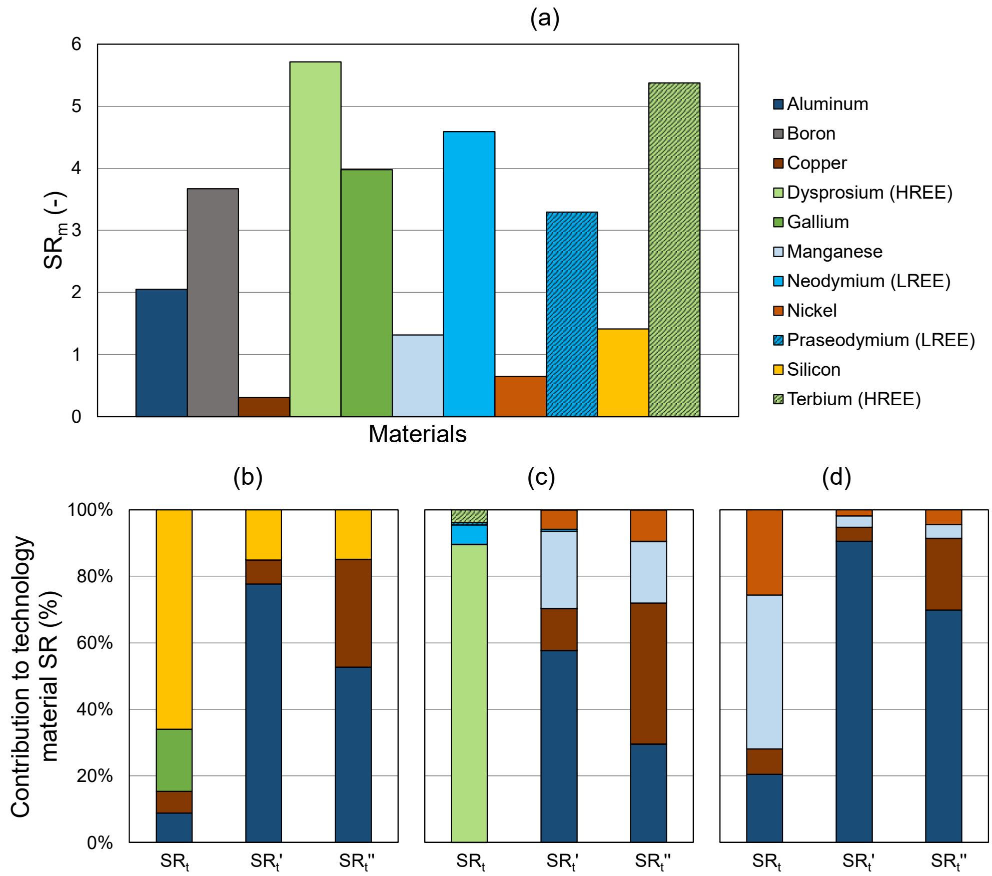

Figure 7. Single material supply risk (a) and comparison between several types of technology material supply risk for solar PV (b), onshore wind (c), and hydropower (d).

2.2.3 Material supply risk function

To derive a function to measure the material SR associated with energy scenarios, the technology material SR indicator presented in Section 2.2.2 must be combined with suitable results from ESOMs. Raw 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 $1/cap$ of SR_t (see Equation (7)), the chosen result was the newly installed capacity, which is measured in unit capacity cap.

Consider an ESOM that incorporates N_{tech} technologies t in its energy system, whose new installed capacity $V\_Capacity_{t,v}$ occurs in the installation years v (also referred to as time vintages [78]) over the model time horizon. Accordingly, Equation (10) defines the function quantifying the overall material supply risk SR_M for the entire energy system over a period from y_{start} to y_{end} within the model time horizon. Consider that, if the technology material SR changes over time, it will be also dependent on the installation year (i.e., $SR_{t,v}$).

$$SR_M(-) = \sum_{\mathrm{v}=y_{start}}^{y_{end}} \sum_{t=1}^{N_{tech}} SR_t \cdot V\_Capacity_{t,\mathrm{v}} \tag{10}$$

2.2.4 Material supply risk and criticality assessments

The evaluation of the SR of RMs as presented in Section 2.2.1 is typically part of broader criticality assessments [11]. The latter also evaluate the potential impacts of a supply disruption (or vulnerability to a supply disruption) [4] and aim to identify materials of concern at the national/regional economy [90], company [93], or technology group [88] level. The indicators adopted to assess the potential impacts of a supply disruption usually link the RM requirement by an economic sector or application with their economic size. For instance, the EC criticality methodology [90] uses a composite indicator named "economic importance". It considers the added values of the sectors in which the analyzed RM is used and a substitution index measuring the techno-economic performance of proven substitutes.

Dedicated vulnerability indicators such as the economic importance were not included in the metric adopted in the second approach for the following reasons. First, a review of the literature revealed no evidence of the integration of specific vulnerability indicators in ESOM frameworks. Second, the impacts of a supply disruption are typically evaluated by looking at the whole economy [4]. This leads to considering sectors and applications that might be out of the ESOM scope, making the direct association between the indicator and the energy technologies included in ESOMs less straightforward than the SR case. Then, many additional data would be needed, increasing complexity and uncertainty of the analysis. These aspects might limit the fulfillment of the reliability and associability criteria adopted to develop the SR metric.

However, the potential impacts of a supply disruption can be considered to a certain extent even though a dedicated indicator is not adopted. Indeed, the IR, trade restrictions, and substitution indicators adopted for the definition of SR_m as in Equation (4) were also used as vulnerability indicators in some methodologies [4]. These indicators sometimes include measures of the RM requirements by the system under analysis and this can be accounted for when using the RM value chain module presented in Section 2.

2.3 Multi-objective optimization of material and energy supply risks

The material SR function defined in the previous section was used alongside an energy SR function in a multi-objective energy system optimization in the last of the approaches presented in this thesis, which is schematized in Figure 8. The scheme also includes the references to SR parameters and equations adopted to define ex-ante the SR functions in the modeling framework.

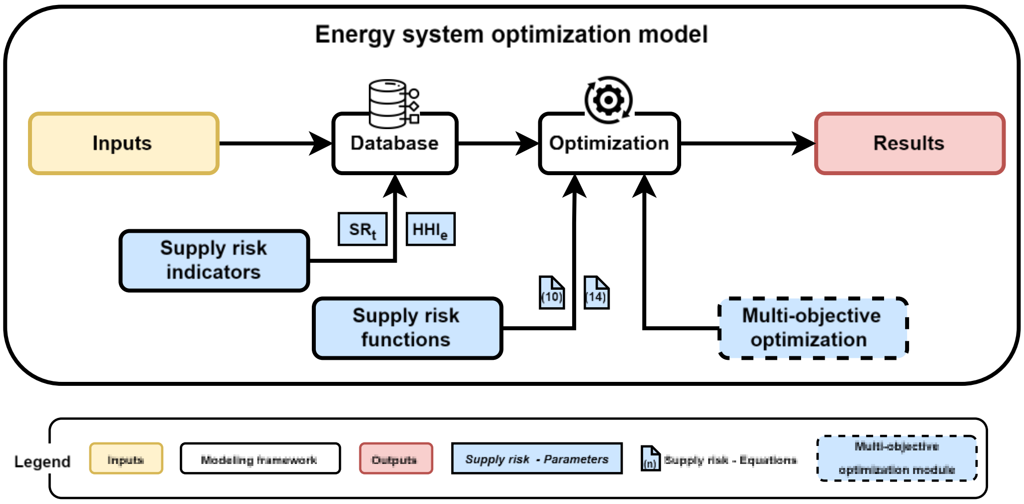

Figure 8. Scheme of the integration of supply risk functions and MOO module in ESOMs. The light blue elements represent the novelties compared to the traditional ESOM framework (as described in Section 1.3) associated with Approach 3.

The methodology workflow encompassed the following steps. First, two coherent SR indicators were consistently identified to adequately relate the material and energy dimensions. The SR_t at technology level, as defined in Equation (7) in Section 2.2.2, was considered for the former. Instead, a SR of energy commodities was defined for the latter, as described in Section 2.3.1. The material and energy SR indicators were designed to be integrated as two parameters in the framework of ESOMs characterizing energy technologies and commodities, respectively.

Subsequently, to develop the SR functions, the SR indicators were combined with suitable decision variables used in ESOMs. It was decided to develop linear functions in accordance with the linear programming problem typically solved in ESOMs. The new installed capacity of technologies $V\_Capacity_{t,v}$ was used to define the material SR function SR_M as in Equation (10) in Section 2.2.3. In this regard, $V\_Capacity_{t,v}$ is to be considered a result in the ex-post approach in Section 2.2, while as a decision variable to be optimized in this section. Instead, the commodity flows were used to define the energy SR function in Section 2.3.2. Lastly, the choice of the MOO method through which minimize the SR functions and its integration in ESOM framework were discussed in Section 2.3.3.

2.3.1 Supply risk of energy commodities

SR indicators are widely used in broader ES metrics to assess the probability of a disruption occurring along the supply chains of fossil fuels. The existing literature points out that the SR of fossil fuels is measured at regional or country level by considering SR factors similar to those of RMs presented in Section 2.2.1. For instance, indicators of supply concentration, governance, and import dependency were used in forty-four studies on ES indicators and dimensions out of more than one hundred reviewed in [10], [94], and [95].

In particular, the supply concentration for the system under analysis is typically measured through the HHI [96]. Instead, the Shannon-Wiener index is used in other cases to put more emphasis on smaller suppliers [86]. Then, concerning the HHI, the square of the market share $S_{c,e}$ of the $N_{countries}^{en}$ countries c supplying the energy commodity e is sometimes weighted by a WGI-like governance indicator g_c as in Equation (11). This definition appears consistent with the one for RMs in Equation (5), except for the absence of a specific trade indicator and provided that the governance indicators are the same.

$$HHI_e^g(-) = \sum_{c=1}^{N_{countries}^{en}} S_{c,e}^2 \cdot g_c^{en} \tag{11}$$

Then, the import reliance IR_e of the energy commodity e is another frequent SR indicator that is typically measured as in Equation (12) (with all the flows measured in unit energy, e.g. PJ), where $Import_e - Export_e$ represents the net imported quantity, while $DomProd_e$ is the domestic production. This is the same definition as IR_m in Equation (6).

$$IR_e(-) = \frac{Import_e - Export_e}{DomProd_e + Import_e - Export_e} \tag{12}$$

Finally, a few studies aggregated HHI and IR indicators into a composite SR indicator SR_e as in Equation (13), which is coherent with the RM case discussed in Section 2.2.1.

$$SR_e(-) = HHI_e^g \cdot IR_e \tag{13}$$

Despite the consistency between the SR factors and indicators of RMs and energy commodities, a difference arises concerning the aggregation of the SR indicators to develop the corresponding SR functions. Indeed, since output flows of energy commodities – i.e., the activity of technologies – are among the decision variables of ESOMs, it seems reasonable to directly associate an energy SR indicator to energy commodities, without aggregating at the technology level as done for RMs in Section 2.2.2. Consequently, the energy flows defining the net import and the domestic production of IR_e in Equation (12) make the IR a derived variable for the optimization problem of ESOMs. For this reason, HHI_e^g in Equation (11) was chosen as the energy SR indicator, while the energy SR function was built upon the SR_e definition in Equation (13), as presented in Section 2.3.2. Consider that, in case the import of energy commodities is modeled by country in an ESOM, the market shares $S_{c,e}$ would be computed as part of the optimization process, making also HHI_e^g a derived variable. However, this is not the case with this approach, where it is assumed that HHI_e^g is evaluated exogenously. This aspect is further discussed in Section 2.4.3.

2.3.2 Energy supply risk function

To derive a function to measure the energy SR of an energy system, the energy SR indicator was linked to the output commodity flows decision variables. The use of the derived variable IR_e in Equation (12) would make the function nonlinear, since IR_e is calculated as a ratio between decision variables. To keep linearity, only the net import was considered.

Consider an ESOM that incorporates N_{en} energy commodities e in its energy system, whose net import $V\_flow_{e,p}^{import} - V\_flow_{e,p}^{export}$ occurs in the optimization year p of the model time horizon. Accordingly, Equation (14) defines the function quantifying the overall energy supply risk SR_E for the entire energy system over a period from y_{start} to y_{end} within the model time horizon. Here, $cons_{en}$ represents a fixed energy consumption level, which is known a priori and is related to the energy system under analysis. It is used as a normalization factor to account for the relative importance of energy commodities in the energy supply.

$$SR_E(-) = \sum_{p=y_{start}}^{y_{end}} \sum_{e=1}^{N_{en}} HHI_e^g \cdot \frac{(V\_flow_{e,p}^{import} - V\_flow_{e,p}^{export})}{cons_{en}} \tag{14}$$

2.3.3 Selection of the multi-objective optimization method

Challenges associated with the energy transition are increasing the complexity of energy systems and the related decisions, which are often shaped by multiple, and often competing, interests. To adequately address these complexities in energy system planning through ESOMs, a MOO approach is more suitable than the conventional cost minimization that is commonly employed [28]. MOO provides a set of optimal solutions from which decision-makers seek the preferred one(s). A solution to a MOO is called Pareto-optimal (or -efficient) if improving one objective necessarily deteriorates at least one of the other ones. The mathematical definition is given below from [97]. Consider the minimization of multiple objective functions $f = (f_1, f_2, \dots, f_n)$: a feasible solution *X* is Pareto-optimal if there does not exist any other feasible solution *X'* such that $f_i(X) \leq f_i(X') \; \forall \; i = 1, \dots, n$, with at least one strict inequality. If this condition is substituted by $f_i(X) < f_i(X') \; \forall \; i = 1, \dots, n$, the solution is called weakly Pareto-optimal. The latter may be "dominated" by other Pareto-optimal solutions, which are those from which the decision-makers chose the preferred solution(s).

Depending on when decision-makers express their preferences concerning the desired solution, the following three approaches are identified [97]. Preferences are made before the optimization process in *a priori* methods (e.g., the assignment of weights to the objectives); preference choice and optimization phases are carried out iteratively in *interactive* methods; preferences are made after the optimization process in *a posteriori* (also referred to as generation) methods, once all the optimal solutions have been computed. The first two methods have a lower computational cost than generation methods, but present as a major drawback the difficulty encountered by decision-makers in expressing preferences without having a complete understating of the results. Conversely, the decision-makers are more aware and confident when selecting the preferred solution(s), as they can base their choice on the actual relation between the objectives, thus avoiding inefficient decisions [28]. The existence of such a trade-off between a computationally expansive method and more efficient solutions was considered in line with the need to adequately assess increasingly complex energy system planning through ESOMs. For this reason, the choice of the MOO method fell on generation methods.

Among the generation methods, the most used are the weighted sum and epsilon-constraint methods [97]. 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 such a method is considered the most intuitive approach in ESOMs, since they usually encompass a cost objective function and other potential objectives (e.g., CO_2 emissions) as constraints [28]. However, the epsilon-constraint method ensures at least weakly optimality. Conversely, Pareto optimality is guaranteed by the AUGMECON method, which was used in [3] for the third approach proposed in this thesis.

The AUGMECON method builds upon the epsilon-constraint method. Its mathematical formulation is given below from [97]. Consider the minimization of multiple objective functions $f = (f_1, f_2, \dots, f_n)^T$. Then AUGMECON reformulates all objectives but one – with index j – into equality constraints and introduces: a positive constant $c \approx 10^{-6} \dots 10^{-3}$; $n-1$ new, non-negative slack variable $s_i, i = 1, \dots, n, i \neq j$ for the constraints; $n-1$ constants $k_i, i = 1, \dots, n, i \neq j$, which reflect the typical order of magnitude of the reformulated objectives:

$$\min\left(f_j - \mathrm{c} \cdot \sum_{i=1}^{n} s_i/k_i\right) \text{ s.t. } f_i + s_i = \epsilon_i \; \forall \; i = 1, \dots, n, i \neq j \tag{15}$$

The main steps to solve the MOO problem (15) 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 are the right-hand side of the equality constraints that are derived by reformulating all objectives but one. Third, the problem (15) is solved for all the caps, providing Pareto-optimal solutions of the initial MOO problem.

The AUGMECON method is comprehensively described in [97], while for applications in ESOMs, see e.g., [28], [98], [99].

2.4 Discussion of the three approaches

This section provides a critical discussion of the three approaches presented in this chapter. They were developed independently of the model identified for their application (i.e., TEMOA). This means they can be applied to any other ESOM, thereby enhancing the reproducibility of the approaches. However, each of them has specific strengths and limitations, which are discussed in the following sections.

2.4.1 Approach 1: strengths and limitations

The integration of material supply disruption constraints in ESOMs, as proposed in the first approach, requires an endogenous modeling of the value chain of RMs that presents three main strengths. First, its structure is relatively straightforward, as it is based on the general modeling of energy commodities in ESOMs, which typically encompasses supply and consumption steps, as outlined in Section 1.3. Therefore, the RM value chain described in Section 2 can be easily implemented in any other ESOMs. Indeed, it aligns with the modeling strategy of the few existing ESOMs and integrated models presented in Section 1.2 that include RM value chain endogenously. Another strength is the possibility to study material efficiency measures by decreasing the MI parameter $f_{m,t}$ used in Equation (2) to calculate the RMs consumption by technology. Lastly, the supply disruption constraint in Equation (3) represents a strength in itself, since it is a novelty compared to the existing similar approaches. Indeed, none of the models that incorporate RMs accounted for maximum availability constraints in their endogenous supply and consumption calculations. Instead, they typically compare ex-post the projected RM demand to existing reserves or resources, as outlined in Section 1.2.

On the one hand, the simple structure of the RMs value chain described in Section 2 facilitates its implementation in ESOMs. On the other hand, it limits the scope of RM supply and consumption that can be considered. In particular, the value chain includes a single-step supply process, while omitting the distinction between various sources of supply, and mining and refining processes. Second, the RM demand is determined by the installation of selected technologies, while the requirements by other sectors of the energy system under analysis are not considered. These two shortcomings might lead to a partial evaluation of the actual risks. Third, recycling flows are not accounted for, which might lead to an overestimation of the actual risks, since recycling is considered among the most effective risk-reading measures [90]. The shortcomings in supply and consumption modeling listed above are, instead, overcome by some of the existing similar approaches, which consider more broadly the global RM value chain. For instance, the TIAM-IFPEN model includes different RM supplier countries and considers conventional and unconventional lithium deposits [50] and different steps of copper refining [51]. Costs and energy required to supply RMs are encompassed, too. Additionally, the TIAM-IFPEN model includes end-of-life recycling as potential alternative RMs source and the demand by other economic sectors, which is linked to exogenous macroeconomic drivers. Another limitation concerns the application of the maximum availability constraint in Equation (3). Indeed, there might be cases where the latter is not consistent with other constraints, leading to model infeasibility. For instance, this can occur when excessively stringent limits are imposed on the availability of RMs required by technologies essential for achieving decarbonization targets, as also shown in the case study discussed in Section 3.2. Since the level of infeasibility cannot be estimated in advance, several iterative attempts may be necessary.

Nevertheless, the RM value chain here proposed does not preclude any of these extensions. The latter can be pursued by two approaches: (i) by linking the ESOM to dedicated models that includes a broader modeling of the RM value chain; (ii) by endogenously extending the value chain within the ESOM. Concerning the latter, possible changes to the value chain proposed in this thesis are outlined below. First, depending on the scope of the analysis, the RM supply can include more than one primary supply process: if this is the case, the right-hand side of Equation (2) would represent the overall RM supply by all the modeled supply processes. In case refining steps are considered between primary supply and demand, the RM balance in Equation (2) is to be guaranteed for each intermediate consumption. Then, recycling might be modeled by using feedback loops or dedicated recycling processes. Instead, an exogenous demand can be fixed as in the case of end-use service demands typically modeled in ESOMs, to account for the consumption by other sectors that might not be explicitly modeled in the ESOM. Also, the techno-economic characterization typically adopted for energy technologies in ESOMs can be also used for RM supply processes. In this case, attention must be paid to possible double counting of costs associated with RM supply, since their prices should be already included in the capital costs of technologies [39]. Finally, to avoid iterations in case of an infeasibility due to the maximum material availability constraint, a fictious process (also referred to as “dummy process”) with a very high cost can be added to the model – for each modeled material – to represent the RM shortage. Indeed, if there are too many stringent limits on RM supply processes, then these fictitious processes would be used as a last resort (due to the high cost) to provide the necessary amount of RM and avoid infeasibility.

2.4.2 Approach 2: strengths and limitations

Three strengths were identified in developing the material SR metric as presented in Section 2.2. First, the metric is based on established methodologies, thereby increasing its reliability. Indeed, the SR indicator of single material SR_m defined in Equation (4) is widely used in the existing literature, particularly in the most important RMs criticality methodologies [4], [11]. Then, despite the literature on material SR of energy technologies SR_t is still not very mature, the reliability of its definition in Equation (7) is corroborated by its existing applications in the ESOM [62] and life-cycle assessment [92] research communities. Second, the use of SR_t as in Equation (7) allows the easy and immediate associability with the results of the ESOMs provided by Equation (10). Third, the definition in Equation (7) also provides flexibility, as recognized in [62], since it allows for the use of alternative MI measures, depending on available data. For instance, $f_{m,t}$ might be provided in unit energy as in [27], [54]: in this case, energy results must be used instead of the newly installed capacity.

On the other hand, some limitations affect the metric completeness. First, SR_m – as defined in Equation (4) – is typically combined with other indicators in more comprehensive RM criticality assessments, such as vulnerability indicators [4]. However, the latter were considered beyond the scope of the second approach, as previously discussed in Section 2.2.4. Second, SR_m only refers to the extraction and processing of RMs. However, the potential bottlenecks along the entire supply chain of a technology, which is the case for most clean energy technologies [1], were omitted in defining SR_t in Equation (7). Instead, the supply concentration along the manufacturing and assembly of technologies components were considered by the JRC [1] and IEA [16]. In particular, the former proposed an evaluation of the SR of components and assemblies in a similar way to Equation (4), while the latter considered, as SR indicator, solely the share of the largest supplier at the global level for all the supply chain steps. While these approaches results more comprehensive than the definition of SR_t in Equation (7), they do not provide a single aggregated value of technology material SR, as they consider each SR along the supply chain steps individually. Furthermore, they necessitate a considerable quantity and diversity of data, whose availability might be limited. Conversely, SR_t in Equation (7) offers a quantitative definition at technology level, which requires much less data and was already applied to ESOM results [27], [54]. For these reasons, the simplification concerning the supply concentration along the entire supply chain of technologies was deemed appropriate and necessary.

2.4.3 Approach 3: strengths and limitations

Strengths and limitations concerning the material SR metric and function discussed in Section 2.4.2 are also valid for the third approach, since the material SR function SR_M defined in Equation (10) was used as an objective function, too. Concerning the energy SR function SR_E, its definition in Equation (14) aligns with well-established methodologies found in the existing literature, which are coherent with the material dimension. This enhances the reliability and consistency of the SR definition. Then, the use of the AUGMECON method, which is among the most widely used MOO framework [97], might be considered positive in terms of credibility and rationality. Moreover, it is worth pointing out that the SR functions were developed independently of AUGMECON. This means that these functions can be employed in other MOO methods, enhancing the reproducibility of the methodology.

Nevertheless, some simplifications were needed to guarantee the linearity required by the optimization problem typically solved in the framework of ESOMs. Indeed, the SR functions were developed as linear functions of: the newly installed capacity of technologies and their associated risk SR_t, in the case of SR_M; flows of energy commodities and their associated supply concentration $HHI_{g,e}$, in the case of SR_E. This was possible by designing SR_t (see Equation (7)) and $HHI_{g,e}$ (see Equation (11)) as exogenous parameters characterizing energy technologies and commodities included in ESOMs, respectively. These two parameters include measures of material and energy commodity trade by supplier countries, which implies two main limitations. Firstly, this involves making assumptions about possible future changes among supplier countries, which increases the uncertainty of the underlying analysis. Then, the supply by country might be endogenously modeled in ESOMs, thereby making nonlinear the SR functions. This would expand the scope of application of the third approach for decision-making (e.g., optimization of market shares), at the expense of the problem linearity.

Although the SR indicators for energy commodities – in particular fossil fuels – and materials are identical, it is important to emphasize that their supply chains are very different, as recognized in [2] and [17]. Fossil fuels present large and liquid global markets, with much higher trade volumes and value than RM ones. However, a multitude of RMs are relevant for the energy sector, each with its own market players and dynamics. Moving to the effects of a supply interruption, a disruption of fossil fuels supply can cause short-term energy shortages and price spikes, impacting consumers' daily lives. Conversely, shortages along the clean energy technologies supply chains affect only new assets, increasing the costs of the energy transition. This occurs because fossil fuels are continuously required for running processes, while RMs are required to manufacture technologies and can be recovered after end-use. For instance, an oil supply crisis immediately impacts on prices of gasoline and gas, which are required by traditional vehicles. Instead, a disruption of RMs required by batteries does not affect existing BEVs but might hinder the penetration of future ones and can be mitigated by using secondary supply.

Chapter 3

The TEMOA-Italy case studies

The Italian energy system was used as case study. The very ambitious energy transition targets [100], alongside the current fossil fuel and import dependence [101] and the still immature legislation on CRMs [12], makes the Italian case study particularly illustrative. Fossil fuels accounted for almost 80% of Italian final energy consumption in 2023, with a net IR of approximately 80% [101], making Italy among the largest energy importers in EU [102]. 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 [100]. For instance, the latest announced policies aim to increase renewable share in the electricity mix up to 60% in 2030 [100], providing for maximum 5% of natural gas-based generation in 2050 [103]. In this regard, the absence of low-carbon dispatchable baseload generation (e.g., nuclear) makes more urgent and sudden the Italian investments in variable renewable generation such as solar PV and wind turbines, with higher associated battery storage requirements, also considering the need to electrify end-uses (e.g., through BEVs). Additionally, the current BEV fleet of ~0.2 million is projected to exceed 4 million vehicles by 2030 [100]. However, the enhancement of power grid stability is the only security measure undertaken in association with the vast penetration of clean energy technologies envisaged in the next decades [100]. Instead, there is a lack of discussion addressing the potential supply chain bottlenecks of these technologies and the required materials. The recently approved Italian first legislation on CRMs offers a more preliminary framework than the ones in other countries [12]. Furthermore, it does not incorporate specific measures in alignment with the energy transition targets [104], while mainly focuses on the exploration stage of RM value chain [105].

This chapter focuses on the case studies adopted for the application of the three approaches. The case studies were built upon the TEMOA-Italy model, an overview of which is presented in Section 3. Then, a detailed description of the specificities concerning the single approaches is provided in Section 3.2, Section 3.3, and Section 3.4. Finally, strengths and limitations are pointed out in Section 3.5.

3.1 The TEMOA-Italy model

The three approaches described in the previous chapter were applied differently to the TEMOA-Italy model [106] as follows, while the details of the model are provided below.

1) **Approach 1:** dedicated scenarios were developed for the whole Italian energy system, as outlined in Section 3.2. The latter is based on [79] and [107]. In particular, the TEMOA-Italy version [82] (also referred to as TEMOA-Italy-materials) including the RM value chain described in Section 2 was used.
2) **Approach 2:** the technology material SR indicator was evaluated for power sector, utility scale batteries, hydrogen production, and cars technologies, as reported in Section 3.3. The latter is based on [79] and [107]
3) **Approach 3:** the MOO was integrated in TEMOA as an additional module in a dedicated version [83] (also referred to as TEMOA-MOO), while the power sector of the TEMOA-Italy model was used as case-study, as reported in Section 3.4. The latter is based on [3].

TEMOA-Italy is a multi-sectorial TEMOA instance of the Italian energy system, which is modeled as a single region. The instance was built upon the TIMES-Italy model [108], as extensively described in [74] and [109], and is mainly adopted with a capacity expansion approach to study energy scenarios on a time scale up to 2050. Then, TEMOA-Italy is fully calibrated (i.e., it matches actual energy statistics) from the base year (i.e., 2006) up to 2020 [110]. Its technology-rich database is openly available at [106] and includes hundreds of technologies belonging to the supply- and demand-side sectors of the Italian energy system. A scheme of the corresponding reference energy system is provided in Figure 9. For graphical reasons, single technologies are aggregated into modules (Upstream, Power sector, Hydrogen module, CCUS module, Storage, and Demand-side sectors). Then, the interconnection between the supply- and demand-side sectors is visualized through energy commodities and arrows representing the direction of the flows.

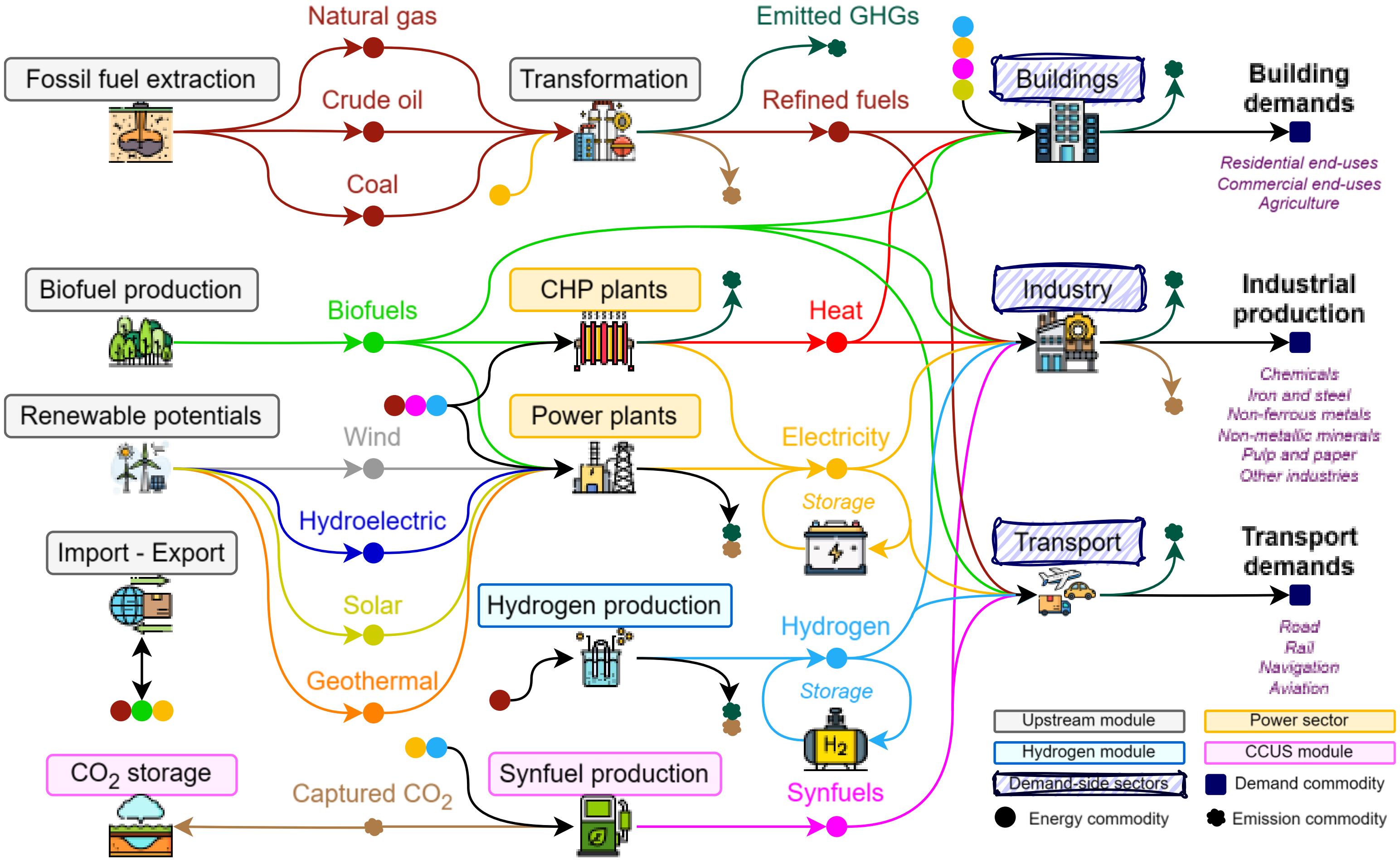

Figure 9. Scheme of the TEMOA-Italy reference energy system.

The supply-side encompasses the upstream sector [110], power and heat production [71], and a comprehensive hydrogen module [111]. Furthermore, the model incorporates carbon capture, utilization, and storage (CCUS) options [112], [72]. Conversely, the demand-side is represented by agriculture [74], residential and commercial buildings [74], industry [113], and transport [114] sectors, each with their own sub-sectors.

A more comprehensive overview of the structure, data, and sources of TEMOA-Italy is presented in [110]. However, two model updates compared to the original version presented in [74] are detailed in the appendix, since they are considered relevant for the purpose of this thesis. The first update is described in Appendix A and concerned the integration of hydrogen and synthetic fuels (hereinafter synfuels) modules as outlined in [72], [111], and [112], and. This update is considered relevant as the supply chains of these fuels might present less material SR than other low-carbon solutions. In particular, supply concentration is currently lower especially across the component manufacturing and assembly steps for hydrogen technologies (e.g., electrolysers and fuel cells (FCs)) [1], and across the RM mining and processing for synfuels [16]. Then, the update of technology-specific hurdle rates – outlined in [115] and [116] – is described in Appendix B. Hurdle rates are economic parameters linked to investment costs and their update is considered relevant as clean energy technologies characterized by potential supply chain bottlenecks are typically highly capital-intensive investments. Thus, the cost of the energy transition significantly depends on hurdle rates applied on capital loans [117], which should be accurately accounted for in ESOMs.

3.2 The TEMOA-Italy-materials model version

Material supply disruption scenarios were studied for the Italian energy system in [79], by using a dedicated model version referred to as TEMOA-Italy-materials [82]. The latter includes the value chain of RMs described in Section 2. The hypotheses behind the development of the supply disruption scenarios are described in Section 3.2.1. Then, the integration of RMs in the TEMOA modeling framework is detailed in Appendix C, while an overview of the materials included in TEMOA-Italy is provided in Section 3.2.2.

3.2.1 Development of material supply disruption scenarios

The supply disruption scenarios were developed considering different possible causes of RM shortage on the global market, which might limit the RM availability and in turn the investments in clean energy technologies in the middle-to-long term. Moreover, these scenarios also include decarbonization targets to investigate the effects of the RM unavailability on the Italian energy transition.

For each RM m included in the analysis in [79], the shortage was accounted for through the $MaxMaterial_m$ parameter used in Equation (3). In particular, the maximum availability was estimated as in Equation (17), where a supply disruption factor d_m was applied to a given RM demand Dem_m^{dec}. The lack of Italian specific analyses led to consider data at global and EU level. The existing literature provides disruption factors at global level only, which were then applied at the Italian supply level. Concerning the choice of the RMs to be considered, only CRMs for the EU economy [18]. Instead, Dem_m^{dec} is the Italian RM requirement in a decarbonization scenario without RMs availability constraints.

$$MaxMaterial_m(t) = d_m \cdot Dem_m^{dec} \tag{16}$$

The scenario analysis performed in [79] is shown in the scenario tree in Figure 10. The first branch concerns the possible application of a CO2 emission constraint. Then, a second branch considers whether a maximum material availability constraint is imposed. In this regard, the range of disruption factors applied to the RMs involved is reported at the beginning of each branch. In addition, the maximum availability is reported by material and main supplier countries (i.e., countries providing at least the 50% of global mining or processing [18]).

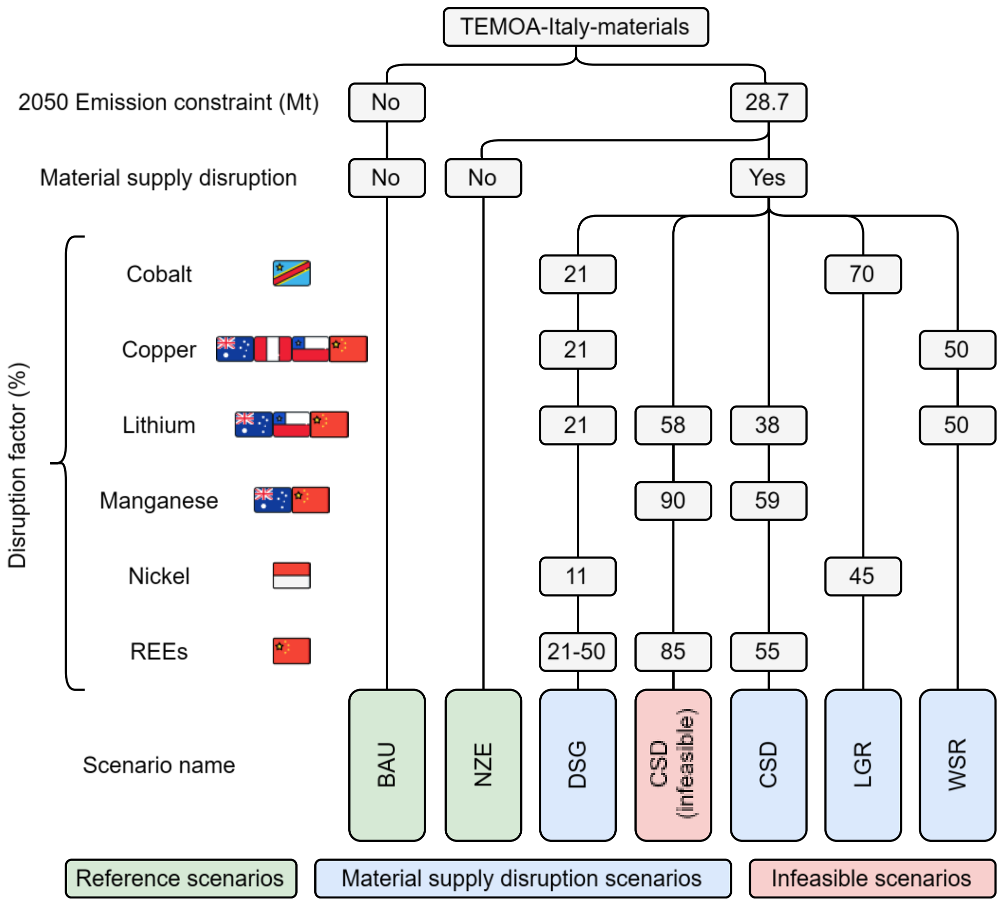

Figure 10. Schematic representation of the scenarios analyzed for Approach 1.

Reference scenarios

Reference scenarios includes the Business-As-Usual (BAU) and Net-Zero Emissions (NZE) ones. The former aims to reproduce the evolution of the energy system according to the national stated energy policies and without decarbonization targets, as described in [74]. Instead, CO_2 emission reduction constraints were included in the NZE both in 2030 and 2050, building upon, respectively, the EU Fit for 55 package [118] and the long-term Italian strategy on greenhouse gasses emission reduction [119], as described in [72].

Material supply disruption scenarios

The following materials supply disruption scenarios were developed considering different potential disruption causes such as economic, geopolitical, and physical ones. Then, the associated disruption factors are reported in Table 4.

- **Demand-Supply Gap (DSG).** This scenario assumes that a strong RM demand growth by clean energy technologies is not adequately supported by a suitable scaling up of the mining industry investments. This can cause a supply-demand imbalance and the consequent unavailability of RMs. The disruption factors were derived from [15], which provided an imbalance range for several RMs and technologies and components (e.g., batteries, magnets, electrolyzers, semiconductors) in different global energy scenarios. The lowest values of the range were used, since [15] envisaged a time horizon up to 2030, while [79] up to 2050: in this regard, a higher potential supply-demand imbalance is expected in the short term compared to the 2030-2050 period [120]. In particular, the "Achieved commitments" scenario was used, where net-zero commitments are achieved. Each of the scenarios studied in [15] is further differentiated into a "Base case" and "High case". The former was used to define the DSG scenario and includes all operating mines and projects under construction in 2023. The latter also considers projects with an initiated prefeasibility study. The RMs involved were cobalt, copper, lithium, nickel and some REEs (i.e., dysprosium, terbium, neodymium, and praseodymium).

- **Chinese Supply Disruption (CSD).** This scenario involves a supply disruption from China, which is currently among the main supplier of processed RMs worldwide [14] and the largest supplier to EU of most CRMs [18]. Indeed, the high supply concentration in China increases the risk of a supply disruption. The materials considered were dysprosium, lithium, manganese, and neodymium. A first attempt was made by including a complete disruption, leading to an infeasible scenario. In particular, the material limits were so stringent that they did not allow the penetration of the technologies needed to meet the decarbonization target. Therefore, the disruption factors were gradually lowered to a maximum acceptable factor of 65%. This value can be considered more realistic than a full disruption from the main supplier country. In particular, it also aligns with the disruption factor of the other scenarios, as well as the RM reliance limit on single third countries provided for by the EU CRMs Act [24].

- **Low Governance Region (LGR).** This scenario considers the risk associated with the supply from countries with high political instability. Indeed, existing mineral mining and processing industries are mainly concentrated in regions categorized as either extremely unstable or unstable in terms of WGI [121]. This is the case for cobalt and nickel [2], for which the Democratic Republic of the Congo and Indonesia accounted for, respectively, around 70% and 45% of global supply in 2023 [14]. A complete disruption from these countries was considered.

- **Water Stress Region (WSR) scenario**. The last scenario encompasses the potential effects of climate change on RM supply, particularly considering potential water crisis. Indeed, the water needed in mining and processing of CRMs might be often very high, especially for copper and lithium [16]. For instance, more than 50% of their global mining was concentrated in areas of high or extremely high-water stress in 2023 [2]. In this regard, the WSR scenario investigates the disruption of copper and lithium, considering a disruption factor of 50%.

Table 4. Disruption factors by material and supply disruption scenario.

Scenario	**Material**	**Disruption factor (%)**	**Cumulative (2025-2050) maximum availability constraint (kt)**
DSG	Cobalt	21	780
	Copper	21	432
	Dysprosium	50	6.49
	Lithium	21	530
	Neodymium	21	4.09
	Nickel	11	2880
	Praseodymium	21	5.58
	Terbium	50	1.07
CSD*	Dysprosium	59 (90)	5.39
	Lithium	38 (58)	420
	Manganese	59 (90)	850
	Neodymium	55 (85)	23.2
LGR	Cobalt	70	300
	Nickel	45	1620
WSR	Copper	50	2730
	Lithium	50	340

* In parenthesis the starting disruption factors that implied infeasibility. For instance, a disruption factor of 38% for lithium corresponds to around 65% of 58%, which is the Chinese global supply share of processed lithium.

3.2.2 The raw materials in TEMOA-Italy

The TEMOA-ITALY-materials model includes many other CRMs besides the ones involved in the supply disruption scenarios described in Section 3.2.1. The full list of CRMs by technology is reported in Table 5, while the MI data and sources, alongside the main assumptions, are detailed in Appendix D. All data refer to present values, thereby neglecting potential MI improvements over time. Then, these RMs here considered are critical for the EU economy according to the latest criticality list [18]. Moreover, the following name differences are present: silicon, titanium, and graphite in this thesis corresponds, respectively, to silicon metal, titanium metal, and natural graphite in the EU CRMs list.

The choice of the CRMs and technologies that require them depended on data availability. Only peer reviewed papers and reports from relevant institutions (e.g., IEA, JRC) were included in the data gathering phase. In particular, the following sectors and technologies were considered.

Power sector

A detailed description of the power sector RMs is provided in Section 3.4.3, since the power sector was the case study adopted for the third approach. Except for some differences concerning the type of RMs and sources, the two sets of data are overlapping. These variations are due to the fact the studies in [79] and [3], in which the second and third approaches were developed and tested, respectively, were conducted separately and individually.

Battery storage sector

The two utility-scale battery storage technologies characterized by a MI were LIBs and vanadium redox flow batteries (VRFBs). The procedure to evaluate the RM requirements by these technologies is detailed in Appendix D.

LIBs represent most of the existing installed capacity [122] and are expected to dominate the future battery market [19]. Lithium-ion cells account for the majority of the battery weight and materials, while the type of RMs required strongly depends on the cathode chemistry [2]. The main ones are lithium-iron-phosphate (also referred to as LFP) and nickel-manganese-cobalt (also referred to as NMC). Despite these differences, the consumption of a generic LIB was considered, since TEMOA-Italy does not distinguish between the different types of LIBs [71]. Instead, graphite is currently the main choice as anode material [2].

VRFBs are not commercially available yet but are considered a breakthrough technology for utility-scale storage [2], thanks to, e.g., long cycling life and independent sizing of output power required and energy storage capacity [123]. These batteries involve a completely different technology than LIBs and exploit redox reactions between vanadium ions that are dissolved in the electrolytes [124]. Consider that VRFBs were included for the first time in TEMOA-Italy as part of the development and testing of the first approach [79]. See [107] for more details on their techno-economic characterization.

Hydrogen production sector

Concerning hydrogen production, the available literature provided MI data mainly for electrolyzers. In particular, three types were considered. Alkaline electrolyzers are the most mature technology and the main RM of concern is nickel, whose MI is expected to decrease in future [2]. Then, proton-exchange membrane (PEM) electrolysis cells (ECs) are less mature than alkaline-ECs, but their market share is going to increase in the following decades, leading to an increasing demand for platinum group metals (PGMs) such as iridium, palladium, and platinum [1], [2]. Finally, despite the low technology readiness level and the low expected future market shares, solid oxide-ECs are considered relevant for their REEs consumption [2].

Transport (cars) sector

Most existing studies on RM requirement by the transport sector involve road transportation, with a major focus on cars. In this regard, the four classes of vehicles modeled in TEMOA-Italy were characterized through a MI: internal combustion engine vehicles (ICEVs), which include traditional vehicles fueled by gasoline, gas oil, liquefied petroleum gas, natural gas, and biofuels; battery electric vehicles (BEVs); full hybrid electric vehicles (FHEVs); fuel cell vehicles (FCVs). Overall, BEVs and FHEVs require a similar amount of the CRMs listed in Table 5, which is on average 6 times – per unit vehicle – the ones required by ICEVs. Instead, the specific consumption of FCVs is around 60% higher than ICEVs.

The gilder of these vehicles requires somehow similar type and quantity of RMs, i.e., mainly copper and manganese, while the powertrain system is the discriminating element [2]. In particular, the powertrain system of a vehicle includes all the components that create energy and transfer it to the wheels, such as the energy storage system, the motor, and the driveshaft [125]. Copper and manganese are still the main RMs in the ICEVs. Instead, electric vehicles differ in their electric motor and battery. The main technology used nowadays for the former, i.e., permanent magnet motors, requires a significant amount of REEs. Concerning the latter, LIBs are typically used, for which the same RM considerations made for utility-scale storage apply. BEVs and FHEVs basically require the same RMs: however, the MI of the latter is lower, due to the smaller size of the components, as detailed in Appendix D. Finally, FCVs require similar RMs to electric vehicles (for the motor and battery) but in smaller quantity. In addition, platinum is required for FC manufacturing.

Table 5. List of RMs by technology included in the TEMOA-Italy-materials model.

	Power sector										**Battery storage**		**Hydrogen production**			**Transport sector (cars)**			
Material	Solar PV	Onshore wind	Offshore wind	Geothermal	Hydropower	Bioenergy	Hydrogen solid oxide FC	Coal	Natural gas	Coal and natural gas w/CCS	LIBs	VRFBs	Alkaline-EC	PEMEC	Solid oxide-EC	ICEVs	BEVs	FHEVs	FCVs
Aluminum	x	x	x								x								
Boron		x	x																
Cerium (LREE)																	x	x	x
Cobalt								x		x	x						x	x	x
Copper	x	x	x		x	x		x	x	x	x	x				x	x	x	x
Dysprosium (HREE)		x	x														x	x	x
Europium (HREE)																	x	x	
Fluorspar											x								
Gadolinium (HREE)																	x	x	x
Gallium	x																x	x	x
Germanium																	x	x	
Graphite											x	x					x	x	
Iridium														x					
Lanthanum (HREE)							x								x		x	x	

Table 5 (continued).

Lithium											x						x	x	x
Magnesium																	x	x	x
Manganese		x	x		x					x	x					x	x	x	x
Neodymium (LREE)		x	x														x	x	x
Nickel		x	x	x	x		x	x	x	x	x		x		x		x	x	x
Niobium										x									
Palladium														x			x	x	
Phosphorus											x								
Platinum														x					x
Praseodymium (LREE)		x	x														x	x	x
Silicon	x																		
Tantalum																	x	x	
Terbium (HREE)		x	x														x	x	x
Titanium						x													
Vanadium										x		x					x	x	x
Yttrium (HREE)							x								x		x	x	x

3.3 The material supply risk of TEMOA-Italy technologies

The technology material SR indicator SR_t in Equation (7) was applied ex-post to the RM supply disruption scenarios described in Section 3.2.1. Three parameters were needed to compute the indicator as pointed out in Section 3.3.1: the SR of single materials SR_m, their consumption in a reference year $cons_m^{yref}$, and the MI $f_{m,t}$. The indicator was computed for the technologies that were characterized by a MI in TEMOA-Italy-materials as detailed in Section 3.2.2.

3.3.1 The technology material supply risk: data and sources

The SR_m were directly taken from the latest EU CRM list [18], because of the lack of specific values for Italy. Indeed, the RMs included in the analysis were the same as the first approach, i.e., CRMs for the EU economy. Therefore, SR_m corresponds to the SR_m^{EC} defined in Equation (4) and is reported by material in Table 6. REEs show the highest SR due to the extremely high geographical concentration in China concerning the processing phase. Then, a more diversified supply chain characterizes other relevant CRMs such as cobalt and platinum, but they still have a high SR due to the high political instability of the main supplier countries. In this regard, such instability (g_c^{mat} in Equation (5)) is measured through the well-established WGI [87]. 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 [18], but they were included in the EU CRM list because of their consumption in EU strategic sectors [1].

Concerning the normalization factor $cons_m^{yref}$, the 2016-2020 average global consumption [126] was used: the time scope is consistent with the one adopted for SR_m in [18]; the global geographical scope is, instead, consistent with the material supply disruption scenarios development, for which global disruption factors were considered. Moreover, when applying ex-post the technology material SR to the disruption scenarios, the $cons_m^{yref}$ was reduced according to the disruption factors considered in Table 4. The global consumption levels are reported in Table 6. They tend to be lower for the materials with higher SR and vice versa, in accordance with [92]: this is especially valid for gallium, REEs, and platinum (for higher SR_m) and for copper, manganese, nickel, and silicon (for lower SR_m), while aluminum is the most consumed, despite a material SR in between. The high aluminum consumption is also due to its use as structural material for many technologies.

Lastly, the CRM specific consumptions of technologies described in Section 3.2.2 were used for $f_{m,t}$.

Table 6. Supply risk and global consumption by critical raw materials considered in Approach 1 and Approach 2.

Material	$SR_m^{EC}(-)$	$cons_m^{yref}(Mt)$
Aluminum	1.2	3.4×10^{2}
Boron	3.8	1.3
Cerium (LREE)	4.0	4.8×10^{-2}
Cobalt	1.7	9.3×10^{-2}
Copper	0.1	2.1×10^{1}
Dysprosium (HREE)	5.6	1.7×10^{-3}
Europium (HREE)	5.6	3.4×10^{-4}
Fluorspar	1.1	6.7
Gadolinium (HREE)	3.3	2.4×10^{-3}
Gallium	4.8	3.0×10^{-4}
Germanium	1.8	1.0×10^{-4}
Graphite	1.8	1.0
Iridium	3.9	7.0×10^{-6}
Lanthanum (HREE)	3.5	3.6×10^{-2}
Lithium	1.9	5.7×10^{-2}
Magnesium	4.1	9.8×10^{-1}
Manganese	1.2	1.9×10^{1}
Neodymium (LREE)	3.6	2.7×10^{-2}
Nickel	0.5	2.1
Niobium	4.4	7.3×10^{-2}
Palladium	1.5	2.1×10^{-4}
Phosphorus	3.3	1.2
Platinum	2.1	1.8×10^{-4}
Praseodymium (LREE)	3.2	8.0×10^{-3}
Silicon	1.4	3.0
Tantalum	1.3	1.5×10^{-3}
Terbium (HREE)	4.9	3.3×10^{-4}
Titanium	1.6	4.5
Vanadium	2.3	9.1×10^{-2}
Yttrium (HREE)	3.5	8.2×10^{-3}

3.3.2 The technology material supply risk: comparison between technologies

The SR_t of battery storage, hydrogen production, and cars technologies are reported in Table 7 and described below. Instead, the SR_t of power sector technologies are reported in Table 19 in Appendix D. In this regard, a detailed description of the SR_t of power sector technologies is provided in Section 3.4.3, since the power sector was the case study adopted for the third approach. The relative differences between technologies are the same, while the absolute values of SR_t vary due to the different assumptions adopted when evaluating the three underlying parameters needed to compute the technology material SR. These variations are due to the fact the studies in [79] and [3], in which the second and third approaches were developed and tested, respectively, were conducted separately and individually.

Consider that the technology material SR here described are based on the $cons_m^{yref}$ reported in Table 6. In this regard, [107] provides a more detailed analysis on the effects on the SR_t on applying or not the supply disruption factors to $cons_m^{yref}$.

Table 7. Technology material supply risk of battery storage, hydrogen production, and cars technologies in Approach 2.

Sector	Technology	$SR_t \left(\frac{1}{GW}\right)$
Battery storage	LIBs	6.5×10^{-2}
	VRFBs	5.2×10^{-1}
Hydrogen production	Alkaline-EC	3.0×10^{-6}
	PEMEC	4.9×10^{-4}
	Solid oxide-EC	3.1×10^{-5}
Transport (cars)	ICEVs	8.2×10^{-7}
	BEVs	1.8×10^{-3}
	FHEVs	7.1×10^{-4}
	FCVs	2.9×10^{-3}

The highest risk is associated with battery storage technologies. In particular, the main contribution for LIBs comes from cobalt, graphite, lithium, and phosphorus. Then, VRFBs present a higher risk than LIBs due to the consumption of vanadium, whose SR_m is higher than the ones of the CRMs required by LIBs. Instead, despite the requirement of the highly risky PGMs, ECs have a SR_t between 2 and 5 orders of magnitude smaller than batteries: this is mainly due to a lower number of CRMs needed for their manufacturing.

Finally, low carbon vehicles present a risk in between batteries and ECs and that is much higher than the traditional ICEVs. BEVs and FCVs have the highest associated risk, due to the requirement of REEs for the electric motor and the same CRMs as LIBs for the battery. Instead, the lower size of these components associated with FHEVs makes their SR_t about 2.5 times lower than the one of BEVs.

3.4 The TEMOA-MOO model version

The MOO was integrated in TEMOA as an additional and optional module, leading to a dedicated version referred to as TEMOA-MOO [83], which also includes the RMs value chain modeling described in Section 2. The MOO problems studied in [3] and outlined in Section 3.4.1 concerned the power sector of TEMOA-Italy, which is described in Section 3.4.2. Then, the evaluation of the SR metrics for the energy technologies and commodities included in the model is presented in Section 3.4.3 and Section 3.4.4, respectively.

3.4.1 Setting of the multi-objective optimization problems

The TEMOA-MOO version was used to study the MOO problems described below, while a detailed description of the integration of such a module in the TEMOA code is provided in Appendix E.

Two types of MOOs were conducted in [3], as sketched in Figure 11. Firstly, total system cost F_{cost} and 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 costs incurred in the system under analysis over the model time horizon [84]. The total cumulative net CO_2 emissions function is described in Appendix E and corresponds to the net CO_2 emissions from all the technologies included in the reference energy system under analysis throughout the model time horizon.

Instead, the SR functions as defined in Equation (10) and Equation (14) 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 1.2. 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 latter involved the minimization of SR_E and SR_M (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, as defined in Equation (17). The constraint on costs mimics real-world policy trade-offs, i.e., tolerating slightly higher costs for higher energy security (or lower SR) [127], [128]. Consequently, this constraint enables the model to explore a broader spectrum of system configuration possibilities.

$$min(SR_E, SR_M) \text{ s.t. } F_{CO2} = F_{CO2}^{MIN} \text{ and } F_{cost} = \\ = s_{cost} \cdot F_{cost}^{MIN} \; \forall \; s_{cost} \in \{1.05, 1.10, 1.15, 1.20\} \tag{17}$$

Concerning the selection of the caps – during the second step of the AUGMECON method described in Section 2.3.3– they were arbitrarily chosen in such a way to obtain ten equal intervals spanning the entire range between the front boundaries.

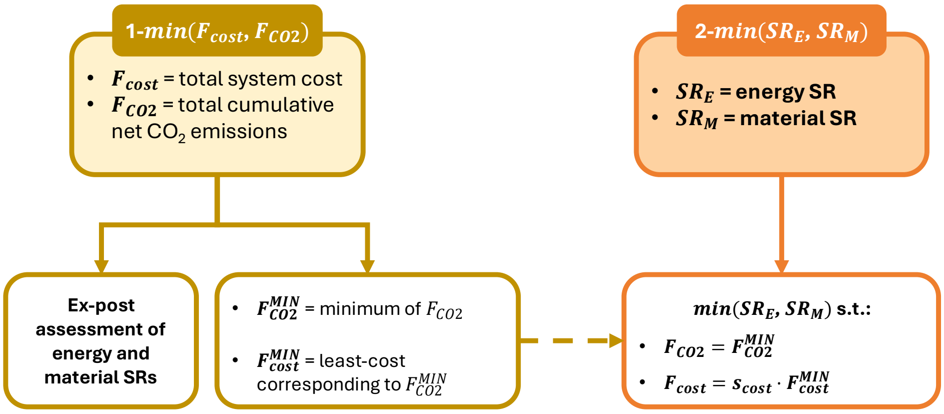

Figure 11. Scheme of the definition of the two MOO problems involved in the case study of Approach 3.

3.4.2 Setting of the case study: the TEMOA-Italy power sector

The two MOO problems defined in Section 3.4.1 were studied in a case study encompassing a simplified version of the TEMOA-Italy power sector, whereas the other sectors of TEMOA-Italy – such as the hydrogen and synfuel production, as well as all the end-use sectors – were not considered.

The case study was limited to a single energy sector to be tractable but, at the same time, sufficiently detailed to facilitate the MOO framework application and result analysis. The reference energy system of the adopted power sector model is schematized in Figure 12. For graphical reasons, single technologies are aggregated into modules (Import, Domestic production, Renewables potentials, Power plants, CCUS module, Storage, and CRM supply). Then, the interconnection between the supply- and demand-side sectors is visualized through energy commodities and arrows representing the direction of the flows. 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 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, LIBs and CCUS are modeled, with the latter also including direct air capture (DAC). The case study time horizon only includes the year 2050, for which the total annual electricity demand was set to 1589 PJ based on TEMOA-Italy decarbonization scenarios [129]. This demand aligns with other Italian electrification projections [28]. Although electricity imports are modeled 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 discussed in Section 2.3.1 is not used for electricity in the current literature. Finally, the power sector model also includes the value chain of CRMs required by power plants and storage technologies.

The power sector database is openly available at [83], while the assumptions behind its techno-economic characterization is further detailed in Appendix F.

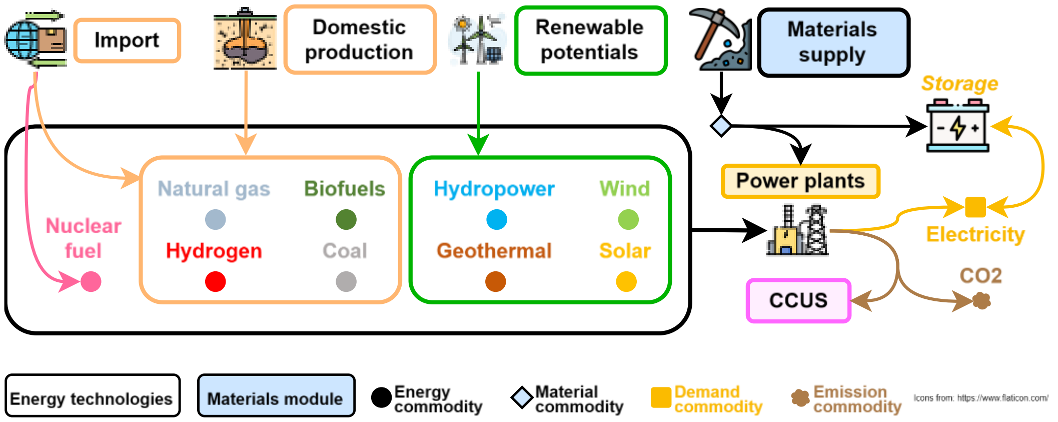

Figure 12. Scheme of the simplified TEMOA-Italy power sector adopted in the case study of Approach 3.

3.4.3 Evaluation of the technology material supply risk indicator

As for the second approach, to compute the technology material SR indicator SR_t in Equation (7) for each power generation technology included in the case study, three parameters were needed: SR_m, $cons_m^{yref}$, and $f_{m,t}$. Values and sources are reported in Table 25 in Appendix G by CRM and technology, alongside the resulting SR_t by technology. The EU geographical scope was used also in this case as for the other approaches.

Supply risk (SR_m) and annual consumption ($cons_m^{yref}$) of CRMs

Equation (4) was used to derive SR_m from the latest EU CRMs list [18]. In particular, the definition adopted in [18] is referred to as SR_m^{EC} in Table 25 and includes material recycling and substitution, too. The latter were neglected for consistency reasons with the energy SR indicator definition, which does not involve such measures. However, the CRM risk ranking was not affected, as can be seen by comparing SR_m and SR_m^{EC}. Concerning the normalization factor

$cons_m^{yref}$, the 2016-2020 average EU consumption [126] was used, since the same time scope approach is adopted in [18].

Material intensity ($f_{m,t}$) of technologies

Differently from Approach 1, 2050 MI projections for $f_{m,t}$ were considered, to account for material efficiency improvement. These variations are due to the fact the studies in [79] and [3], in which the first and third approaches were developed and tested, respectively, were conducted separately and individually.

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 [37] was used as a data source since it is widely used in literature [130] and belongs to the same EU CRM analyses framework [131] such as [18] for SR_m and [126] for $cons_m^{yref}$.

The main solar PV technologies identified by [37] 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 cell-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 TEMOA-Italy, 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_k^{tech}, according to Equation (18).

$$SR_t^{st}\left(\frac{1}{cap}\right) = \sum_{m=1}^{N_{mat}^{tech}} \frac{\left(\sum_{k=1}^{N_{sub-tech}^{tech}} f_{m,t}^{st}\left(\frac{t}{cap}\right) \cdot f_k^{tech}(-)\right)}{cons_m^{yref}(t)} \cdot SR_m(-) \tag{18}$$

Projections for 2050 were considered, namely MRs from [37] and IEA market shares in a base scenario (i.e., projecting the 2020 situation) [2]. The latter are reported in Table 8: 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 [37] 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, 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 [2] are reported in Table 8. The neodymium consumption is given here as an example of calculating the corresponding average neodymium requirement of onshore wind turbines.

Consider the MI in [37] and the market shares in Table 8, 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 MI by the market shares, obtaining a value of around 4.1 t/GW.

Table 8. Sub-technological shares adopted to derive a generic technology material supply risk.

Technology	**Sub-technology**	**2050 share** [2]
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%)

Data availability and reliability were lower for the other technologies. Their 2050 MI were estimated as averages between different sources. Among renewables, hydropower, and bioenergy have the lowest MI (excluding the cement and concrete needed by the former [2], 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 [2]. Concerning the other low-carbon sources, LWR plants have very low MI, while the available literature on hydrogen FCs focuses on PEMFCs and platinum. Despite a poor literature on fossil fuels [132], 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 (referred to as w/ CCS in Table 25): the additional materials compared to the traditional plants (referred to as w/o CCS in Table 25) concerns the CO_2 capture and pipeline infrastructures. Finally, the material consumption of the generic LIB technology modeled in TEMOA-Italy 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 [2].

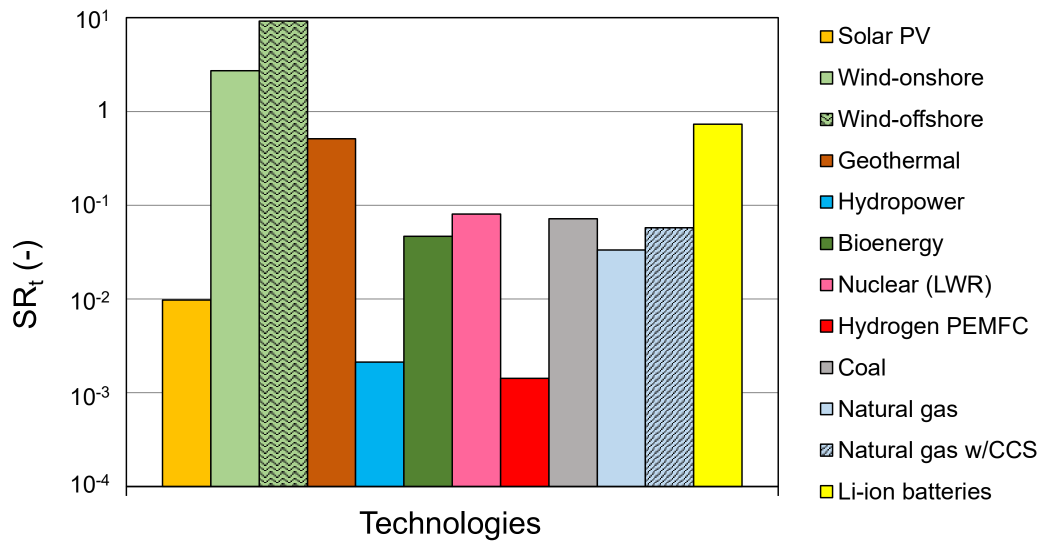

Figure 13. Technology material supply risk by technology.

The resulting SR_t for the technologies reported in Table 25 are also shown in Figure 13 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} e 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 in Table 8 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 [1]. Bioenergy, nuclear, and fossil-based power generation present a SR_t about one 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, LIBs and geothermal have higher but similar associated risks: the latter presents comparable values with the most debated clean energy technologies due to significant nickel consumption, as also pointed out by [54]. Lastly, wind turbines have the highest SR_t with an order of magnitude between 1 and 10. This is due to REE requirement, which have a very high SR_m and a lower $f_{m,t}$ than other CRMs. This points out the importance of using Equation (7) to avoid the dominance of $f_{m,t}$ over SR_m in the contribution to SR_t. Further details on data and sources used to evaluate the technology material SR indicator are available in Appendix G.

3.4.4 Evaluation of the energy supply risk indicator

To compute the energy SR indicator HHI_e^g in Equation (11) for each importable commodity considered in the case study, two parameters were needed: $S_{c,e}$ and

g_c^{en}. Values and sources are reported in Table 9, along with the resulting HHI_e^g, which is also depicted in Figure 14.

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 discussed in Section 2.3.1. The latest complete data, mostly from 2022, were used for all commodities except hydrogen, for which 2030 projections were considered. Although only the top three supplier countries are listed in Table 9, all supplier countries were included in the calculations. Moreover, the geographical scope changes across the energy commodities depending on the availability of data. Then, the political stability g_c^{en} was measured through the same governance index as for the materials [18], [87]. Note that a high value for g_c^{en} refers to a low stability while a low g_c^{en} value refers to a high stability. It is worth mentioning that the energy SR indicator 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 energy SR discussed in Section 2.3.1 do not affect the domestic sourcing.

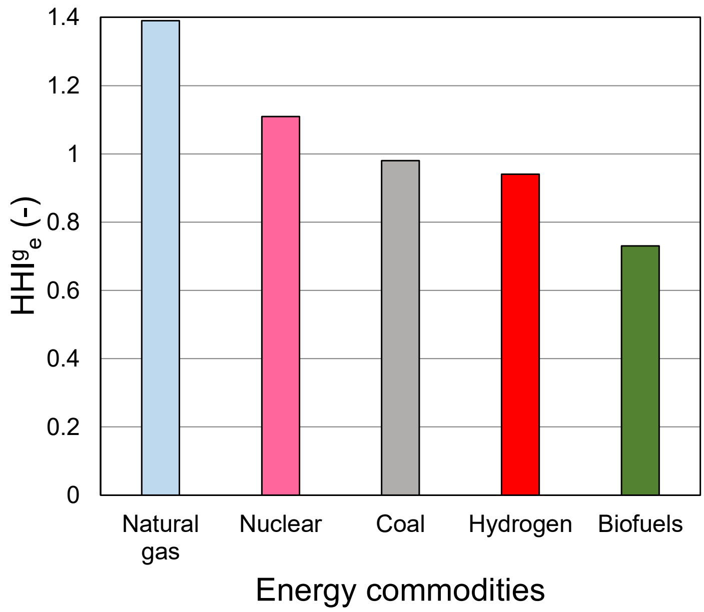

Figure 14. Energy supply concentration index by commodity.

Table 9. Data and sources of the parameters needed to compute the energy SR indicator for the case study of Approach 3.

Energy commodities	Geographical scope	Top three supplier countries	$S_{c,e}$	$g_c^{en}(-)$ [87]	$HHI_e^g\ (-)$
Natural gas	Italy [133]	Algeria	37.0%	6.72	1.39
		Russia	20.2%	6.29	
		Azerbaijan	14.6%	6.39	
Coal	Italy [134]	Russia	32.8%	6.29	0.98
		South Africa	18.2%	4.69	

		United States	13.0%	2.68	
Nuclear	EU [135]	Kazakhstan	27.0%	5.72	1.11
		Niger	25.4%	6.50	
		Canada	22.0%	1.79	
Hydrogen	EU [136]	Australia	59.7%	1.92	0.94
		Brazil	15.0%	5.40	
		Chile	15.0%	3.08	
Biofuels	Global [137]	United States	38.1%	2.68	0.73
		Brazil	21.8%	5.40	
		Indonesia	10.5%	5.32	

Italy is a major energy importer in the EU, with a high fossil fuel IR [138]. Compared to most of EU, the Italian supply chain of both natural gas and coal is less diversified and politically unstable. When looking at the origin countries, the combination of very high supply concentration and very low political stability makes natural gas the commodity with the 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 [133] and have the highest political instability among the supplier countries [87]. Instead, around 60% of 2022 EU imports was covered by four countries, with the more politically stable Norway and United States in the middle between Russia and Algeria [139]. A more diversified and stable supply chain characterizes the Italian and EU coal import, with Russia, South Africa, and United States among the main importers [139]. In particular, the Italian supply chain accounted for 14 supplier countries [134]. 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% of natural uranium was supplied by three countries, among which Kazakhstan and Niger have a very high political instability [135]. Hydrogen is not yet imported in Italy. In this regard, while dedicated national strategies are still under development, global hydrogen trade is in its early stages, with few hydrogen pipelines in EU and pilot projects on shipping [140]. Moreover, a common EU strategy is envisaged for hydrogen imports [136]. For these reasons, memoranda of understanding between EU and countries worldwide were considered to estimate the potential hydrogen imports to EU in 2030 [141]: the corresponding HHI_e^g results very close to the coal one. Finally, biofuels are characterized by the lowest HHI_e^g due to a 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 [137]. The use of global statistics introduces a greater uncertainty level than the EU data: however, the impact of this uncertainty is partially mitigated by the marginal and diminishing role of biofuels in the Italian power sector [142], [143]. Further details on data and sources used to evaluate the energy SR indicator are available in Appendix G.

3.5 Discussion of the case studies

This section provides a critical discussion of the case studies presented in this chapter. The approaches were applied to the TEMOA framework [78], which is regarded as being among the well-established open-source ESOMs in the literature [76]. In particular, the case studies were built upon the TEMOA-Italy model. On the one hand, its validity was proven by several studies in literature (see Section 3), and this provides robustness to the application of the approaches. On the other hand, the focus on the Italian case study might limit the scope of the analysis. However, the common vulnerabilities of many developed countries worldwide to CRM unavailability still frame the analysis as more globally relevant. For instance, securing the supply of essential RMs for clean energy, digital, and defense applications is becoming a primary goal of EU member states [24], as well as the Group of Seven countries [144]. Finally, all data and assumptions were made openly available. These aspects, alongside the openness of the ESOM used, can improve the reproducibility and transparency of both the methodology and the case studies. Additionally, the use of data belonging to the same EU CRM framework to define the material SR indicators and some MI provides consistency to the analyses.

However, also some common limitations are acknowledged. The first type of limitation comes from the amount and type of data and assumptions. Indeed, many data and assumptions were needed to develop the CRM supply disruption scenarios and SR functions, in addition to those behind the TEMOA-Italy model. This makes the approaches and their application highly data-driven, thus implying uncertainty concerns. The latter might be also due to the use of global or EU data, because of the lack of Italian specific analysis, also considering that the Italian legislation in terms of CRMs is still not mature if compared to other countries [12]. However, the implications in terms of uncertainty and validity of the case studies are considered limited. In particular, the following reasons led us to not consider reasons why there should be differences in terms of SR and availability of CRMs. First, the existing literature has provided disruption factors at global level only, which were then applied at the Italian supply level. Nevertheless, this assumption appears reasonable, being Italy a region without many RM reserves and heavily dependent on extra-EU imports [18]. Concerning the choice of the RMs to be considered, only CRMs for the EU economy were included [18]. Again, this approach appears reasonable given the proven marginal role of single EU countries in the global material supply chain [1]. Moreover, the EU aims to tackle the CRMs issue through common strategies among the member states [24]. Another source of uncertainty concerns the dataset adopted. Present values of the parameters needed across the three approaches – apart from $f_{m,t}$ in Approach 3 – were assumed along the entire time horizon. This is a strong assumption, implying that the present MIs and supply chains do not change in the future. Concerning MI Indeed, although CRM supply concentration is expected to remain relatively constant in the next decade [14], it is likely that the increasing dedicated policies (discussed in Section 1.1) will change the present market shares, affecting SR_m and $cons_{m,yref}$, and in turn the criticality of RMs and the material SR of technologies. These indicators are also strongly influenced by the absence of RM supply from recycling and domestic sources, which can partially mitigate the SR associated with the existing primary supply. The recycling was not included for the following reasons: (i) there is a lack of dedicated data [145], so that further assumptions could increase uncertainty; (ii) recycling contribution depends on the sufficient availability of end-of-life volumes, which will be available in the long-term [1]. Nonetheless, recycling was indirectly considered since it is one of the factors influencing the evaluation of CRMs (see Section 2.2.1). The same reasons are behind the choice of neglecting domestic primary supply. Despite the renovated interest at EU [24] and Italian [146] level, new mining projects usually take between 10 and 15 years to become operational in EU [147].

The second type of limitation concerns some features of TEMOA-Italy, which has low spatial and time resolutions in the form it was used for the application of the approaches. The former (i.e., single region) reflects in the absence of the power grid, whose components require high amount of some CRMs, such as aluminum and copper [2]. This, alongside the coarse time resolution (i.e., 16 annual time steps, considering 4 representative seasons and 4 representative times of day [71]), reduces the model capabilities in reproducing power sector operations involving highly CRM-intensive technologies. Some examples are: the use of batteries for variable renewable energy sources integration; vehicle-to-grid and demand side management operations involving BEVs; the competition between nuclear power and renewable sources integrated with battery storage. Besides the common features described above, each of the case studies has specific strengths and limitations, which are discussed below.

Approach 1 and Approach 2

The case study of the first and second approaches study includes 30 CRMs required by 19 technologies across 4 different sectors. None of the existing models evaluating ex-ante RMs in an integrated way (see Section 1.2.1) cover so many materials, technologies, and sectors at the same time. Indeed, TIAM-IFPEN model focuses only on lithium [50] and copper [51] requirements in several sectors, while the TIMES US Model RES includes more or less the same materials described in Section 3.2.2, but focusing on the power sector technologies only [52]. Conversely, TIAM-IFPEN also models the energy requirement by material supply chains, which was not considered in the first approach, as discussed in Section 2.4.1.

By including many CRMs and technologies allows to leverage the multi-sectorial TEMOA-Italy-materials to include MR in the economic competition between energy technologies. However, some of them were not considered due to lack of data, despite they require CRMS. For instance, this is the case of: (i) heat pumps, H2 direct reduced iron processes, and electric arc furnaces; (ii) medium- and heavy-duty road transport. The implications of these absences can be considered limited for the following reasons. The SRs associated with the technologies of (i) are currently lower than the other clean energy technologies [1]. Then, the expected contribution to CRM requirement by the technologies of (ii) is much lower than the cars ones [2]. Indeed, the electrification of medium- and heavy-duty vehicles presents more technological and economic barriers than light-duty ones [148]. The MR by the rest of the economy was not considered, assuming that CRM supply disruption affects all the sectors requiring them equally. This assumption seems reasonable, due to the minor contribution to total CRM consumption from the non-energy sectors. For instance, the consumption levels associated with information and communication technologies (referred to as ICT) and aerospace and defense applications are around 3 orders of magnitude smaller than clean energy technologies ones for some CRMs [1]. Instead, more relevant is the absence of nuclear power plants, which require less CRMs than the other low-carbon electricity sources (see Table 25) and might be beneficial in reducing the material SR of the power sector.

Approach 3

In the third approach, 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 the latest stated and announced energy policies worldwide [149]. 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 4.2.2: along slices, between slices horizontally, and between slices vertically.

Limitations concerning data, assumptions, and model used involves the third approach, too. First, the absence of harmonized and comprehensive datasets providing MI of technologies, and a consistent geographical coverage for the energy imports, introduce further uncertainty into material and energy SRs calculations. Moreover, as for the CRMs, the present market shares were used to define the energy SR in 2050. This assumption is strong also for the energy commodities. Indeed, recent policies following the Russian-Ukrainian conflict are reshaping fossil fuel supply chains, especially concerning Russian supplies, prompting strategic planning in hydrogen and biofuels markets [141]. Finally, the absence of relevant sectors other than the power one such as power grid infrastructure and transportation limits the scope and the insights of the results. Nevertheless, the simplified TEMOA-Italy power sector enables a comprehensive analysis. Among the sectors affected by energy and material supply chains risks, the power sector was chosen for two main reasons. First, it allows for a comprehensive assessment involving many technologies and their mutual substitutions, also leveraging the technological richness and explicitness of ESOMs [150]. Second, it presents high availability and reliability of MI data in the existing literature. Also, the sector choice does not affect the methodology at all and is not expected to dramatically change general findings on the potential trade-off between energy and material SR. Indeed, the decarbonization targets that are adopted in Approach 3 would entail the transition from highly risky fossil-fuels to highly risky clean energy technologies – to a different extent – in all the energy sectors of TEMOA-Italy.

Chapter 4

Results and discussion

This chapter presents the results from the application of the three approaches described in the previous chapter:

1) **Approach 1:** the corresponding results are presented in Section 4 and are based on [79].
2) **Approach 2:** the corresponding results are presented in Section 4 – as for the first approach – and are based on [79]. Indeed, as mentioned in Section 3.3, the material SR indicator was applied ex-post to the RM supply disruption scenarios of the first approach.
3) **Approach 3:** the corresponding results are presented in Section 4.2 and are based on [3].

4.1 Material supply disruption effects on the energy system decarbonization

The effects of CRM supply disruption on the Italian energy system decarbonization are evaluated in terms of technology mixes in Section 4.1.1, material consumption in Section 4.1.2, and material SR in Section 4.1.3. The results are then discussed in Section 4.1.4, by highlighting the effectiveness and advantages of using the proposed approaches over the existing studies, as well as the specific limitations. The focus is on the sectors for which CRM consumption is modeled in TEMOA-Italy-materials, namely power, battery storage, hydrogen production, and car sectors. Conversely, details on more general results are provided in [79] and [107].

For the sake of clarity, the scenarios here analyzed – and described in detail in Section 3.2.1 – are listed below:

- Business-As-Usual (BAU): aiming to reproduce the evolution of the energy system based on national stated energy policies.
- Net-Zero Emissions (NZE): aiming to fulfill decarbonization targets in 2030 and 2050.
- Demand-Supply Gap (DSG): assuming a shortage of cobalt, copper, lithium, nickel, and some REEs, due to inadequate supply from mining industry.
- Chinese Supply Disruption (CSD): assuming a shortage of dysprosium, lithium, manganese, and neodymium from China.
- Low Governance Region (LGR): assuming a shortage of cobalt and nickel from countries with high political instability.
- Water Stress Region (WSR): assuming a shortage of copper and lithium from region with potential future water crisis.

4.1.1 Technology mixes

The power sector technology mix in 2050 is shown in Figure 15 (left y-axis) across the scenarios described in Section 3.2.1. The decarbonization scenarios – including NZE and the supply disruption ones – were identical in terms of absolute electricity production and technology mix. The electrification level was about 20% higher than in the BAU scenario, reaching almost 1400 PJ. This increase was reflected in a higher share of solar PV and wind energy, which accounted for almost 50% and 30% of the total electricity produced, respectively. Instead, natural gas plant contribution was reduced from providing baseload to meeting peak demand, while the production by other renewables, such as hydropower, geothermal, and bioenergy remained constant. The results highlight that the competition in the power sector was mainly driven by the CO2 emission reduction constraints. Conversely, it was not influenced by material supply disruption, despite power sector technologies requiring CRMs involved in disruption constraints, like copper, nickel, and some REEs.

Differences are noticeable in the battery storage technology mix in 2050 that is shown in Figure 15 (right y-axis). The higher penetration of variable renewables sources – like solar PV and wind energy – increased the use of LIBs in NZE, DSG, and LGR scenarios compared to the BAU one. In particular, the highest use occurred in the DSG and LGR scenarios. Instead, the battery storage production decreased to approximately the BAU levels in the CSD and WSR scenarios. This is due to the fact that they imposed the strictest constraints on lithium availability among the supply disruption scenarios. This implied the penetration of VRFBs as an alternative, since it does not require lithium.

Concerning the hydrogen production sector, alkaline and solid oxide-ECs are the only technologies requiring a CRM – i.e., nickel – involved in the supply disruption scenarios. However, their direct influence is not noticeable in the results, as no EC penetrated in the NZE scenario. Then, alkaline and solid oxide ECs did not even appear in all the supply disruption scenarios, while PEMECs penetrated in the CSD and WSR ones. The reason why only PEMECs are present in the system should not be attributed to the requirement for nickel by the other two technologies. Indeed, nickel is only limited in the DSG and LGR scenarios, whereas PEMECs are present in the CSD and WSR ones. Instead, the reason is likely to be the techno-economic characterization of ECs: while the SOEC is the most expensive technology, alkaline-ECs and PEMECs are cheaper and comparable in terms of cost, but the latter are more efficient . Then, their use is directly linked to battery storage one. In particular, the PEMEC electricity consumption corresponded to approximately the average difference of battery storage production between the CSD and WSR scenarios and the NZE one, which is ~40 PJ. Overall, the very low penetration of ECs led to a negligible contribution to the material consumption and in turn to the material SR of the Italian energy system. For this reason, they are omitted from the result presentation in Section 4.1.2 and Section 4.1.3.

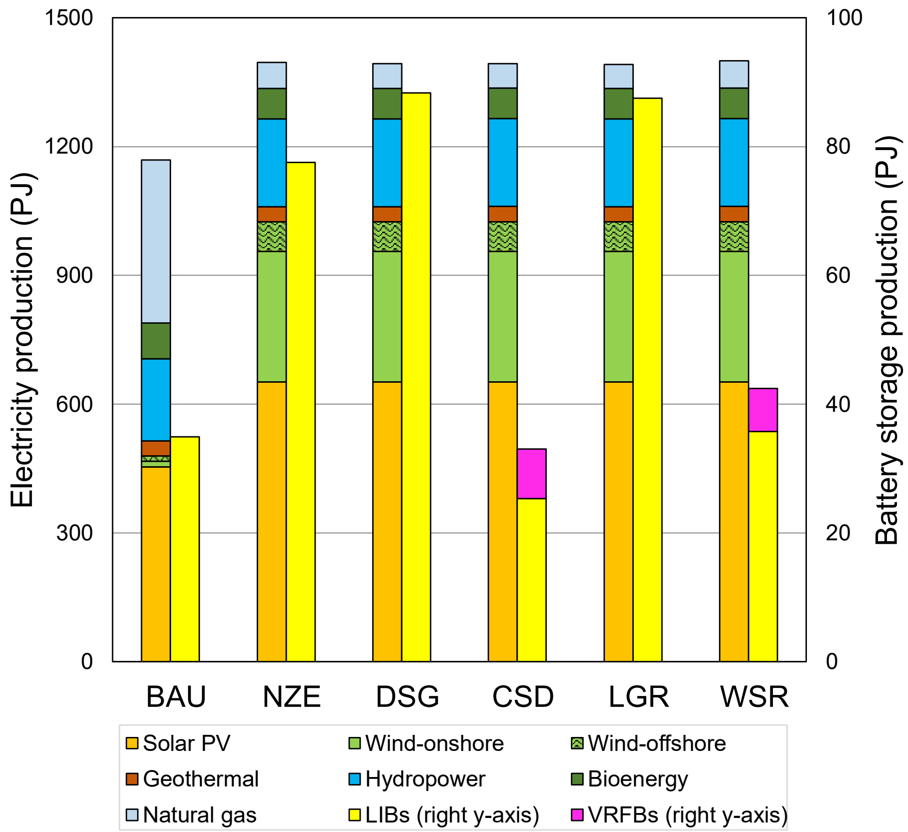

Figure 15. Electricity (left y-axis) and battery storage (right y-axis) production by technology in 2050 across the scenarios analyzed.

The car sector technology mix in 2050 is shown in Figure 16 in terms of share of demand satisfaction. This is equivalent to showing the mix in absolute terms, as car transport demand is exogenous and remains constant across the scenarios [110]. ICEVs fueled by gasoline, gas oil, liquefied petroleum gas, and natural gas dominated the mix in the BAU scenario. Instead, they were replaced by low-carbon alternatives in the decarbonization ones. BEVs satisfied the whole demand in the NZE scenario, and this is in line with the higher electrification level than in the BAU one. Instead, the CRM unavailability in the supply disruption scenarios limited the penetration of BEVs. In the DSG and LGR ones, they were partially substituted by FHEVs, which require the same – but in smaller quantities – materials, such as cobalt, copper, lithium, nickel, and REEs, as discussed in Section 3.2.2. The reduced presence of BEVs in the DSG and LGR scenarios was concomitant with the highest penetration of LIBs in the battery storage sector, highlighting how supply disruption scenarios mainly influence the car sector. The share of BEVs was further reduced in the CSD and WSR cases, which involve the strictest constraints on copper, lithium, and REEs. Moving from the DSG scenario to the CSD one, BEVs – with a ~60% share – were completely replaced by FCVs, which are more expensive than electric vehicles, but require less of the CRM mentioned above, as discussed in Section 3.2.2. Moving from the LGR scenario to the WSR one, the BEVs substitution was partial, since the constraints are less strict than in the CSD scenario: the BEV share was reduced to 15%, with a replacement by FCVs and ICEVs. The latter require much less RMs than electric and FC vehicles and penetrated in all the CRM supply disruption scenarios, despite the decarbonization constraint: this was mainly due to the use of gas oil blends including ~60% – in energy terms – of biodiesel , whose biogenic CO2 emissions are not considered climate-altering in the model [72].

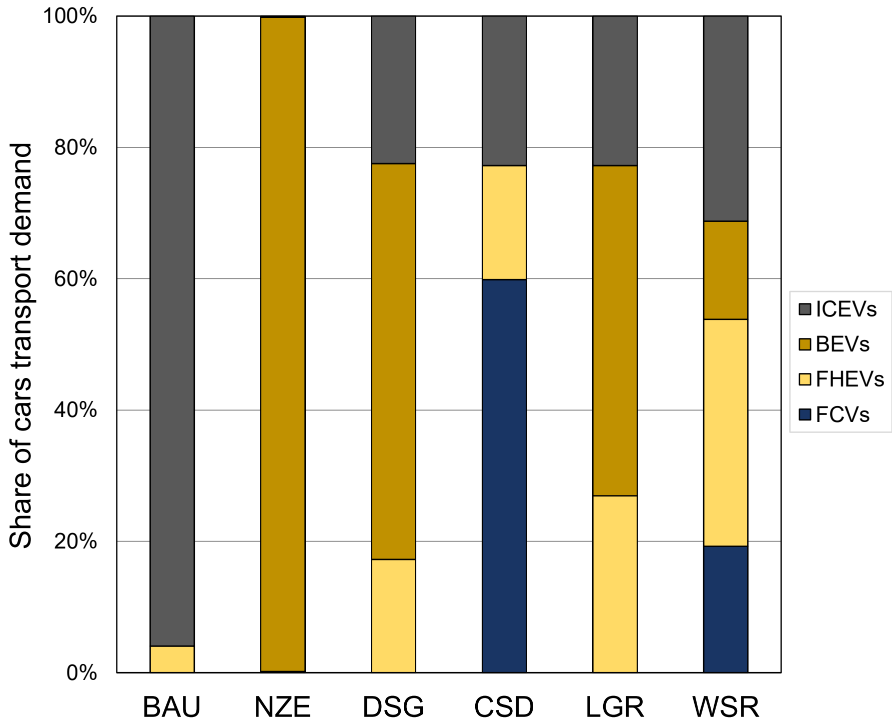

Figure 16. Share of car transport demand by technology in 2050 across the scenarios analyzed.

4.1.2 Material consumption

Figure 17a shows cumulative CRM consumption and installed capacity from 2025 to 2050 by technology of power and battery storage sectors, for all the scenarios described in Section 3.2.1. The consumption in the NZE scenario exceeded 4 Mt, which is ~65% higher than the BAU one. Then, the consumption in the supply disruption scenarios remained between 3.5 Mt and 4.5 Mt. The higher CRM consumption was due to the higher capacity installation. The latter is very similar in all the decarbonization scenarios and averaged around 410 GW, which is ~55% higher than in the BAU scenario (see Figure 17a, right y-axis). However, the overall MI of these sectors remained almost constant and very close to the BAU one, which is around 10.2 t/MW. This was due to two factors: the BAU scenario results already included CRM intensive technologies, such as solar PV and LIBs; the decarbonization scenarios did not show major changes concerning the contribution to the total cumulative capacity of the most CRM intensive technologies, such as solar PV, wind turbines, geothermal, and batteries.

Power sector technologies covered between 80% and 90% of material consumption, as they require more CRMs and presented a higher installed capacity than batteries. Specifically, solar PV accounted for ~60% of total consumption in the power sector across all the decarbonization scenarios. This share increased to ~85% if considering also wind energy: this was in line with the fact that solar PV and wind energy represented more than 70% of the total cumulative installed capacity in the power sector (see Figure 17a, right y-axis) and are among the most CRM intensive technologies in the power sector, according to Table 15. The contribution to material consumption by the remaining technologies was also in line with the corresponding MI – presented in Appendix D – and installed capacity, these being the two factors used to compute materials consumption (see Equation (1)). In particular, geothermal, LIBs, and VRBs presented a higher and lower contribution to, respectively, the CRM consumption and the installed capacity, than hydropower, bioenergy, hydrogen FCs, and natural gas. The latter was entirely replaced by hydrogen FCs in the WSR scenario, despite FCs did not produce electricity, according to Figure 15. This was because hydrogen FCs were used to satisfy the reserve margin constraint in place of the copper-intensive natural gas plants, which are limited by the WSR supply disruption constraint on copper. In addition, hydrogen FCs and the lower penetration of batteries were responsible for the lower CRM consumption in the WSR scenario than the other decarbonization ones.

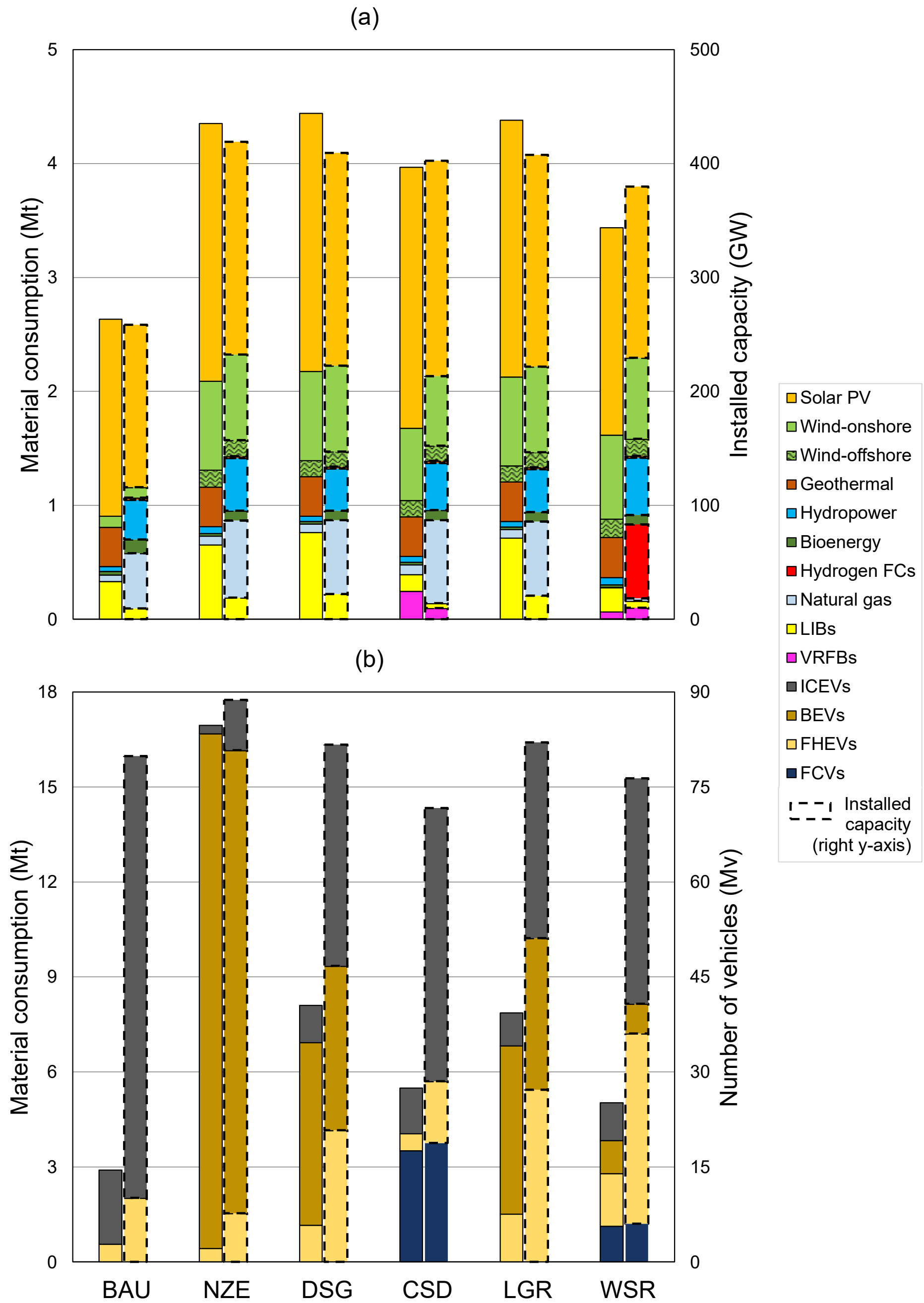

Figure 17. Cumulative material consumption and installed capacity (from 2025 to 2050) by technology across the scenarios analyzed by: power and battery storage (a) and car (b) sectors.

The car sector presented an increase in CRM consumption from BAU to decarbonization scenarios, which was much higher than the sectors analyzed above, as shown in Figure 17b. Moreover, the cumulative number of vehicles did not change from BAU to decarbonization scenarios as much as power and storage sectors, remaining between 70 Mv and 90 Mv (see Figure 17b, right y-axis). Therefore, changes in CRM consumption were mostly due to changes in the car fleet mix. In particular, the full electrification of the sector in the NZE scenario – depicted in Figure 15 – required more than six times the CRMs consumed in the BAU one. Moving to the supply disruption scenarios, the lower BEV penetration implied a decrease in CRM consumption compared to NZE scenario, to levels between 2 and 3 times higher than in the BAU scenario. For instance, CRM consumption was more than halved when moving from a BEV contribution of ~80% to the cumulative car fleet in the NZE scenario, to ~30% in the DSG and LGR ones. CRM consumption was further reduced by ~20% when the BEV contribution was ~6% in the WSR scenario and zero in the CSD one, where no BEV investments were present because of the unavailability of lithium and REEs. This suggests a diminishing marginal utility in reducing BEV penetration below certain shares. Unlike the power and storage sectors, the MI of cars changed across the scenarios: the higher the BEV penetration, the higher the MI. In particular, the MI increased from ~34 kg/vehicle in the BAU scenario to ~207 kg/vehicle, while decreasing across the decarbonization scenarios until an average MI ~82 kg/vehicle. This reflects the MI of the specific vehicles listed in Table 18.

The cumulative CRM consumption from 2025 to 2050 by material required by power and battery storage sectors is reported in Figure 18a, for all the scenarios described in Section 3.2.1. Only CRMs involved in the supply disruption constraints are shown, while the remaining materials modeled in TEMOA-Italy-materials – and listed in Table 5 – are incorporated under the heading "Others". In particular, they accounted on average for ~16% of the total consumption. Then, aluminum and copper represented on average almost 70% of the total consumption, being construction materials for most of the technologies involved. Instead, REEs share is not visible in Figure 18a and remained quite constant around 0.4% of total consumption, as their MI is on average 2 orders of magnitude lower than the CRMs with the highest MI, according to Appendix D and Appendix G. Lastly, battery storage technologies were responsible for the only relevant difference in terms of type of CRM consumed. Indeed, vanadium appeared only in the CSD and WSR scenarios due to the penetration of VRFBs.

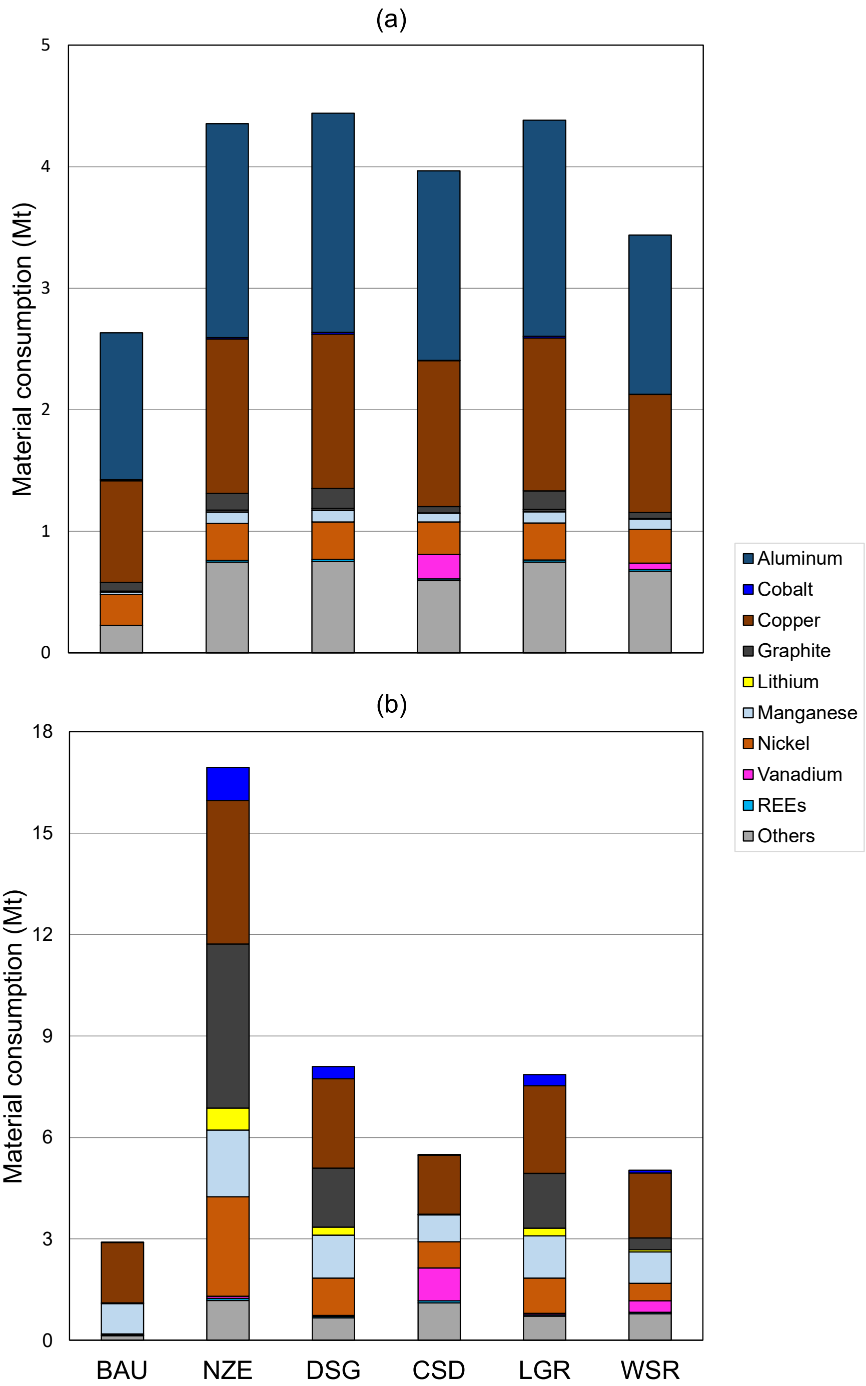

Figure 18. Cumulative material consumption (from 2025 to 2050) by CRMs across the scenarios analyzed by: power and battery storage (a) and car (b) sectors.

Copper and a portion of manganese, which are the main CRMs required by the gilder of all vehicles, ICEV power train, and electric motors – as discussed in Section 3.2.2 – represented more than 90% of total car consumption in the BAU scenario, as ICEVs dominated the technology mix. As the BEVs penetrated in the system, this share decreased in favor of CRMs required by batteries, i.e., cobalt, graphite, lithium, manganese, and nickel: they covered most of the car CRM consumption in the NZE, DSG, and LGR scenarios, with shares between ~57% and ~67%. This is in accordance with the highest contribution to the MI of the specific vehicles from the battery-related materials listed in Table 18. Instead, as for the power and storage sectors, REE share is not visible in Figure 18b and remained quite constant around 0.7% of total consumption.

Table 10. Cumulative material consumption (from 2025 to 2050) by CRMs across the scenarios analyzed.

Material	Total system CRM consumption (Mt)					
	BAU	NZE	DSG	CSD	LGR	WSR
Aluminum	1.2	1.8	1.8	1.6	1.8	1.3
Cobalt	1.2×10^{-2}	1.0	0.4	2.1×10^{-2}	0.3	0.1
Copper	2.6	5.5	3.9	2.9	3.9	2.9
Graphite	0.1	5.0	1.9	0.1	1.8	0.4
Lithium	1.4×10^{-2}	0.7	0.3	0.0	0.2	0.1
Manganese	0.9	2.1	1.4	0.9	1.3	1.0
Nickel	0.3	3.2	1.4	1.0	1.3	0.8
Vanadium	8.6×10^{-3}	0.1	3.8×10^{-2}	1.2	4.2×10^{-2}	0.4
REEs	1.1×10^{-2}	8.3×10^{-2}	5.7×10^{-2}	6.9×10^{-2}	6.2×10^{-2}	6.4×10^{-2}
Others	0.4	1.9	1.4	1.7	1.5	1.5
Total	6	21	13	9	12	8

The previous figures indicates that the car sector provided the primary contribution to total system CRM consumption, which is summarized in Table 10 by material and across all the scenarios analyzed. While the consumption in the BAU scenario was equivalent and around 3 Mt, cars consumed almost 6 times the CRMs required by power and battery storage sectors in the NZE scenario, for a total system requirement of ~21 Mt. Moreover, cars covered almost 90% of the consumption increase from the BAU one. This share decreased across the supply disruption scenarios and averaged around 70%. The highest consumption increases among CRMs occurred for cobalt, graphite, and lithium, mainly due to the presence of BEVs. When comparing the BAU and NZE scenarios, this increase was about 80 times for cobalt, 60 times for graphite, and 50 times for lithium. Then, it at least halved in the supply disruption scenarios. Instead, REEs were the only materials for which the increase was higher in the power sector than in the car one, due to the penetration of wind energy: the former presented an average 10-fold increase due to wind energy, while the latter an average 5-fold increase.

Finally, it is important to point out that only some maximum availability constraints resulted binding across the CRM supply disruption scenarios. The penetration of technologies may be limited by the presence of only one binding constraint, since they can require more CRMs involved in the supply disruption scenarios. This occurred for: dysprosium in the DSG one and cobalt in the LGR, which limited the penetration of BEVs; manganese and neodymium in the CSD one and copper in the WSR one, which limited the penetration of LIBs and BEVs.

4.1.3 Material supply risk of the energy system

The cumulative material supply risk SR_M from 2025 to 2050 of power and battery storage sectors is reported in Figure 19a, for all the scenarios described in Section 3.2.1. The values are normalized with respect to the BAU scenario. SR_M increased by ~6 times in NZE, LGR, and WSR scenarios, and by ~10 times in DSG and CSD ones. This was due to an increase of the two components influencing the indicator, i.e., the installed capacity (see Figure 17a) and the material supply risk SR_t of technologies, as defined in Equation (10). Wind energy contributed between 60% and 80% of the total SR_M in all the decarbonization scenarios, despite its contribution to cumulative material consumption and installed capacity were much lower and averaged around 20%, as shown in Figure 17. Additionally, the contribution to the SR_t of wind energy came almost completely from REEs – as shown in Figure 7 – while their consumption was around 0.4% of the total CRMs. These two key results about wind energy highlight that higher material consumption does not necessarily imply a higher material SR, which is in line with the discussion in Section 2.2.2.

As shown in Figure 17a, the cumulative installed capacity across power and battery storage sectors was similar across all the decarbonization scenarios. However, DSG and CSD scenarios presented higher values than NZE and LGR ones, whose SR_M is very similar. This means that differences in SR_M were mainly due to the SR_t of the technologies installed. Concerning the power sector, the technology mix did not change significantly (see Figure 17a). Instead, the supply disruption of the REEs required by wind turbines involved in the DSG and CSD scenarios led to an increase of their SR_t of ~85% and ~65%, respectively. Indeed, a lower global CRM supply is a risk increasing factor in the definition of SR_t in Equation (7). In this regard, the supply disruption constraints were included in the calculations for the case study of the second approach, as discussed in Section 3.3.1. In addition, the penetration of VRFBs in the CSD further increased the SR_M: despite a contribution to the cumulative installed capacity and material consumption of ~2% and ~6% (see Figure 17a), respectively, their share over the total SR_M reached ~37%. This is since VRFBs are among the riskiest technologies across power and battery storage sectors, together with wind turbines.

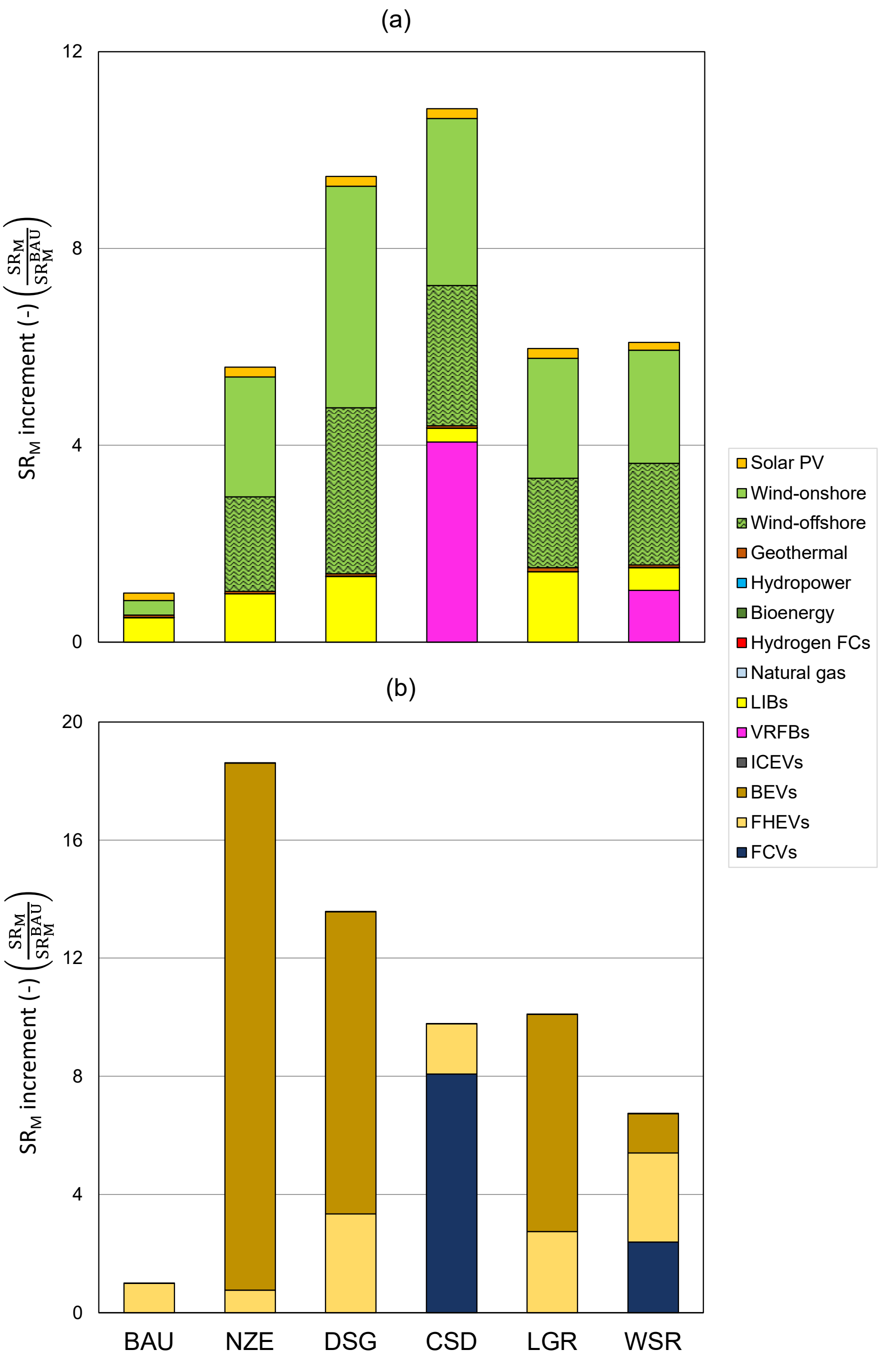

Figure 19. Material supply risk increment compared to BAU by technology across the scenarios analyzed by: power and battery storage (a) and car (b) sectors.

As for the material consumption discussed in the previous section, car sector presented an increase in SR_M consumption from BAU to decarbonization scenarios, which was much higher than the sectors analyzed above, as shown in Figure 19b. In the NZE scenario, the increase was ~20-fold, while it was less pronounced in the other ones, reaching at least ~7 times in the CSD scenario. Overall, the decreasing car fleet across the supply disruption scenarios (see Figure 17b) is a risk decreasing factor, according to Equation (10). However, as for CRM consumption, changes in the cars fleet had a minor effect than the changes in the technology mix. BEVs contributed between 75% and 95% in NZE, DSG, and

LGR scenarios, where they played a major role in terms of CRM consumption and car fleet, as shown in Figure 17b. Despite the absence of BEVs and a smaller cars fleet, the CSD scenario presented an equivalent SR_M to the LGR one. In particular, BEVs were entirely replaced by FCVs, whose SR_t is more than 1.5 times higher than BEVs, according to Table 7. Moreover, CSD scenario also showed a lower CRM consumption than the LGR one (see Figure 18b). As for the wind turbines case discussed above, this highlights that higher SR_M are not necessarily positively correlated with higher material consumption, as discussed in Section 2.2.2. To further support this, the ICEV contribution to total car SR_M was negligible, despite they represented between 15% and 25%, and 40% and 60%, respectively, of car CRM consumption and fleet (see Figure 17b): indeed, their SR_t is between 3 and 4 orders of magnitude lower than the other low-carbon vehicles.

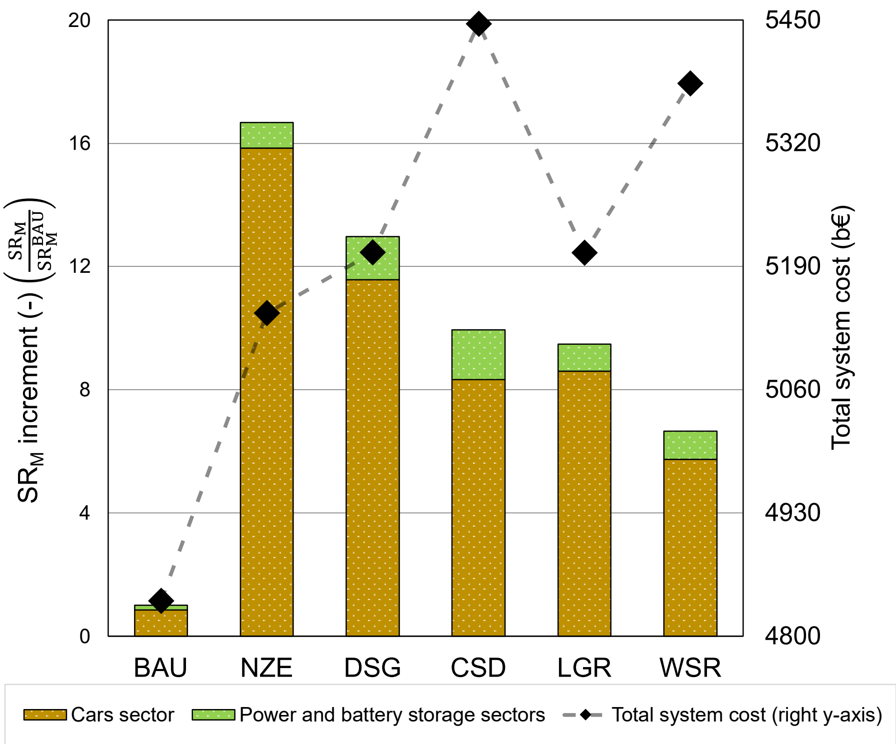

Figure 20. Material supply risk increment compared to BAU by sector across the scenarios analyzed.

Finally, Figure 20 presents the total cumulative SR_M of the system from 2025 to 2050 by involved sectors, while also indicating the total system costs, for all the scenarios described in Section 3.2.1. As expected, the decarbonization scenarios presented a higher SR_M than the BAU one, reflecting the sector behavior analyzed above. The magnitude of the increase and its trend across the scenarios were mostly driven by the cars sector. In particular, the relative increases were slightly lower than the ones shown in Figure 19b. Then, car contribution to the total system SR_M covered between 85% and 95%, which is very similar to the contribution to the total system material consumption presented in the previous section. This was due to two factors. First, cars consume more CRMs than power and battery storage sector technologies (see Table 5 and Appendix D), increasing the number of required materials. Second, the cumulative installed capacity reflected a higher number of units for cars (i.e., vehicles) than power and battery storage sectors (i.e., plants). Moreover, the latter factor was also the main reason behind the higher car contribution to the total system SR_M than the other sectors, since the average technology material SR is comparable between the technologies of the different sectors (see Table 7 and Appendix D).

The total system cost associated with the scenarios analyzed is also depicted in Figure 20, right y-axis. First, reaching decarbonization targets increased the costs compared to the BAU scenario. Then, decreasing the SR_M further increased the costs moving from the NZE scenario to the supply disruption ones. In particular, the cost increase was very small in DSG and LGR scenarios, namely slightly more than 1% for a SR_M reduction of ~22% and ~43%, respectively. Instead, CSD and WSR scenarios required a cost increase of ~6% while decreasing the SR_M of ~40% and ~60%, respectively. The higher cost increase in CSD and WSR scenarios than DSG and LGR ones was mainly due to investments in technologies like VRFBs and FCVs, which are more expensive than the other low-carbon alternatives [71], [116]. Overall, the average ratio between the total system cost increase and the percentage decrease of SR_M between NZE and the supply disruption scenario was ~4 b€/%.

4.1.4 Discussion of results

Overall, the results presented so far are in line with the existing studies discussed in Section 1.2. The energy transition is expected to increase CRM demand in the next decades, mainly due to solar PV, wind turbines, and BEVs. However, in contrast to the earlier studies that typically adopted an ex-post approach or focused on single materials or technologies, the first and second approaches embed SR consideration directly into the energy system design. This integration enables ESOMs to provide insights on how the energy systems can adapt to potential CRM unavailability.

The full decarbonization by 2050 is always possible across the material supply disruption scenarios. This means that the partial unavailability of some of the main CRMs – even up to 50%-70% of global primary supply (see Table 4) – does not preclude the achievement of CO_2 emission reduction targets. However, the supply disruption mostly affects the cars sector. Indeed, the power and battery sectors mixes remained almost unchanged, while the constraints on cobalt, lithium, and nickel limited BEV penetration much more than LIBs, despite both the technologies require these materials. This suggests that the decarbonization of power and battery storage sectors is prioritized over the cars one in the pure-cost minimization process, as also pointed out in [116]. Cars were responsible for the vast majority of the increase in CRM consumption from BAU to decarbonization scenarios, which is in accordance with the outcomes of [2]. The latter pointed out that battery storage and especially transport technologies might account for around half of the global mineral demand growth by clean energy technologies in 2040, according to stated energy policies. The NZE scenario showed the highest increase (~4 times) in CRM consumption compared to the BAU one. The magnitude of this increase finds evidence in earlier studies, which compared the expected demand in 2050 to current values, such as in [1] and [36]. The same applies to single materials, such as cobalt, graphite, lithium, and REEs (e.g., between 7-fold and 40-fold increase in [2]), and technologies, such as wind turbines (e.g., between 3-fold and 5-fold increase in [37]). The only exception is copper: its increase was much lower than in other studies that also included electricity networks [14], whose MR was not considered in TEMOA-Italy-materials. The unavailability of some CRMs reduced material consumption in all supply disruption scenarios. The latter revalue the contribution to the decarbonization of technologies such as VRFBs, FHEVs fueled by low-carbon fuels, and FCVs, which typically play a secondary, if not marginal role in many existing energy scenarios studies.

The combination of the first and second approaches allows to clearly distinguish between the CRM consumption and the associated SR, differently from the existing studies. The results point out how higher consumption does not necessarily imply higher risks, which is in accordance with the discussion in Section 2.2.2. For instance, the higher contribution to the system material SR came from cobalt, lithium, and REEs, which instead accounted for a minor contribution to the system material consumption. These materials are mainly required by BEVs and wind turbines, which in fact contributed more to the system SR than other technologies. Similar approach and results, but at European level, were found in [27] and [60], where the authors pointed out how the future material SR of the European power sector might increase mainly due to wind energy deployment. As for the material consumption, the unavailability of some CRMs reduced the SR across the supply disruption scenarios. However, this came at the expense of the total system cost, which increased on average by ~3.5% compared to NZE scenario. Despite this might seem a small increase, it equals almost 170 b€, and it can be associated with relevant changes in the optimal energy system configuration in ESOMs [151].

From a policy perspective, these findings suggest that investing in energy systems with high shares of wind turbines, batteries, and especially BEVs implies the highest material SR for countries like Italy, and therefore the EU. In particular, BEVs appear to be the most affected in the case of supply disruption of materials. This result is very relevant considering the recent EU policy concerning the ban on sales of CO_2 emitting vehicles from 2035 [152], which has boosted large investments by the automotive industry in electric-based solutions [153]. To reduce the material SR associated with car sector decarbonization, two possibilities – that are not mutually exclusive – are: (i) diversifying the primary supply and reducing the import dependency of the CRMs required by BEVs and that are involved in the supply disruption (i.e., cobalt, lithium, nickel, and REEs); (ii) investing in other low-carbon solutions that are currently more expansive, but require less CRMs, such as FCVs and FHEVs fueled with low carbon fuels (i.e., biofuels and synthetic fuels [72]). In this regard, these technologies would increase the decarbonization cost, while decreasing the total system material SR, thereby suggesting a potential trade-off. The latter might be used to evaluate optimal incentives to support either material supply diversification or low-carbon solutions with lower associated SR.

Some limitations concerning methodology and case study reduce the extent to which the results discussed above might support decision makers. First, the are no insights on how to actively manage the material SR (e.g., minimizing the risk as in the third approach), since energy system design and operations can only adapt to the material SR changes modeled through CRM unavailability constraints. Additionally, the absence of factors that might reduce the material SR by reducing the import dependency, such as recycling and domestic sourcing, does not allow to consider ex-ante mitigation strategies. This means that results on CRM consumption and risk are conservative. Moving to the case-study limitations, they cover the absence of: key technologies for the energy transition, MI improvement assumptions, and supply disruption constraints for other materials and energy commodities. Concerning technologies, electricity networks and nuclear power plants are the great absentees. The former consumes most of the main CRMs demanded by clean energy technologies [2] and involves massive investments in the next decade to facilitate the integration of variable renewable energy sources [154]. The absence of electricity networks in the case study might therefore strongly influence the actual feasibility of the material supply disruption scenarios. Then, nuclear power plants require less CRMs than other low-carbon electricity sources (see Appendix G) and can reduce the battery storage requirement [71], alongside the related SR. Moving to the MI, the choice of using present values can be considered conservative, since material efficiency is expected to decrease the MR of clean energy technologies in the next decades. In this regard, the existing literature includes a few energy scenario studies considering changes in MI due to technological improvements [20]. However, all of them argue that material use per unit capacity could dramatically fall, e.g., by ~50% on average by 2050 – through known efficiency improvements and economies of scale – for RMs (such as cobalt, lithium, and REEs) and technologies (such as solar PV, wind, and LIBs) [37], [155]. This means that accounting for such MI reduction might significantly affect the results here discussed, thereby suggesting the usefulness of uncertainty analyses in this regard. Finally, concerning supply disruption constraints, VRFBs and FCVs penetration in some supply disruption scenarios is not limited because of the absence of constraints on vanadium and platinum, which have high SR (see Table 6) mainly due to the high supply concentration in China and South Africa, respectively [18]. Moreover, the scenarios studied only focused on possible CRM supply disruption causes without considering energy commodities supply disruption. Consequently, this restricts the potential to derive actionable insights into the expected trade-off between energy and material SRs, as instead is the case of the third approach.

4.2 Material and energy supply risks in the decarbonization of the power sector

The outcomes of the MOOs formulated in Section 3.4.1 are described, respectively, in Section 4.2.1 and Section 4.2.2, looking both at Pareto fronts in the objective space and at the system design and operation in the variable space. The results are then discussed in Section 4.2.3, by highlighting the effectiveness and advantages of using the proposed approach over the existing studies, as well as the specific limitations. The complete set of results presented is available in the Supplementary Material of [3].

4.2.1 Minimization of total system cost and emissions

The Pareto front from $min(F_{cost}, F_{CO2})$ is shown in Figure 21a. As expected, reducing emissions increased the total system cost. Specifically, lowering net CO_2 emissions from the maximum of ~86 Mt to zero resulted in a cost rise from the global minimum of ~117 b€ to ~138 b€. Pareto-optimal solutions represent emission reduction scenarios, whose corresponding electricity production by technology is shown in Figure 21b. In the least-cost system, the power mix was 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 made a minor contribution from F_{CO2}~17 Mt, while CCUS technologies (i.e., natural gas w/CCS and DAC) enabled net-zero emissions by capturing nearly 4 Mt of CO_2 from residual natural gas combustion. 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 [28].

Instead, insights on material and energy SRs can be evaluated by applying the definitions in Equation (10) and Equation (14) to the capacity and activity results ex-post. The ratio between SRs values in each scenario – referred to as realized SR – and the maximum between all the scenarios – referred to as SR^{MAX} – is shown in Figure 21b. The lower the emissions were, the lower became the SR_E, with its linear decline reflecting the gradual reduction in natural gas-based generation. Indeed, the corresponding lower natural gas requirement implied the phasing out of imports until all the natural gas consumed in the net-zero scenario was produced domestically, which is more cost-effective than imports. This ultimately resulted in zero SR_E at zero emissions. Conversely, SR_M increased with decreasing emissions, mainly due to the penetration of onshore wind, which is among the technologies with the highest material SR, according to Figure 13. The maximum SR_M across emission reduction scenarios occurred 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, reduced SR_E while simultaneously increasing the level of SR_M. In particular, the least-cost net-zero scenario (hereinafter base case) presented zero energy imports, thus zero SR_E. Conversely, SR_M was around 450, which is about 37 times the level in the least-cost scenario. However, this analysis can be extended by studying the MOO of the two SRs as presented in the next section.

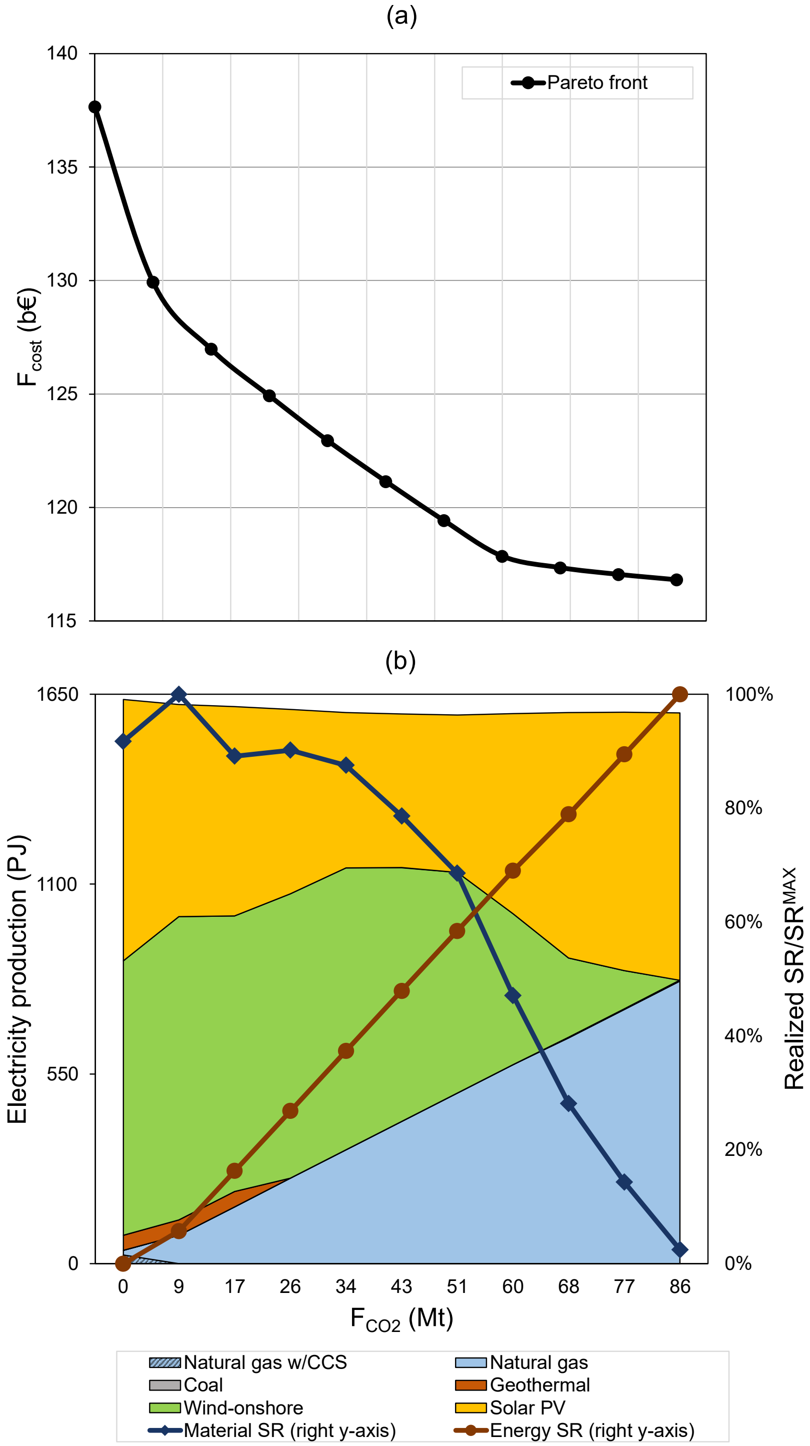

Figure 21. Pareto front (a) and electricity production by technology across the Pareto front (b), of the MOO problem $min(F_{cost}, F_{CO2})$.

4.2.2 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 Equation (17) are shown in the objective space in Figure 22. 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 the previous section, while allowing for a higher total system cost. Moreover, the variable spaces in Figure 23 and Figure 24 allows for the assessment of how these objectives are achieved, by illustrating the impact of minimizing the two risks on system design and operation. Consider that results on DAC are not visualized, since this technology and the commodities it consumes were not characterized by, respectively, technology material and energy SRs.

The shape of the fronts in Figure 22 reveals a trade-off between SR_M and SR_E. Indeed, the reduction of the former came at the expense of an increase of the latter, by reducing the renewable electricity production from onshore wind and solar PV, as depicted in Figure 23. This was due to the high technology SR of wind and battery storage systems, according to Figure 13. Although solar PV has a lower SR_t than other renewable energy sources, the reduction in LIB use (see blue line in Figure 23) limited the variable solar PV production. Solar PV and onshore wind were replaced by natural gas-based generation, mainly with CO_2 sequestration, due to the net-zero emission target. This, in turn, resulted in an increase in natural gas consumption and imports, which consequently increased SR_E, according to Figure 22.

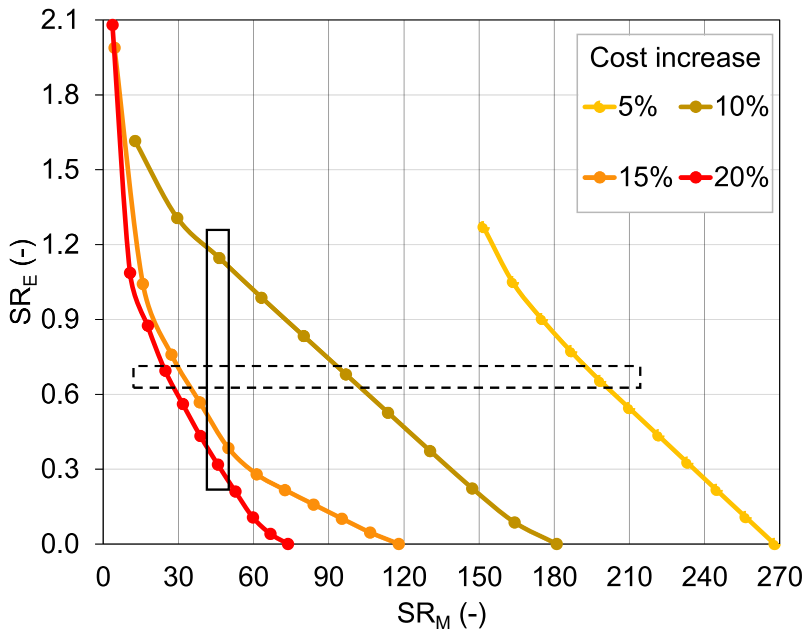

Figure 22. Pareto fronts of the MOO problem $min(SR_E, SR_M)$ for net-zero emissions and different total system cost levels.

The trade-offs between the SRs and total system cost were evaluated at fixed SR_E and SR_M. For a fixed energy SR of ~0.7 (see dashed black boxes in Figure 22, Figure 23, and Figure 24-top), an increase in extra cost from 5% to 10% resulted in reduction of SR_M from ~198.3 (yellow line) to ~105.2 (gold line). This corresponded to a reduction potential of ~13.5 units per b€ increase in total system cost. Then, higher cost increases further reduced 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 was associated with the substitution of wind energy with less risky technologies in material terms, such as solar PV and natural gas plants to allow for reductions of material SR without increasing both net emissions and energy SR, as shown in Figure 23. Particularly, when fixing the SR_E ~0.7, increasing the total system costs led to higher overall installed capacity (e.g., ~25% increase from 5% to 20% cost increase, see dashed black boxes in Figure 24-top). This increase was mainly driven by solar PV for two reasons. Firstly, a constant SR_E limited import possibilities as per Equation (14), limiting also natural gas plants investments due to a small domestic production (see the Supplementary Material of [3] for more details on domestic production potential). Secondly, reducing SR_M limited investments in technologies like onshore wind and LIBs, which have among the highest SR_t, according to Figure 13. This required higher PV capacities to replace wind energy and to compensate for lower PV utilization rates due to decreased LIB use. Moving to trade-offs between cost and SR_E at a fixed SR_M of around 46 (see solid black boxes in Figure 22, Figure 23, and Figure 24-top), an increase in extra cost from 10% to 15% reduced 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% implied 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 was associated with the substitution of natural gas generation – and hence captured CO_2 – with solar PV, as shown in Figure 24. Particularly, at SR_M around 46, moving from 10% to 20% increases saved ~5% of consumed – and imported – natural gas per b€ in total system cost.

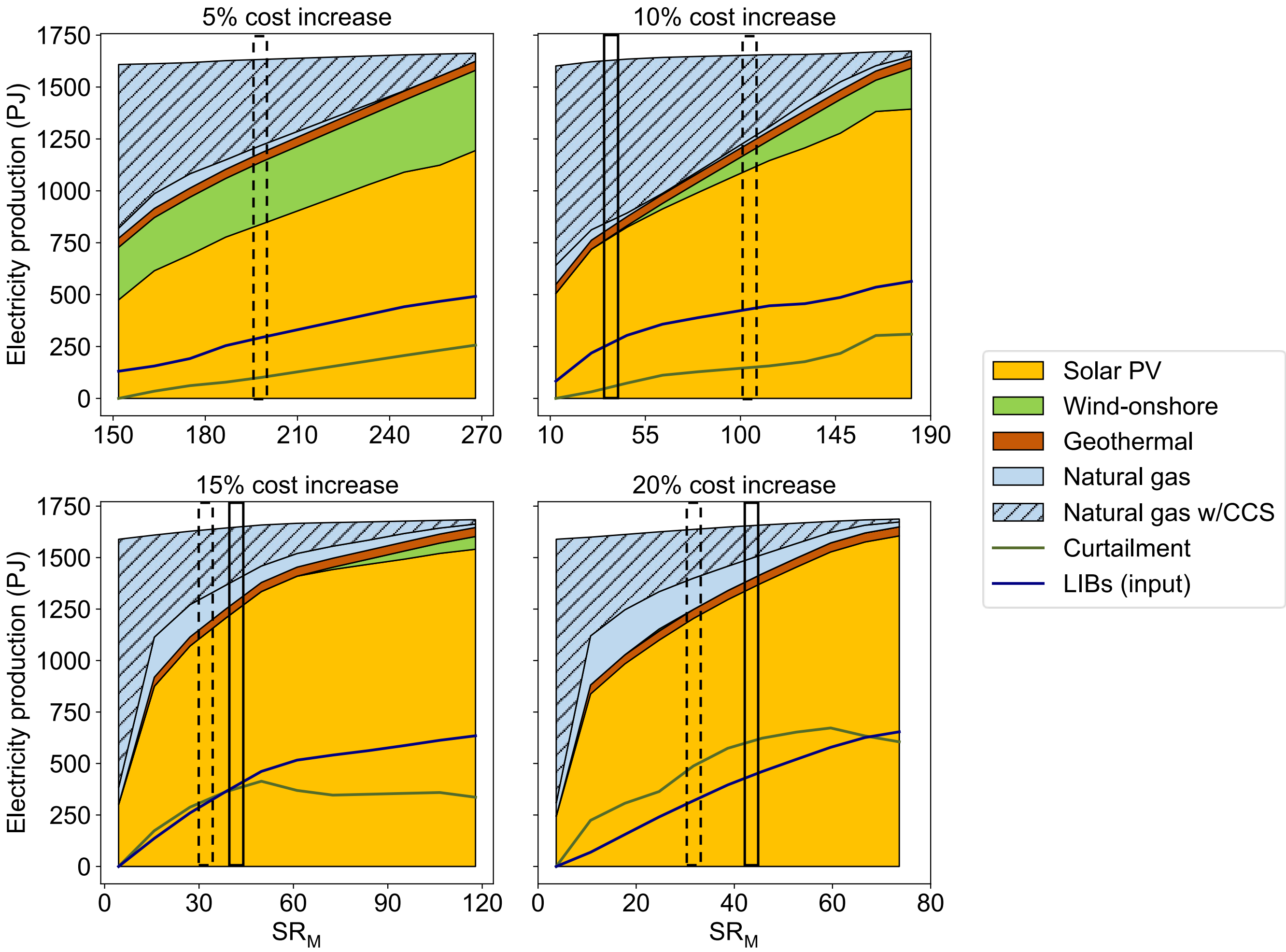

Figure 23. Electricity production by technology along the Pareto fronts across all the cost increase analyzed.

Now consider how the Pareto front boundaries – i.e. the lowest feasible energy and material SR at net-zero emissions – varied with the cost limits. With increasing costs, zero SR_E – i.e., zero energy imports, right boundaries in Figure 22, Figure 23, and Figure 24 – could be achieved at a progressively lower SR_M compared to the base case, which was ~450. For instance, the highest reduction compared to the base case (i.e., ~85%) occurred for a 20% cost increase (see red line in Figure 22). This was achieved by gradually phasing out wind energy in the electricity mix, as can be seen in the left-hand edges of the subfigures in Figure 23, from a share of almost 50% in the base case (see left-hand edge in Figure 21b). Moreover, the lowest SR_M at zero SR_E – occurring for a 20% cost increase – provided for the highest solar PV production, as can be seen in the rightmost edge of the 20% cost increase in Figure 23. This also came with the maximum curtailment of ~605 PJ (see dark green line in Figure 23), which was around 35% of the produced electricity. Unlike the other cost increases, the curtailment in the 20% case was equal to the battery storage utilization (see blue line in Figure 23), which was constrained by its high technology material SR. Moving towards the leftmost boundaries of the Pareto fronts in Figure 22, allowing for higher costs resulted into a lower SR_M minimum but at a higher SR_E maximum. This was reflected in a shift from a renewable-based to natural gas-based power mix, as shown in Figure 23. Particularly, the highest material SR reduction compared to the base case (i.e., almost 99%) occurred for 15% and 20% cost increases, as shown in Figure 22. This corresponded to the highest natural gas imports ~2380 PJ, with CO_2 captured reaching its maximum value of ~137 Mt.

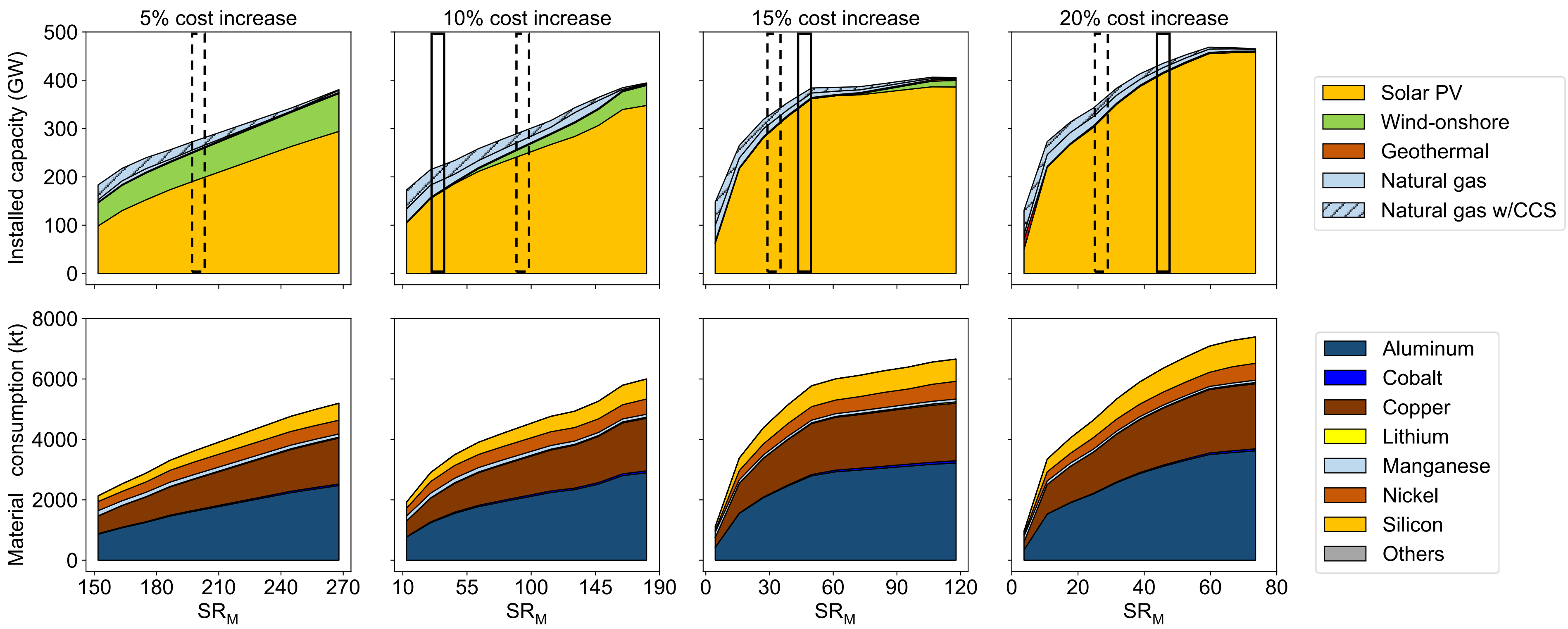

Figure 24. Installed capacity by technology (top) and material consumption by material (bottom), along the Pareto fronts across all the cost increases analyzed.

The electricity production mix in Figure 23 is reflected in the invested capacities shown in Figure 24-top. The reduction in SR_M was associated with a decline in total installed capacity, which was mainly due to lower investments in onshore wind and solar PV. Conversely, there was an increase in the capacity and utilization rate of natural gas plants: moving from the rightmost to the leftmost SR_M, these plants shifted from serving peak loads to baseload generation. Then, when allowing for higher total system cost, wind turbines were completely replaced by solar PV and natural gas plants. In particular, when the former reached the maximum installed capacity (i.e., between 290 GW and 460 GW), the installation for the latter was the lowest (i.e., between 3 GW and 6 GW), supporting the trade-off between the two SRs. Anyway, solar PV and natural gas plants are characterized by lower technology SR than wind turbines. Additionally, allowing higher costs led to investments in highly expansive CCUS technologies, which were essential for offsetting the residual CO_2 emissions from the combustion of natural gas. The latter, when imported, involved in turn a higher energy SR.

Finally, the CRM consumption is depicted in Figure 24-bottom. General trends followed installed capacities, as material consumption is directly proportional to it, as defined in Equation (1). Material consumption qualitatively and quantitatively reflected the MI data of Table 25. For instance, the consumption of aluminum, copper, and silicon was mainly driven by solar PV and natural gas plants. Instead, geothermal accounted for most of the nickel demand, despite a low installed capacity (i.e., ~2 GW on average). Other materials with consumption below 5 kt were 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 was much lower than other materials consumption. However, REEs strongly affected the material SR. Indeed, wind energy disappearance from 5% to 20% cost increase was associated with a SR_M decrease of about one order of magnitude. Lastly, the overall minimum ~0.9 Mt and maximum ~7.4 Mt consumption across all the scenarios occurred, respectively, at the leftmost and rightmost SR_M for the 20% slack: the overall MR of ~3.4 Mt in the base case was in the middle.

4.2.3 Discussion of results

The trade-off between energy and material SRs is suggested already by evaluating ex-post the results of the minimization of total system cost and CO_2 emissions in Section 4.2.1, which represents a proxy of the state of the art presented in Section 1.2. Shifting from natural gas-based to renewable-based electricity generation led to a higher material SR and a lower energy SR. Concerning the former, the highest contribution to the system risk came from wind turbines, due to the requirement of REEs. This is in accordance with the outcomes of the ex-post assessment in Approach 2 – presented in Section 4.1.3 – where wind turbines contributed to most of the material SR associated with power and battery storage sectors. 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 the risks in energy planning. Conversely, minimizing both material and energy SRs under cost and emission constraints, as it is possible with the novel framework proposed in the third approach, provides actionable insights for managing these risks.

The lack of previous studies employing an ex-ante approach makes a quantitative comparison difficult. However, the policy-relevance of the results can still be discussed. Achieving full decarbonization of the Italian power sector while reducing material SR requires accepting higher energy SR and total system costs. In particular, the rightmost regions of $min(SR_E, SR_M)$ comply with stated and announced Italian energy policies. Indeed, the latter advocate for a marginal role for natural gas-based generation of up to maximum 5% in the electricity mix [103], [143]. Overall, this is not the case when aiming to further reduce SR_M. This implied the increase in SR_E and led to the following results. First, investments in wind energy and batteries were reduced, until a complete absence from the power mix, while they play a central role in the announced policies [103]. This was associated with increased solar PV investments – up to a maximum of ~460 GW, in line with the most recent targets [143] – and higher curtailment levels. Also, higher investments in natural gas plants and gas and CCUS occurred, whose maximum values reached around 2400 PJ of imported natural gas and 140 Mt of captured CO_2. The former is close to 2022 imports [142] and nearly double the latest targets [143]. The latter is almost twice the 2050 target of equivalent CO_2 emissions to be compensated through CCUS [103]. Also, the absence of nuclear power in the results contrasts with the latest debates at the EU [156] and national [157], [158] level, offering insights into its apparent limited economic and SR competitiveness in achieving net-zero emissions. Lastly, overall CRM demand increased from leftmost natural-gas based mixes to rightmost renewable-driven systems by a factor of two to almost eight, which is consistent with other studies estimating the potential future MR in decarbonized power sectors [1], [2]. 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.

Three main factors contributed 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 CRM consumption, is not cost-effective and limited overall. Third, clean energy technologies currently on the market consume many CRMs. The general trends and measures mentioned above can provide insights on making balanced and conscious trade-off decisions in energy system planning. Moreover, the insights can be generalized to other case studies at least at EU level, since the Italian energy system planning is strongly linked to the EU framework. To manage material and energy SRs, strategies should include diversifying supply chains and technology mixes, by reducing import dependency and supporting investments in domestic supply chains. These strategies might be effectively assessed using the MOO proposed in the third approach. 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 [2]) or the evaluation of optimal incentives to support low-carbon solutions with lower associated supply chain risks than traditional renewable sources, like solar and wind energy. For instance, this might include domestic sourcing of biofuels and hydrogen or investing in nuclear-based generation.

However, as for the other approaches, limitations concerning methodology and case study reduce the comprehensiveness of trade-off results. Methodology-related limitations cover two aspects. First, the competition between technologies in material SR terms does not cover the whole supply chain steps (e.g., manufacturing of components) and risks (e.g., exposure to ESG and climate risks). The first lack mainly favors solar PV over other clean energy technologies, by making it an optimal choice across the results. The second lack favors cobalt and nickel [14] over other CRMs and reduce the technology material SR of natural gas plants (see Appendix G). Instead, the second aspect concerns the impossibility of controlling and managing directly the concentration along the supply chains of both energy commodities and CRMs. This limits the variety of optimal configurations of the Italian power sector that might be derived from the MOO. The same limitation (i.e., variety of optimal configurations) is likely to be related to some choices for the case study, too. First, studying two MOO problems instead of a single problem with more than two objective functions reduces computational burden and complexities, at the expense of more comprehensive Pareto fronts. Then, the use of a power sector model with a low time resolution does not allow to properly consider: the sectorial competition in terms of SR (e.g., cars and wind turbines concerning REEs), which is instead captured by the first and second approaches; the power sector operations, which might be one of the reasons behind the complete absence of nuclear power plants in the results.

Chapter 5

Conclusions and perspectives

This thesis presents three approaches for integrating CRM aspects into energy system modeling. This meets the growing interest among stakeholders in accessing more holistic energy system models that can provide insights into supply chain risks associated with clean energy technologies and the materials they require. In this regard, existing studies have addressed this concern mainly ex-post and turned out to be limited to represent policy interest in reducing the material SR of the energy transition. In particular, they lack: energy scenarios including ex-ante CRM supply disruption constraints; the assessment of material SR at energy-system level; the analysis of trade-offs between the energy and material SRs due to the transition from fossil-fuels to low-carbon alternatives.

Aiming to address these research gaps, the three approaches were developed for implementation in open-source ESOMs, which have emerged in recent years as tools to improve the capability of the traditional energy system planning frameworks. Also, their development occurred independently of the ESOM to which they were subsequently applied. The choice fell on TEMOA, which is considered among the most mature and well-established open-source ESOM. In particular, the case studies were built upon the multi-sectorial TEMOA-Italy model. The Italian energy system was considered particularly illustrative, since the Italian CRM legislation is still at a preliminary stage and does not include specific links to the energy transition targets, and vice versa.

The first approach concerns the development of material supply disruption constraints to be included in ESOMs. They were integrated by means of a material value chain, which involves the supply of the materials and their need for technology manufacturing. The value chain was included in the dedicated TEMOA-Italy-materials version and several decarbonization scenarios were developed by considering possible supply disruption causes, such as economic, geopolitical, and physical ones. The second approach concerns the ex-post application of a material SR indicator at technology level. It was derived based on established literature, by including supply concentration, import reliance, political stability, and material intensity of the CRMs required by technology. The indicator was then applied to the results of the first approach. They are aligned with earlier studies, by highlighting how the decarbonization – without supply disruption – requires much more CRMs (~4 times) and accepting a higher SR (~17 times) than a baseline evolution. However, unlike existing studies, the two approaches have provided more comprehensive insights, since they allow to assess the feasibility of the energy transition in case of CRM unavailability, by evaluating the related SR with a systemic perspective. First, the net-zero emission target was still achieved across the supply disruption constraints. While CRM consumption and the associated SR almost halved, the total system cost increased by almost 4% (i.e., ~170 b€). Indeed, the constraints on CRMs like cobalt, lithium, nickel, and REEs mainly limited LIB and BEV penetration, favoring low-carbon alternatives which are more expensive, but require less CRMs, such as VRFBs, FHEVs fueled by low-carbon fuels, and FCVs. Second, BEVS, and more in general cars, were major contributors to total system CRM consumption and material SR. These results strongly fit into the recent discussions on revising the binding EU policies on road transport (i.e., ban on sale of CO_2 emitting vehicles from 2035). Third, higher material consumption did not necessarily imply higher material SR. Materials like cobalt, lithium, and REEs, and technologies like wind turbines, provided the highest contribution to the total system material SR, despite their much lower contribution to total system CRM consumption. These outcomes have identified how energy systems like the Italian one might adapt to CRM supply disruption, by suggesting which materials and technologies influence more the total system consumption and SR. However, they lack actionable insights into minimizing the SR, as it is possible, instead, by means of the third approach.

The third approach concerns the first-of-a-kind integration in ESOMs of material and energy SR objective functions. The material SR function is the same as the second approach, while the energy one was consistently derived based on established literature. Then, the functions were employed in a MOO with AUGMECON, which is a widely consolidated multi-objective framework. However, it is worth pointing out that the SR objective functions were developed independently of the MOO method adopted. The decarbonization of the Italian power sector by 2050 was used as a case study. First, material and energy SRs were evaluated ex-post in a MOO of total system cost and CO_2 emissions, revealing that while decarbonizing the electricity production reduced the energy SR, it increased the material SR and the total system cost. These results can be considered a proxy of the capability of the state of the art, which can only offer limited guidance on efficient means and costs of reducing both these risks in energy planning. Building on this, four Pareto fronts were generated in MOO problems that included ex-ante material and energy SR as objective functions. These problems involved a net-zero emission constraint and varying upper limits on total system cost. The results have highlighted a significant trade-off between the two risks, revealing that minimizing the material SR implies a higher energy SR. First, reducing investments in wind turbines and batteries led to greater reliance on natural gas generation with carbon capture, which increased both natural gas imports and energy SR. 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 latter involved maximum values that are almost twice the targets of the most recent Italian energy policies. This suggests that managing trade-offs between material and energy SR should require a balanced approach in energy transition strategies. Then, the results also have indicated diminishing marginal utility in reducing SRs as total system costs rise. An additional cost of up to 15% resulted in substantial further reductions in SRs, but beyond this point, significant gains can only be realized in the very low energy SR range. Finally, REEs – which are required by wind turbines – had the most significant impact on material SR, despite their much lower consumption levels than other materials. This aligns with the outcomes from the application of the first and second approaches.

The three approaches presented in this thesis provide a more holistic framework than traditional ESOMs, allowing for more informed energy system planning. Unlike earlier studies, the approaches allow the underlying energy system to adapt and mitigate CRMs supply chain risks. The outcomes – summarized above – have highlighted the extent to which the approaches can support the decision-making process behind combined CRMs and energy transition policies. The strategies that can be derived include the diversification of supply chains and technology, as well as the reduction of import dependency and supporting domestic supply chains. Credibility, reproducibility, and transparency of the approaches are ensured using established and referenced methods and tools, as well as making openly available all data, assumptions, and results. Nevertheless, further improvements are possible, as discussed below.

The following perspectives were identified, which aim to address the limitations associated with both methodology and case studies. First, the three approaches could be improved by covering aspects that are missing in their current implementation. The material value chain proposed in the first approach can be extended to include more steps. Depending on the scope of the analysis, the supply could include more than one primary supply process, such as, e.g., different supplier countries or distinguishing between domestic supply and import. The former would allow to account for the regional dimension of the SRs. However, when considering them endogenously as in Approach 3, non-linear problems would be solved, increasing the complexity and computational burden of the analysis. Instead, the latter would allow to assess the effects of policy incentives to stimulate domestic RM supply chains, by differentiating them from the import in term of supply availability and/or supply costs. Then, recycling can be modeled by using RM feedback loops or dedicated recycling processes. It is worth pointing out in this regard that such integration would not affect the application of Approach 2 and Approach 3 at all. Also, an exogenous demand can be fixed as in the case of end-use service demands typically modeled in ESOMs, to account for the consumption by other sectors that might not be explicitly modeled in the ESOM. Finally, the techno-economic characterization typically adopted for energy technologies in ESOMs could be also used for RM supply processes, including energy requirement. However, attention must be paid to possible double counting of costs, since the RM price might be already included in the capital cost of technologies [39]. The other – currently missing – steps of the clean energy technology supply chain should be included in the technology material SR definition. For technologies like solar PV, the manufacturing and assembly of components present higher SR than the primary supply of the RM required [1]. Moreover, different ways to aggregate the SR of single materials into the technology material SR can be explored. Examples are a cost-based aggregation or considering only the CRMs with the highest risk. In this regard, few studies on technology material SR are available in the existing literature. Therefore, a comparison between different metrics might be beneficial to enhance the state of the art. Moving to the third approach, more exhaustive trade-off results might be obtained by simultaneously minimizing SRs and other objectives such as costs and emissions, especially if a techno-economic characterization of material supply chains is included in the ESOM. This is necessary to extend the current SR metrics to other critical aspects of clean energy technology supply chains, such as social and environmental factors [14].

Concerning the case studies, the CRM requirement in TEMOA-Italy-materials could be extended to other technologies and sectors. Electricity networks, freight transport, and nuclear power plants are the great absentees. In this regard, the use of higher spatial and time resolutions than the ones adopted in this thesis are essential to better capture power sector operation dynamics that might be affected by material supply chain bottlenecks, including: nuclear power plant dispatch (low CRM requirement), batteries and vehicle-to-grid (high CRM requirement), and curtailment (associated with low usage of batteries). In addition, more policy-relevant findings for both natural gas with CCUS could be derived from the third approach by using a multi-sectorial model – like TEMOA-Italy-materials – capable of capturing sector coupling possibilities that strongly affect the CCUS adoption. Also, other RMs might be involved in the supply disruption constraints. For instance, despite vanadium, required by VRFBs, and platinum, required by FCVs, having a high material SR, their availability was not limited at all. Accounting for potential shortages of such materials would allow to extend the findings on competition within car and electricity storage sectors, to assess, e.g., to which extent other technologies might penetrate in the system (e.g., pumped hydro storage, flow batteries, etc.).

Finally, uncertainty analysis appears useful due to the many input data and assumptions that are needed for the application of all three approaches. This might be the case of the present and projected values of the parameters involved in the calculations across the approaches, such as the MI of technologies and market shares and political stability of the supplier countries of RMs and energy commodities. The latter is an alternative more easily implementable than the endogenous modeling of the supply by country, which was mentioned before. Alternatively, structural uncertainties, e.g. in the form of interests and criteria that cannot or are not captured by the model equations and data, could be addressed by Modeling to Generate Alternatives [159]. 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 and operation [160].

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Appendix A

This appendix provides an overview of the integration of hydrogen and synfuel modules in TEMOA-Italy. The overview is based on [111] and [161], which include a detailed description of the technological modules alongside a scenario analysis. Additionally, there is also a mention of the dynamic emission accounting method proposed in [72] and [112], which allowed the modeling of fossil- and low-carbon fuel mixes. Consider that the 2024 version of the modules includes an update compared to the first update presented in the sources mentioned above. In particular, the 2024 version does not include the distinction between size and location of hydrogen production processes that was previously considered.

The hydrogen module of TEMOA-Italy is schematized in Figure 25. For graphical reasons, single technologies are aggregated into modules. Then, the interconnection between the supply- and demand-side sectors is visualized through energy commodities and arrows representing the direction of the flows. The module consists of production, distribution and storage, and consumption steps covering a wide spectrum of technologies, which are listed in Table 11 alongside data sources. Hydrogen can be produced from fossil fuels (i.e., grey hydrogen), fossil fuels with CCS (i.e., blue hydrogen), renewables (i.e., green hydrogen), and electricity (i.e., yellow hydrogen, that might be green in case of renewable-based electricity). Then, different storage (i.e., tanks and underground) and delivery options are available before consumption in all the sectors of the Italian energy system. Indeed, hydrogen can be consumed in blends with methane or pure. The latter includes the consumption by stationary fuel cells, transport and industry sub-sectors, and for synfuel production.

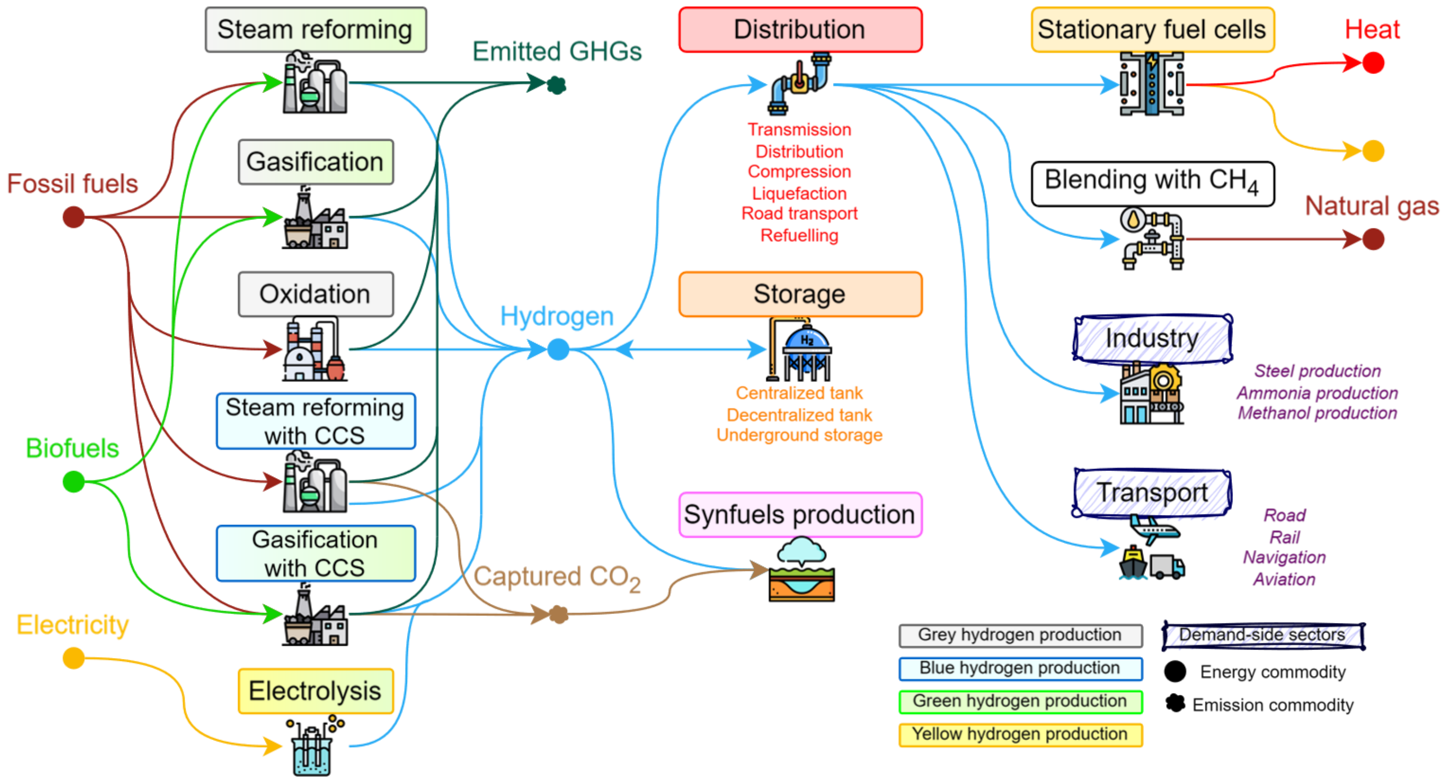

Figure 25. Scheme of the hydrogen value chain of TEMOA-Italy.

Table 11. List of the technologies included in the hydrogen module of TEMOA-Italy.

Step (production source/sector)		**Technology/hydrogen type**	**Source**
Production	Fossil	Natural gas steam reforming (w/ and w/o CCS)*	[162]
		Coal gasification (w/ and w/o CCS)	
		Heavy fuel oil partial oxidation	
	Biomass	Biomass steam reforming	
		Biomass gasification (w/ and w/o CCS)	
		Ethanol steam reforming	
	Electrolysis	Alkaline	[163]
		Proton exchange membrane	
		Solid oxide	
		Anion exchange membrane	[164]
Storage		Centralized tank	[165]
		Decentralized tank	
		Underground storage	
Distribution		Blending with natural gas	
	Residential	Gas	
	Commercial		
	Industry		
	Transport	Gas and liquid	
Consumption	Synfuels production	Hydrogenation (production of synmethane, synmethanol, syndiesel, synkerosene)	
	Power	PEMFC	
	Residential	PEMFC – mCHP**	[166]
	Commercial		
	Industry	Ammonia synthesis via electrolysis	[167]
		Methanol synthesis via electrolysis	
		Direct reduced iron	[168]
	Transport	Road vehicles	[114]
		Aviation	[169]
		Navigation	
		Rail	[170]

* w/ and w/o refer to, respectively, “with” and “without”.

** mCHP refers to micro-combined heat and power technologies.

The hydrogen-based production of synfuels from hydrogen represents a sector coupling possibility between the hydrogen and the CCUS modules. The latter is schematized in Figure 26. For graphical reasons, single technologies are aggregated into modules. Then, the interconnection between the supply- and demand-side sectors is visualized through energy commodities and arrows representing the direction of the flows. The sequestration of CO_2 can occur in plants equipped with sequestration units: refineries (i.e., upstream sector), hydrogen production processes, power plants, and some industry sub-sectors, such as chemical, iron and steel, and non-metallic mineral production. Moreover, atmospheric CO_2 can be directly captured through DAC, which is a system that leads to negative net emissions [171], [172]. Sequestrated CO_2 can be stored in depleted gas fields or employed in the production of synfuels, which include synthetic methane, methanol, diesel fuel, and kerosene. These synfuels can then be blended with their fossil counterparts prior to utilization in conventional fossil-based technologies (e.g., natural gas boilers or gasoline- and gas oil-based transports).

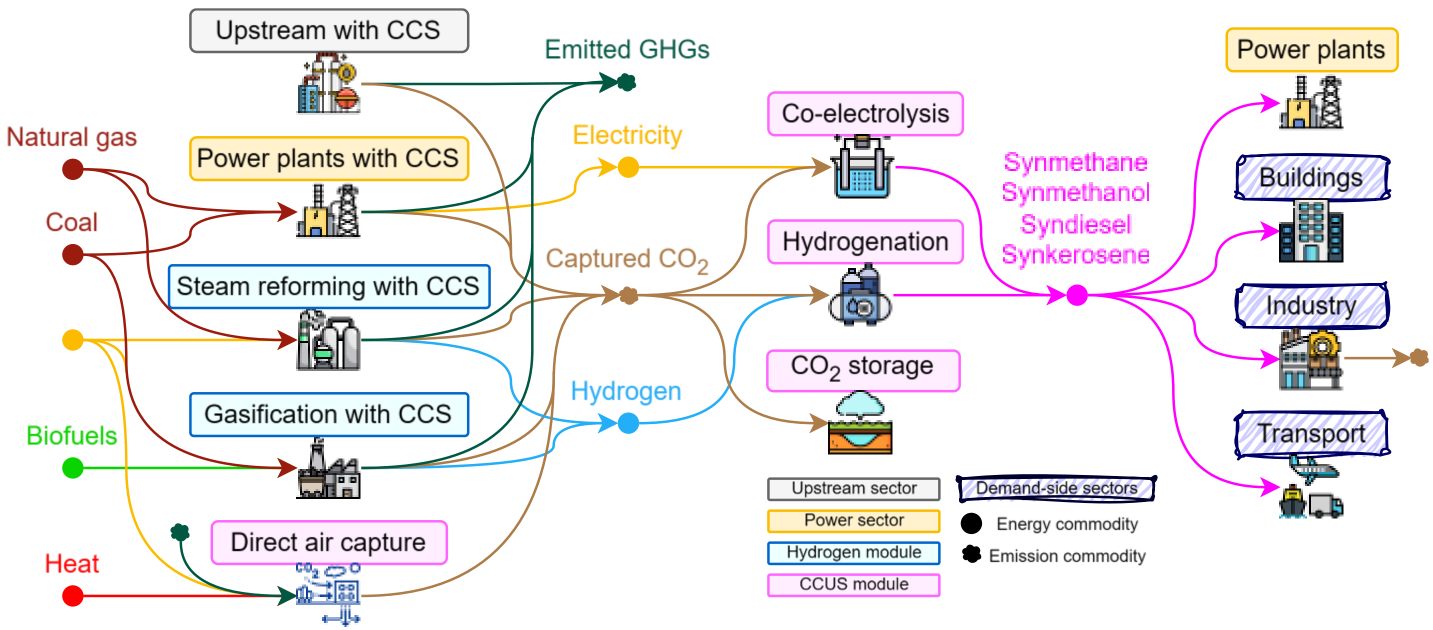

Figure 26. Scheme of the CCUS module of TEMOA-Italy.

In addition to hydrogen and synfuels, biofuels can also be blended with fossil fuels in TEMOA-Italy. However, the modeling of blending required the extension of the methodology typically adopted in ESOMs to calculate emissions from fuels combustion. The latter includes emission factors which are based on a given static fuel composition (referred to as commodity emission factors) [173], [174]. Therefore, these static emission factors are not capable of accounting for the avoided emissions from the low-carbon fraction in blends with fossil fuels, with a variable composition across the model time horizon. Indeed, the combustion of low-carbon fuels such as hydrogen, synfuels, and biofuels is not considered to affect the atmospheric CO_2 concentration, since: hydrogen does not contain any carbon atoms; synfuel combustion emits about the same amount of CO2 needed to produce them [162]; a null climate change potential is typically associated with biofuels [175]. To address this shortcoming, a dynamic CO_2 emissions accounting methodology was developed as described in [72] and [112], and was applied to TEMOA-Italy. The methodology is dynamic in that it provides an overall fuel emission factor that is dependent on the fuel composition. In particular, the overall emission factor is made of two parts: the static commodity emission factor, which is used to calculate the emissions as if the fuel was a purely fossil fuel; negative emission factors (referred to process emission factors), which are proportional to the low-carbon fuels fractions and are used to calculate the corresponding avoided emissions. All the possible blends between fossil and low-carbon fuels in TEMOA-Italy are listed in Table 12. Moreover, minimum and maximum blending shares are considered based on dedicated regulatory frameworks (e.g., renewables transport fuels [176], [177]) and technical constraints (e.g., injection of hydrogen in the methane transmission and distribution infrastructures [178]), respectively. Consider that conventional fossil-based technologies can be used without the need for retrofitting below certain low-carbon fuels mixing fractions.

Table 12. List of blending possibilities between low-carbon and fossil fuels by sector in TEMOA-Italy.

		Mixable low-carbon fuels							
Sector	**Fossil fuel**	Hydrogen	Biomethane	Biodiesel	Bioethanol	Synmethane	Syndiesel	Synkerosene	Synmethanol
Power	Natural gas	x	x			x			
Agriculture	Natural gas	x	x			x			
	Gas oil						x		
	Gasoline								x
Residential	Natural gas	x	x			x			
Commercial	Natural gas	x	x			x			
Industry	Natural gas	x	x			x			
	Oil						x	x	
	Naptha								x
Transport	Natural gas	x	x			x			
	Gas oil			x			x		
	Gasoline				X				x
	Gasoline for aviation								x
	Jet kerosene							x	

Appendix B

This appendix provides an overview of the update of technology-specific hurdle rates (HRs) of TEMOA-Italy. The overview is based on [115] and [179], which include a detailed description of the methodology used to carry out the update, and on [116], which includes a sensitivity analysis on the updated HRs.

Two strategies were adopted to find appropriate HRs for the technologies typically included in an ESOM instance. First, the weighted average cost of capital (WACC) methodology was chosen as a reference. This well-established method to calculate discount factors is described in [180]. Second, in case of lack of the data needed to define the WACC, the existing literature was extensively studied to find evidence of adopted HRs or, alternatively, formulating own assumptions. The updated HRs are then listed by technology in Table 13. The cost of capital is considered an effective indicator for assessing investment risks as it represents a weighted average of the cost suffered by a company to finance a project, given by equity and debt. Moreover, it has been widely used in the energy system modeling field (see e.g., [181] and [182]). WACC is calculated as a weighted average between the cost of debt and equity, that indirectly include risks associated with technologies investment, as detailed in [115]. This methodology was used to compute the HRs of industry and fossil-based transport technologies (the latter are referred to as "traditional" in Table 13 for the navigation and aviation sub-sectors).

Concerning electricity production options, due to the lack of some parameters involved in the cost of capital computation, process-specific values were adopted from an analysis conducted on WACCs in Italy in 2015 [183]. Moreover, the abovementioned parameters are usually taken from listed companies, and such values are not yet widely available for the hydrogen supply chain. Therefore, HRs for hydrogen production technologies were set equal to the assumption made in [184] (where global average HRs are provided): since that report only considered the production technologies, the value was also assumed for hydrogen storage and utility-scale FCs. Similar difficulties were encountered with hybrid, electric, and hydrogen vehicles. For this reason, assumptions based on the corresponding traditional technology options were formulated. Specifically, the HR of electric trucks was assumed to be equal to 10%, which is slightly higher compared to ICEVs, to represent the lower technology readiness level. Instead, the HR of FCVs was assumed to be equal to 15%, which is significantly higher compared to ICEVs, to consider the current absence of an infrastructure for hydrogen distribution for road transports in Italy [185]. Assuming higher HRs for electric and hydrogen vehicles is consistent with the approach proposed in [186], also considering the limited access to capital and the current lack of infrastructure for the spreading of hydrogen-based technologies. Concerning the HRs for hydrogen, ammonia, and methanol non-road transport systems (i.e., railways, aviation, and navigation, and referred to as “innovative” in Table 13) the values from the TIAM-Grantham model [186] were used.

Table 13. List of the updated hurdle rates and the associated source by technology.

Sector	Sub-sector	Technology/type	Source	HR
Power	Power plants	Solar PV	[183]	5.7 %
		Onshore wind	[183]	7.6 %
		Offshore wind	[183]	8.6 %
		Geothermal	Assumption	5.2 %
		Hydropower	[183]	5.2 %
		Bioenergy	[183]	6.7 %
		Fuel cell	[184]	8.0 %
		Coal and oil	[183]	6.2 %
		Natural gas	[183]	2.7 %
	Storage	Li-ion batteries	Assumption	8.0 %
Hydrogen	Hydrogen production		[184]	8.0 %
		with CCS	Assumption	10.0 %
	Storage	Tanks	Assumption	8.0 %
CCUS		Synfuels production	Assumption	10.0 %
		DAC	Assumption	10.0 %
Industry	Chemicals	High value chemicals	WACC	7.9 %
		Ammonia	WACC	10.0 %
		Methanol	WACC	9.2 %
		Chlorine	WACC	8.4 %
		with CCS	Assumption	15.0%
	Iron and steel		WACC	9.5 %
		with CCS	Assumption	15.0 %
	Non-ferrous metals	Aluminum	WACC	7.4 %
		Copper	WACC	9.4 %
		Zinc	WACC	9.8 %
	Non-metallic minerals	Cement, lime, ceramics	WACC	9.4 %
		Glass	WACC	6.5 %
		with CCS	Assumption	15.0 %
	Pulp and paper		WACC	9.9 %
Transport	Two wheelers	ICEs	WACC	4.9 %
		Electric	Assumption	10.0 %
	Cars	ICEs, hybrid, electric	WACC	7.3 %
		Fuel cell	Assumption	15.0 %
	Light commercial vehicles	ICEs, hybrid, electric	WACC	6.0 %
		Fuel cell	Assumption	15.0 %
	Buses Medium trucks Heavy trucks	ICEs	WACC	6.0 %
		Electric	Assumption	10.0 %
		Fuel cell	Assumption	15.0 %
	Rail	ICEs, electric	WACC	4.2 %
		Fuel cell	[186]	32.0 %
	Navigation	Traditional	WACC	5.8 %
		Innovative	[186]	32.0 %
	Aviation	Traditional	WACC	6.0 %
		Innovative	[186]	32.0 %

Appendix C

This appendix provides an overview on how the RM value chain described in Section 2 was integrated in the dedicated TEMOA-Italy-materials version [82], which was used for the development and testing of the first approach. The overview is based on the Supplementary Material of [3] and [79].

The parts related to the RM value chain in the TEMOA-Italy-materials version that are additional compared to the original framework [84] are reported in Table 14. The RM consumption in Equation (1) involved the definition of the MI parameter "MaterialIntensity" and of the "MaterialConsumptionConstraint" constraint. Then, the RMs balance in Equation (2) is ensured through the "MaterialBalanceConstraint". Finally, the RMs maximum availability in Equation (3) involved the definition of the "MaxMaterialReserve" parameter, which was used to define the supply disruption scenarios in [79], and the "MaxMaterialReserveConstraint" constraint. A comprehensive overview of the content and structure of the TEMOA files that were affected by the RM value chain-related changes is provided in Appendix E.

Table 14. List of the raw material value chain-related parts of TEMOA-Italy-materials.

TEMOA file	Raw material consumption (Equation (1))	Raw material balance (Equation (2))	Raw material availability (Equation (3))
database.sql*	- *MaterialIntensity (input table)* - *Output_VMat_Cons (output table)*		*MaxMaterialReserve (input table)*
temoa_config	- *MaterialIntensity* - *commodity_material*		*MaxMaterialReserve*
temoa_model	- *M.commodity_materials* - *M.MaterialIntensity* - *M.V_MatCons* - *M.MaterialConsumptionConstraint*	*MaterialBalanceConstraint*	- *M.MaxMaterialReserve* - *M.MaxMaterialReserveConstraint_rt* - *M.MaxMaterialReserveConstraint*
temoa_rules	*MaterialConsumption_Constraint*	*MaterialBalance_Constraint*	*M.MaxMaterialReserve_Constraint*
pformat_results	Extract and save m.V_MatCons		

* database.sql refers to the generic input/output database.

Appendix D

This appendix provides details on data, sources, and assumptions adopted to define the MI of technologies in TEMOA-ITALY-materials [82], which was used for the development and testing of the first and second approaches. The appendix is based on the Supplementary Material of [79]. All the data refer to present values, thereby neglecting potential MI improvements over time. Moreover, the technology material SR of power sector technologies is also reported after the discussion on MI. While the MI of power sector technologies (reported in Table 15) was directly taken from literature, some elaborations were needed for the other technologies involved.

Battery storage

The MI of battery storage technologies is reported in Table 16. The one of LIBs is based on a JRC report on the potential future RM demand from clean energy technologies [1]. In particular, the MI was estimated as the ratio between projections of the RM demand in EU for LIBs and their installed capacity.

Instead, the vanadium requirement for VRFBs manufacturing was taken from [187]. Then, the MI for copper and graphite was estimated starting from the MI for vanadium and the typical RM composition of VRFBs provided by [132] (i.e., 83% of vanadium, 8% of graphite, and 9% of copper in weight).

Hydrogen production

The MI of electrolyzers reported in Table 17 were originally provided in unit mass per unit energy by [73]. Since the RM requirement of technologies in TEMOA-Italy-materials is evaluated from the installed capacity (see Equation (1)), the original data $MI_{elcz}^{original}$ in GW/PJ_a were converted in unit mass per unit capacity (i.e., yearly energy production in PJ_a for the electrolyzers) as in Equation (19). In particular, the full load hours of 5000 h assumed by [73] and the conversion factor 0.0317 GW/PJ_a were used.

$$MI_{elcz}\left(\frac{t}{PJ_a}\right) = MI_{elcz}^{original} \cdot 5000 \cdot 0.0317 \tag{19}$$

Transport (cars)

The MI of cars reported in Table 18 were originally provided in unit mass per vehicle. As for the electrolyzers, a conversion was needed to refer the MI to the unit capacity of cars, which is billions vehicle-kilometers *bvkm* (i.e., billions of kilometers driven by all the cars of the energy system under analysis) in TEMOA-Italy-materials. The original data were then divided by the average annual travelled kilometers by cars, which is around 11771 km for Italy [188].

Concerning hybrid vehicles, only values for plug-in-hybrid vehicles were found. However, since the latter are not included in TEMOA-Italy-materials, they were used as basis to estimate the MI of FHEVs. In particular, the RMs required for the manufacturing of motor and battery of plug-in-hybrid vehicles were scaled proportionally to the size of those components, by considering the following average sizes from [189] and [190]: electric motor of 48 kW and a LIB of 12.5 kWh for plug-in-hybrid vehicles; electric motor of 32 kW and a LIB of 1.5 kWh for FHEVs.

Table 15. Material intensity of power sector technologies of TEMOA-Italy-materials.

Technology	Material	$f_{m,t}$ $(\frac{t}{GW})$	Sources
Solar PV	Aluminum	7.5×10^3	[2], [26], [62], [130]
	Copper	4.6×10^3	
	Gallium	4.0×10^{-2}	
	Silicon	3.8	
Onshore wind	Aluminum	1.3×10^3	
	Boron	9.4×10^{-1}	
	Copper	1.8×10^3	
	Dysprosium (HREE)	4.7	
	Manganese	7.8×10^2	
	Neodymium (LREE)	4.0×10^1	
	Nickel	4.0×10^2	
	Praseodymium (LREE)	5.8	
	Terbium (LREE)	1.1	
Offshore wind	Aluminum	6.7×10^2	
	Boron	5.3	
	Copper	2.7×10^3	
	Dysprosium (HREE)	1.5×10^1	
	Manganese	7.9×10^2	
	Neodymium (LREE)	1.6×10^2	
	Nickel	2.7×10^2	
	Praseodymium (LREE)	3.0×10^1	
	Terbium (LREE)	6.1	
Geothermal	Nickel	1.2×10^5	[2], [120]
Hydropower	Copper	1.0×10^3	
	Manganese	2.0×10^2	
	Nickel	3.0×10^1	
Bioenergy	Copper	2.3×10^3	
	Titanium	4.0×10^2	
Hydrogen solid oxide FC	Lanthanum (HREE)	2.0×10^1	[73], [132], [90]
	Nickel	2.0×10^2	
	Yttrium (HREE)	5.0	
Coal	Cobalt	2.0×10^2	[130], [132], [191]
	Copper	1.2×10^3	
	Nickel	7.2×10^2	
Natural gas	Copper	1.1×10^3	
	Nickel	1.6×10^1	
Coal and natural gas w/ CCS	Cobalt	7.5	
	Copper	6.9×10^2	
	Manganese	3.8×10^3	
	Nickel	1.2×10^3	
	Niobium	1.0×10^2	
	Vanadium	1.0×10^2	

Table 16. Material intensity of storage technologies of TEMOA-Italy-materials.

Technology	Material	$f_{m,t}$ ($\frac{t}{GW}$)	Sources
LIBs	Aluminum	1.4×10^{4}	[1]
	Cobalt	6.2×10^{2}	
	Copper	5.1×10^{3}	
	Fluorspar	2.3×10^{1}	
	Graphite	7.3×10^{3}	
	Lithium	8.7×10^{2}	
	Manganese	7.0×10^{2}	
	Nickel	2.0×10^{3}	
	Phosphorus	4.1×10^{3}	
VRFBs	Copper	2.2×10^{3}	[187], [132]
	Graphite	2.0×10^{3}	
	Vanadium	2.0×10^{4}	

Table 17. Material intensity of electrolyzers technologies of TEMOA-Italy-materials.

Technology	Material	$f_{m,t}$ ($\frac{t}{PJ_a}$)	Sources
Alkaline-EC	Nickel	1.4	[73]
PEMEC	Iridium	1.3×10^{-4}	
	Palladium	3.5×10^{-4}	
	Platinum	3.5×10^{-3}	
Solide oxide-EC	Lanthanum (HREE)	3.2×10^{-2}	
	Nickel	2.2×10^{-1}	
	Yttrium (HREE)	4.0×10^{-3}	

Table 18. Material intensity of cars technologies of TEMOA-Italy-materials.

Technology	Material	$f_{m,t}$ ($\frac{t}{bvkm}$)	$f_{m,t}$ ($\frac{t}{vehicle}$)	Sources
ICE vechicles	Copper	1.9×10^{3}	34	[2], [188]
	Manganese	9.5×10^{2}		
BEVs (FHEVs)	Cerium (LREE)	1.0×10^{-2}	222 (187)	[2], [130], [188], [189], [190]
	Cobalt	1.1×10^{3} (4.7×10^{1})		
	Copper	4.5×10^{3} (2.0×10^{3})		
	Dysprosium (HREE)	1.4×10^{1} (7.2)		
	Europium (HREE)	2.0×10^{-2} (1.0×10^{-2})		
	Gadolinium (HREE)	1.0×10^{-2} (1.0×10^{-2})		
	Gallium	8.0×10^{-2} (7.0×10^{-2})		
	Germanium	1.0×10^{-2} (4.0×10^{-3})		
	Graphite	5.6×10^{3} (1.1×10^{2})		
	Lanthanum (HREE)	5.9×10^{-1}		
	Lithium	7.6×10^{2} (4.6×10^{1})		
	Magnesium	1.7×10^{1}		
	Manganese	2.1×10^{3} (9.9×10^{2})		
	Neodymium (LREE)	4.7×10^{1} (6.8×10^{1})		
	Nickel	3.4×10^{3} (2.6×10^{2})		
	Palladium	1.0×10^{-2}		
	Praseodymium (LREE)	6.5		
	Tantalum	6.8×10^{-1} (7.6×10^{-1})		
	Terbium (HREE)	2.2 (7.4×10^{-1})		
	Vanadium	6.7×10^{1} (7.2×10^{1})		
	Yttrium (HREE)	3.0×10^{-2} (2.0×10^{-2})		
FCVs	Cerium (LREE)	6.3×10^{1}	55	[130], [188]
	Cobalt	5.8×10^{1}		
	Copper	2.5×10^{3}		
	Dysprosium (HREE)	2.9		
	Gadolinium (HREE)	4.2×10^{-1}		
	Lithium	1.6×10^{1}		
	Magnesium	1.7×10^{1}		
	Manganese	8.8×10^{2}		
	Neodymium (LREE)	4.9×10^{1}		
	Nickel	3.4×10^{3}		
	Platinum	1.2		
	Praseodymium (LREE)	2.1		
	Terbium (HREE)	2.0×10^{-2}		
	Vanadium	4.4×10^{3}		
	Yttrium (HREE)	2.0×10^{2}		

Technology material SR of power sector technologies

The technology material SR of power sector technologies involved in the second approach is reported in Table 19. Consider that a detailed description of the SR_t of power sector technologies is provided in Section 3.4.3, since the power sector was the case study adopted for the third approach.

Table 19. Technology material supply risk of power sector technologies in Approach 2.

Technology	$\boldsymbol{SR_t\left(\frac{1}{GW}\right)}$
Solar PV	1.3×10^{-3}
Onshore wind	4.1×10^{-2}
Offshore wind	1.8×10^{-1}
Geothermal	3.1×10^{-2}
Hydropower	2.5×10^{-5}
Bioenergy	5.5×10^{-5}
Hydrogen solid oxide FC	4.1×10^{-3}
Coal	4.1×10^{-3}
Natural gas	1.2×10^{-5}
Coal and natural gas w/ CCS	9.3×10^{-3}

Appendix E

This appendix provides an overview of how the MOO was integrated in the TEMOA-MOO version [83]. The overview is based on the Supplementary Material of [3].

Such integration involved many parts of the TEMOA modeling framework, as shown in Figure 27. Before detailing this, it might be useful to provide an overview of the main parts of the TEMOA modeling framework and how they are interconnected. The original code consists of seven main python files [84]. The overall definition of sets, parameters, variables, and equations is contained in "temoa_model.py". Then, the actual implementation of the equations needed to solve the optimization problem is provided by "temoa_rules.py", while the model is initialized (i.e., sparse matrix indexing and checks on parameters and constraints specifications) in "temoa_initialize.py". The code devoted to the model execution is in "temoa_run.py": a deterministic model is solved unless the stochastic option is enabled in "temoa_stochastic.py". The stochastic optimization is then an optional module as well as "temoa_mga.py", which executes the modeling-to-generate alternatives algorithm. The choice of the latter has to be eventually specified in a configuration file: it allows to specify several settings among which the input and output file paths and the type of solver (input and output data are stored using relational databases in .sqlite format). The storing and visualization of results are then handled through the "pformat_results.py". Lastly, the extended version [80] of the TEMOA framework that was used for this thesis also includes two additional modules for input data pre-processing, as detailed in [74], and for results post-processing, to derive aggregated results by technologies and commodities.

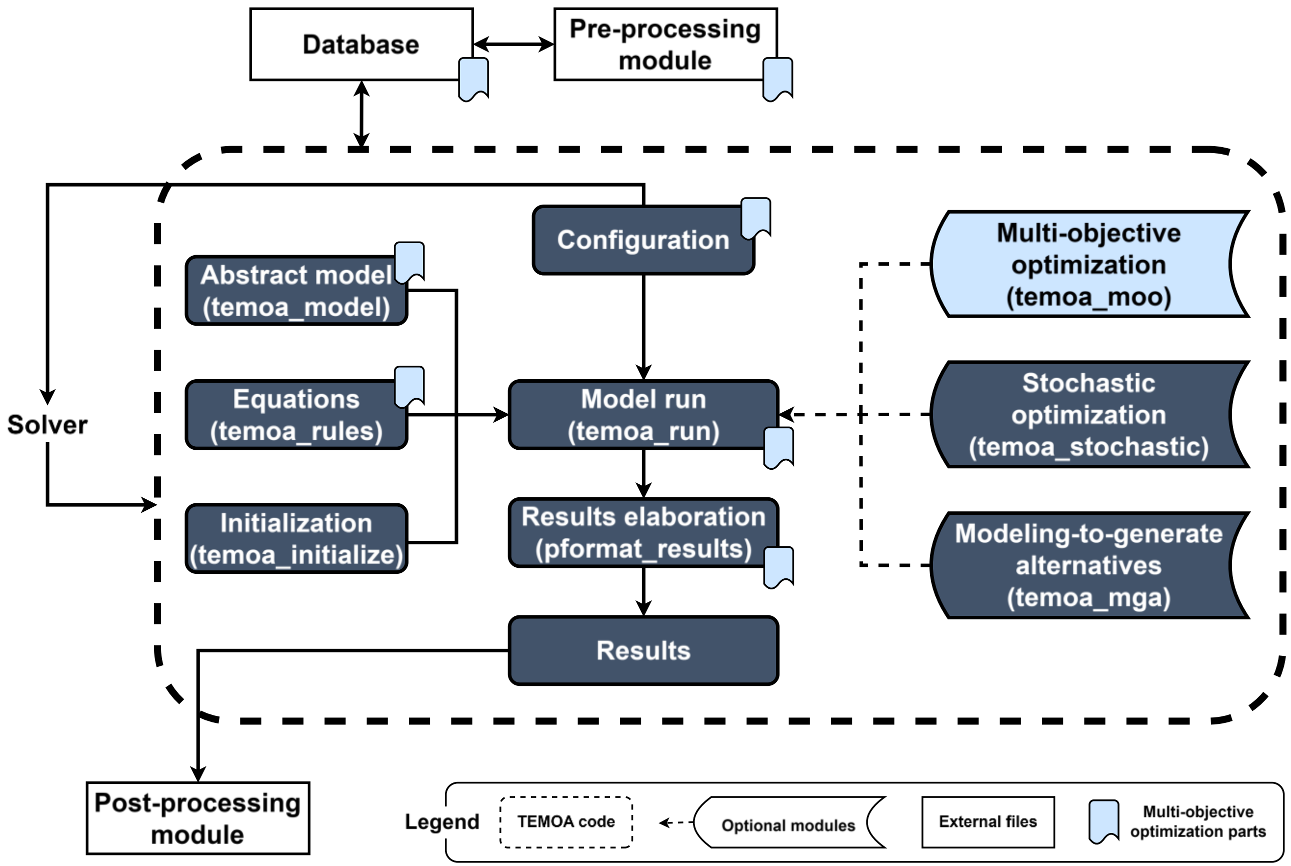

Figure 27. Scheme of the TEMOA-MOO modeling framework.

The equations needed to execute the MOO problem are defined in a completely new file compared to the original framework [84], which is named “temoa_moo.py”. These equations import the objective functions that are defined in “temoa_model.py” (high-level definition) and “temoa_rules.py” (actual implementation). As for the modeling-to-generate alternatives algorithm, the MOO option has to be eventually enabled through the configuration file. Then, the code for running the MOO problem is included in “temoa_run.py”: this code reproduces the steps of the MOO method adopted (i.e., AUGMECON in this thesis) and retrieves the equations included in “temoa_moo.py”. Finally, the elaboration of the results related to the MOO objective functions is accounted for in “pformat_results.py”. The parts related to AUGMECON in the TEMOA-MOO version that are additional compared to the original framework [84] are reported in Table 20. Moreover, these parts are identified through the tag “#MOO” in the corresponding files. Instead, additional parts relating to the objective functions involved in the MOO problems studied in [3] are described below.

Table 20. List of the AUGMECON-related parts of the MOO version of TEMOA.

TEMOA file	MOO parts
database.sql*	*Output_Slack_MOO (output table)*
temoa_config.py	- *States = (‘moo’, ‘exclusive)* - *tokens = (‘moof1’, ‘moof2’, ‘mooc’, ‘mooncaps’)* - *self.__moo_todo and self.__moo_done* - *self.moo_f1, self.moo_f2, self.moo_c, and self.moo_ncaps* - *msg += ... for f1, f2, c, and number of caps* - *def t_begin_moo, t_moof1, t_moof2, t_moo_mooc, t_moo_mooncaps, t_moo_end, and next_moo* - *if self.moo_ncaps*
temoa_moo.py	- *from temoa_rules import* the objective functions to be studied - *f1lowest_rule* - *f2lowest_rule* - *f12highest_rule* - *f1SlackedObjective_rule* - *f2SlackedConstraint_rule*
temoa_run.py	- *from temoa_moo import* the equations of temoa_moo - *import math, numpy as np* - *def solveWithMOO* - *elif hasattr(self.options, 'moo_c') and self.options.moo_c*
config_sample**	Settings of the MOO problem
pformat_results.py	Extract and save m.V_slack

* database.sql refers to the generic input/output database.

** config_sample is the configuration file.

Table 21 reports the parts related to the combined minimization of total system cost F_{cost} and total cumulative net CO2 emissions F_{CO2} (i.e., $min(F_{cost}, F_{CO2})$) that are additional compared to the original framework.

Moreover, these parts are identified through the tags “#CostMOO” and “#EmissionsMOO” in the corresponding files. The function F_{cost} is defined through the equation “Costs_moo” in the same way as the traditional total system cost objective function, which is used in the single minimization case through the equation “TotalCost_rule” [84]. Instead, the function F_{CO2} in Equation (20) is defined through the equation “Emissions_moo”.

$$F_{CO2}(Mt) = \sum_{p=1}^{N_p} \sum_{em=1}^{N_{emi}} Emissions_{r,p,em} \tag{20}$$

The latter is the sum of the left-hand side $Emissions_{r,p,em}$ of the constraint “EmissionLimit_Constraint” for the region under analysis *r* (already implemented in the original framework) over the entire time horizon (comprising N_p optimization years p) and over the N_{em} emission commodities em defined in the “comm_emi_MOO” set, which includes CO_2 only in this thesis. Constraints on F_{cost} and F_{CO2} can be internally defined in “temoa_rules.py” through, respectively, “MaxCost_Constraint” and “MaxEmi_Constraint”. These constraints can be used to fix the total system cost and total cumulative net CO2 emissions when other objectives are studied. Lastly, the minimized F_{cost} and F_{CO2} are stored, respectively, in the derived variables named “V_Costs _MOO” and “V_Emissions_MOO”, through the equations “TotalCost_Constraint” and “Emissions_Constraint”, respectively. Consider that for each objective, two separate equations are needed. The first one refers to the objective function that will be part of the MOO. The second one is needed to store the realized value of the objective function in the result database.

Table 22 reports the parts related to the combined minimization of energy supply risk SR_E and material supply risk SR_M (i.e., $min(SR_E, SR_M)$) that are additional compared to the original framework. Moreover, these parts are identified through the tags “#EnergySR” and “#MaterialSR” in the corresponding files. The material supply risk of technologies SR_t in Equation (7) is defined through the “TechnologyMaterialSupplyRisk” parameter. Then, “MaterialSupplyRisk_moo” involves the objective function SR_M definition in Equation (10), whose minimum value is stored in the “M.V_MaterialSupplyRisk” derived variable through the equation “MaterialSupplyRisk_Constraint”. Instead, the Herfindahl-Hirschman index HHI_e^g in Equation (11) is defined through the “EnergyCommodityConcentrationIndex” parameter. Then, “EnergySupplyRisk_moo” involves the objective function SR_E definition in Equation (14), whose minimum value is stored in the “M.V_EnergySupplyRisk” derived variable through the equation “EnergySupplyRisk_Constraint”.

Table 21. List of the $min(F_{cost}, F_{CO2})$-related parts of the MOO version of TEMOA.

TEMOA file	$\boldsymbol{F_{cost}}$	$\boldsymbol{F_{CO2}}$
database.sql	- *Output_TotalCosts (output table)*	- *comm_emi_MOO (input table)* - *Output_TotalEmissions (output table)*
temoa_config		*comm_emi_MOO*
temoa_model.py	- *M.V_Costs_MOO* - *M.TotalCostConstraint* - *M.MaxCostConstraint*	- *M.comm_emi_MOO* - *M.V_Emissions_MOO* - *M.EmissionsConstraint* - *M.MaxEmiConstraint*
temoa_rules.py	- *TotalCost_Constraint* - *MaxCost_Constraint* - *Costs_moo*	- *Emissions_Constraint* - *MaxEmi_Constraint* - *Emissions_moo*
temoa_moo.py	*from temoa_rules import Costs_moo*	*from temoa_rules import Emissions_moo*
pformat_results.py	Extract and save V_Costs _MOO	Extract and save V_Emissions_MOO

Table 22. List of the $min(SR_E, SR_M)$-related parts of the MOO version of TEMOA.

TEMOA file	SR_M	SR_E
database.sql	- *TechnologyMaterialSupplyRisk (input table)* - *Output_MaterialSupplyRisk (output table)*	- *tech_imports (input table)* - *tech_exports (input table)* - *EnergyCommodityConcentrationIndex (input table)* - *Output_EnergySupplyRisk (output table)*
temoa_config	*TechnologyMaterialSupplyRisk _material*	- *tech_imports* - *tech_exports* *EnergyCommodityConcentrationIndex*
temoa_model.py	- *TechnologyMaterialSupplyRisk* - *M.V_MaterialSupplyRisk* - *M.MaterialSupplyRiskConstraint*	- *M. tech_imports* - *M. tech_exports* - *M.EnergyCommodityConcentrationIndex* - *M.V_ImportShare* - *M.V_EnergySupplyRisk* - *M.ImportShareConstraint_rpc* - *M.ImportShareConstraint* - *M.EnergySupplyRiskConstraint*
temoa_rules.py	- *MaterialSupplyRisk_Constraint* - *MaterialSupplyRisk_moo*	- *EnergySupplyRisk_Constraint* - *EnergySupplyRisk_moo* - *ImportShare_Constraint*
temoa_moo.py	*from temoa_rules import MaterialSupplyRisk_moo*	*from temoa_rules import EnergySupplyRisk_moo Emissions_moo*
pformat_results.py	Extract and save m.V_MaterialSupplyRisk	Extract and save m.V_EnergySupplyRisk

Appendix F

This appendix provides data and sources of the simplified TEMOA-Italy power sector model used as case study of the third approach and is based on the Supplementary Material of [3] .

Power sector technologies

The power sector model was derived from TEMOA-Italy model [106]. Table 23 includes the techno-economic characterization of the power sector technologies included in the model. The complete database, which includes the upstream and CCUS modules, is openly available at [83]. In addition, the following assumptions specific to this case study were adopted:

- **Power sector.** In some cases, the TEMOA-Italy power sector encompasses different technologies that utilize the same electricity sources (e.g., mini- and micro-hydroelectric power plants). To simplify, a single technology by averaging the techno-economic parameters. This was the case for all the technologies listed in Table 23, except for offshore wind, hydrogen PEMFC, coal, natural gas w/CCS, and LIBs. Moreover, time-dependent capacity factors were used for solar PV, wind, and hydropower, given that their production varies with the hours of the day and seasons [63].
- **Hydrogen supply.** The possibility of importing hydrogen into the energy system represents a novelty compared to the TEMOA-Italy model [106]. In this regard, an average import price ~37 M€/PJ was derived from the levelized costs of imported hydrogen carriers from North Africa and Latin America discussed in [140]. Moreover, a maximum hydrogen supply from both imports and domestic production was set to 1000 PJ in accordance with the latest official projections for Italy in [192].
- **Electricity demand.** The 2050 electricity demand of 1589 PJ was computed as the average of the electricity consumption projections in Italian decarbonization scenarios from [28]. Moreover, a specific demand distribution was considered based on the reference TEMOA-Italy time slices, namely four times of the day and four seasons [129].

Table 23. Techno-economic parameters of the power sector technologies considered in the power sector case study of Approach 3.

Technology	Efficiency (%)	Lifetime (years)	Investment costs (M$/GW)	Fixed costs (M$/GW)	Variable costs (M$/PJ)	Currency	Capacity factor (%)	HR (%)
Solar PV		30	686	12		$M\$_{2020}$		5.7
Wind-onshore		20	765	33		$M\$_{2020}$		7..6
Wind-offshore		20	2905	64		$M\$_{2020}$		8.6
Geothermal	10	15	3840	60		$M\$_{2010}$	88	5.2
Hydropower		30	3375	56		$M\$_{2010}$		5.2
Bioenergy	40	12	2263	96	1.42	$M\$_{2020}$	60	6.7
Nuclear (LWR)	33	60	5250	130	0.93	$M\$_{2020}$	94	10.0
Hydrogen PEMFC	47	15	1000	56	8.33	$M\$_{2013}$	90	8.0
Coal steam cycle	44	30	2240	74	2.22	$M\$_{2020}$	76	6.2
Natural gas w/o CCS	54	30	771	25	0.98	$M\$_{2020}$	93	2.7
Natural gas w/ CCS	55	30	1330	38	0.56	$M\$_{2010}$	90	2.7
LIBs	85	15	908	23		$M\$_{2020}$		8.0

CRM value chain

The power sector model also includes the value chain of the CRMs listed in Table 24. The value chain was modeled as described in 2. In particular, the maximum material availability involved in the constraint in Equation (3) was evaluated at Italian level according to Equation (21).

$$MaxMaterial_m(Mt) = GDP_f^{IT} \cdot Reserve_m^{global} \tag{21}$$

For each CRM m, its maximum availability was estimated by applying the Italian share of global gross domestic product GDP_f^{IT} to the global reserve $Reserve_m^{global}$. This approach was also used in other studies such as [26] and [29]. For this case study, the 2023 GDP_f^{IT} of 1.85% and the latest global geological surveys were used. The maximum availability is reported in Table 24 by CRM and corresponding sources and assumptions.

Direct estimates were found for almost all the CRMs included in the analysis except for platinum and REEs. Concerning the latter, the single HREEs and LREEs concentrations in the Earth upper crust [126] were applied to aggregated REE reserve data [193] to estimate the single potential reserves. A similar approach was adopted for platinum, since only aggregated reserves data for PGMs were available (PGMs include six metals, namely ruthenium, rhodium, palladium, osmium, iridium, and platinum) [126]. The platinum potential reserves were then calculated considering that palladium and platinum account for more than 90% of PGM reserves and that their concentrations in the Earth crust and upper crust are similar (i.e., 45% of PGM reserves) [126].

Table 24. Maximum critical raw material availability in the power sector case study of Approach 3.

Material	$\mathrm{MaxMaterial}_m$ (Mt)	Sources and assumptions
Aluminum	5.7×10^2	Bauxite reserves [193]
Boron	2.0×10^1	[126]
Cobalt	1.5×10^{-1}	[193]
Copper	1.6×10^1	[193]
Dysprosium (HREE)	5.7×10^{-2}	Estimation from aggregated REE reserves [126], [193]
Gallium	1.2×10^{-3}	Derived from estimates of gallium by-production from bauxite and zinc [193]
Hafnium	1.9×10^{-2}	Global resources [126]
Lithium	4.8×10^{-1}	[193]
Manganese	3.1×10^1	[193]
Neodymium (LREE)	4.1×10^{-1}	Estimation from aggregated REE reserves [126], [193]
Nickel	1.9	Minimum estimate [193]
Niobium	3.1×10^{-1}	Minimum estimate [193]
Phosphorus	1.3	Phosphate rock [193]
Platinum	5.9×10^{-4}	Estimation from aggregated PGM reserves [126]
Praseodymium (LREE)	1.1×10^{-1}	Estimation from aggregated REE reserves [126], [193]
Silicon	1.9×10^3	Very large value set since no estimates were available and it is the most abundant element in Earth crust [194]
Terbium (HREE)	1.0×10^{-2}	Estimation from aggregated REE reserves [126], [193]
Titanium	4.6	Indirect estimation [126]
Vanadium	4.8×10^{-1}	[193]
Yttrium (HREE)	3.0×10^{-1}	Estimation from aggregated REE reserves [126], [193]

Appendix G

This appendix provides further details on data and sources adopted to define the SR indicators for the energy technologies and commodities included in the power sector case study of the third approach. The appendix is based on the Supplementary Material of [3].

The material supply risk indicator (SR_t)

Values and sources used to evaluate SR_m, $cons_m^{yref}$, and $f_{m,t}$ are reported in Table 25 by CRM and technology, alongside the resulting SR_t by technology.

The European Union (EU) material consumption in a reference year $cons_m^{yref}$ was directly retrieved from [126], which provides data for both extraction and processing phases. The choice between them was based on which phase is considered in the 2023 EU CRMs assessment [18] that was used as a reference for the SR of the single RMs. In this regard, the consumption of processed materials was considered for lithium, niobium, phosphorous, and vanadium, while the extraction values were used for the other materials. In particular, the EU consumption corresponded to the EU internal extraction for cobalt, manganese, and nickel.

The Excel file entitled "MaterialIntensities.xlsx" in the Supplementary Material of [3] contains the complete set of data and sources from which the 2050 MI of technologies $f_{m,t}$ were derived.

Table 25. Data and sources of the parameters needed to compute the technology material supply risk indicator for the case study of Approach 3.

Material	**SR of single CRM** [18]		$\boldsymbol{cons_m^{yref}}$ $(\boldsymbol{Mt})$ [126]	$\boldsymbol{f_{m,t}}$ $(\frac{\boldsymbol{t}}{\boldsymbol{GW}})$											
	$\boldsymbol{SR_m^{EC}}$ $(-)$	$\boldsymbol{SR_m}$ $(-)$		Solar PV [37], [2]	Wind [37], [2] On-shore	Wind [37], [2] Off-shore	Geo-thermal [2], [132]	Hydro-power [2], [195]	Bio-energy [2], [195]	Nuclear (LWR) [2], [132]	Hydrogen PEMFC [32], [187], [196], [197], [198], [199]	Coal [2], [132]	Natural gas [132], [187] w/o CCS	Natural gas [132], [187] w/ CCS	LIBs [76]
Aluminum	1.2	2.1	1.6×10^{1}	6750.0	901.4	478.8		3400.0	3900.0				4.8	4.8	5796.0
Boron	3.6	3.7	1.9×10^{-2}		0.1	0.5									
Cobalt	2.8	3.7	1.1×10^{-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	1.1×10^{-6}		0.5	1.6									
Gallium	3.9	4.0	3.3×10^{-5}	0.015											
Hafnium	1.5	1.6	1.1×10^{-5}							0.5					
Lithium	1.9	2.0	1.8×10^{-3}												438.0
Manganese	1.2	1.3	2.7×10^{-1}		564.5	569.9	4325.0	200.0				4.6	24.1	3785.1	660.0
Neodymium (LREE)	4.5	4.6	1.2×10^{-4}		4.1	16.3									
Nickel	0.5	0.6	2.6×10^{-1}		287.3	194.4	120155.0	215.0	20.0	778.0		721.5	29.2	1174.2	2160.0
Niobium	4.4	4.6	2.8×10^{-3}										5.3	5.3	
Phosphorus	3.3	3.4	7.4×10^{-2}										0.9	0.9	

Table 25 (continued)

Platinum	2.1	2.5	7.2×10^{-5}								$4.0 \cdot 10^{-2}$				
Praseodymi- -um (LREE)	3.2	3.3	1.1×10^{-4}		0.6	3.1									
Silicon	1.4	1.4	4.2×10^{-1}	1900.0									17.3	17.3	
Terbium (HREE)	4.9	5.4	5.9×10^{-6}		0.1	0.6									
Titanium	1.6	1.6	1.4×10^{-2}				1634.0		400.0	1.5		23.0	4.8	4.8	
Vanadium	2.3	2.7	4.4×10^{-3}							0.6			8.2	8.2	
Yttrium (HREE)	3.5	3.9	2.2×10^{-4}							0.5					
			$\boldsymbol{SR_t\left(\frac{1}{GW}\right)}$	9.7×10^{-3}	2.7	9.2	0.5	2.1×10^{-3}	4.7×10^{-2}	8.1×10^{-2}	1.4×10^{-3}	7.2×10^{-2}	3.3×10^{-2}	5.7×10^{-2}	0.7

The energy supply risk indicator (HHI_e^g)

Concerning the supplier country statistics, values not corresponding to a specific country ("Altri" for natural gas [133] and "Others" for biofuels [137]) were redistributed among the countries for which values were specified by using their market shares.

Then, the original coal statistics [134] in unit mass were converted into unit energy using the lower heating values of the different coal types modeled in TEMOA-Italy [74]. In particular, the following correspondence between the latter and the coal type in the statistics [200] were assumed:

- **Hard coal:** "Antracite e carboni magri", "Carbon fossile da coke", "Carbone da vapore".
- **Coke oven coke:** "Carbone di carbon fossile".
- **Petroleum coke:** "Coke di petrolio".
- **Brown coal:** "Ligniti e agglomerati".
- **Coal tar:** "Pece".

Lastly, hydrogen potential imports ~4.7 Mt from Kazakhstan, Oman, and Saudi Arabia were excluded, since no memoranda of understanding with EU were signed [201]. Their inclusion in this analysis would have increased the supply diversification and decreased the hydrogen HHI_e up to 0.71.

The Excel file entitled "EnergyMarketShares.xlsx" in the Supplementary Material of [3] contains the complete set of data and sources used to calculate the supply concentration indicator HHI_e^g of energy commodities.