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Modeling energy storage in long-term capacity expansion energy planning: an analysis of the Italian system

Matteo Nicoli [a,b,*], Victor Augusto Duraes Faria [c], Anderson Rodrigo de Queiroz [b,c,d], Laura Savoldi [a]

[a] MAHTEP Group, Dipartimento Energia "Galileo Ferraris", Politecnico di Torino, Torino, Italy
[b] Department of Civil, Construction & Environmental Engineering, NC State University, Raleigh, NC, USA
[c] Graduate Program on Operations Research, NC State University, Raleigh, NC, USA
[d] School of Business, NC Central University, Durham, NC, USA

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ABSTRACT

This paper presents a framework to represent short-term operational phenomena associated with renewables capacity factors and final service demand distributions in a capacity-expansion and integrated energy system optimization model. The aim is to study the potential role of energy storage technologies coupled with renewable energy sources aiding the decarbonization of the overall energy system. The proposed methodology is implemented in an energy system optimization model named Tools for Energy Model Optimization and Analysis (TEMOA) and then tested in a case study focused on the Italian energy system. We examine a collection of scenarios that includes reference time scale scenarios, time scale sensitivity scenarios, and technology alternative scenarios. This paper's findings indicate that energy storage is crucial for fully decarbonizing the Italian power sector by 2050 in the absence of a low-carbon baseload. Additionally, it suggests that approximately 10 % of Italy's electricity generation in 2050 should be routed through short-term energy storage devices.

1. Introduction

Renewable energy sources are expected to play a significant role in the supply side of future energy systems as governments around the world are promoting efforts toward decarbonization [1]. Although variable renewable energy (VRE) resources such as solar, wind, and hydro can be considered carbon-neutral technologies in the operation phase, they depend on the availability of natural resources to produce electricity. Thus, production from such VRE technologies is considered uncertain and intermittent. On the contrary, thermal power plants are typically characterized by higher and constant capacity factors (CFs) [2]. Therefore, it is likely that a higher deployment of VRE will lead to higher operational challenges in electricity power systems for decision-makers to properly accommodate higher shares of uncertain resources in a dispatch network originally designed for traditional power plants. In this context, energy storage is a candidate to help tackle this issue, allowing for storing and releasing energy and providing flexibility at different times of the day according to the system's needs [3].

Many recent energy policies and incentives have increasingly encompassed energy storage technologies. For instance, the US introduced a 30 % federal tax credit for residential battery energy storage for installations from 2023 to 2034 [4]. Recognizing the crucial role of batteries in future energy systems, the European Commission committed to establishing a "strategic battery value chain" in Europe focusing on recycling to reduce the dependency on critical raw materials import [5]. The same European Commission also recommended member states [6] to accelerate the deployment of energy storage facilities within the European Green Deal [7] and the REPowerEU [8] frameworks. Finally, in the European landscape, the Italian government has plans for substantial investments in electrochemical energy storage systems, aiming at 6.3 B€ of total investments by 2030 [9] to reach between 30 to 40 GW and 70 to 100 GWh of rated power and installed capacity, respectively, by 2050 [10].

In achieving the targets mentioned above, energy system optimization models (ESOMs) are essential tools that allow the assessment of possible future energy and economic dynamics across diverse spatial, temporal, and sectoral scales [11]. From the literature, ESOMs have been used so far to assess the contribution of energy storage in supporting renewables development on local (e.g., microgrids [12], or islands like Pantelleria [13]) and regional (e.g., North Carolina [14,15], Western Interconnection [16], US [17,18], Europe [19]) scales, showing

* Corresponding author at: MAHTEP Group, Dipartimento Energia "Galileo Ferraris", Politecnico di Torino, Torino, Italy.
E-mail address: matteo.nicoli@polito.it (M. Nicoli).

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Nomenclature

CAES	Compressed Air Energy Storage
CCS	Carbon Capture and Storage
CCUS	Carbon Capture Utilization and Storage
CHP	Combined Heat and Power
CHPR	Combined Heat to Power Ratio
ESOM	Energy System Optimization Model
GHG	Greenhouse Gas
LULUCF	Land Use, Land Use Change and Forestry
O&M	Operation and Maintenance
SC	Supercapacitor
SMES	Superconducting Magnetic Energy Storage
TEMOA	Tools for Energy Modeling Optimization and Analysis
VRE	Variable Renewable Energy

Subscripts and superscripts

Constant	Constant cost component
d	Time of day
D	Set of times of day
Energy	Energy cost component
f	First
H_d	Set of hours in the time of day d
IN	Input commodity
Invest	Total investment cost
l	Last
M_s	Set of months in the time season s
n	Number of items according to the index
OUT	Output commodity
p	Previous
r	Region
R	Set of regions
Rated	Rated power
s	Time season
S	Set of time seasons
y	Year
Y	Set of years

Parameters

CF	Capacity factor
CapToAct	Capacity to activity factor
SegFrac	Time slice duration
$Storage^{Duration}$	Storage capacity (in hours)

Decision variables

Act	Technology activity (in PJ)
Cap	Technology capacity (in GW)
Flow	Total commodity flow (in PJ)
Power	Technology active power (in GW)
$Storage^{Energy}$	Stored energy time slice by time slice (in PJ)
$Storage^{Level}$	Energy stored in the technology (in PJ)

that storage plays a critical role in low emissions scenarios. Specifically, energy storage was found to be deployed in the analyzed electric system when assuming an investment cost reduction of 50 % to the 2013 cost levels in [16], while [19] estimated the optimal storage capacity to be between 80 and 350 GWh for the European Union by 2050.

While ESOMs usually evaluate the whole energy system evolution on a long-time horizon (several years to decades ahead), including supply and demand sectors [20,21], electric system models only focus on the power sector [22] and may adopt a capacity expansion (or planning) [23] or focus on the operational dispatch and resources coordination problems [24,25]. Capacity expansion models operate over the long run to evaluate the future available capacity of power sector technologies, according to the scenario under analysis by performing a constrained economic optimization analysis [20,23]. Such a process aims to provide useful information for policymakers and energy companies' future investments and how the technologies will be used to satisfy system demand. On the other hand, operational models focus on unit commitment and economic dispatching problems (with a more precise representation of technical details such as ramping rates, generator commitment decisions, spinning reserves requirements, etc.) given pre-determined capacity levels, demand, and environmental short-term forecasts. These models typically look from hours to several days or weeks ahead. Moreover, operational models usually do not account for investment costs, focusing only on the operations and maintenance costs.

The distinction between such modeling strategies implies a different burden on the computational time, which may become too high when combining the finer time resolution of dispatching models with the long-time horizon typical of ESOMs. Usually, dispatching models have hourly or shorter time steps representation with planning horizons ranging from a day to a month ahead, while capacity expansion ESOMs have time steps represented as a subset of hours or times of day within a month or season (for operational decisions) and modeled as a single or a number of years (for investment decisions) with planning horizons usually ranging from 5 to 30 years in the future. The impact of varying the time resolution within the ESOMs was studied in [26], highlighting that representative days are required to retain the chronology of operational dynamics. This point is crucial to properly model phenomena occurring across time, such as the storage charge and discharge phases.

A relevant dependency of renewable penetration in the system on the selected time steps is revealed in [27], as also discussed for ESOM tools in general in [28]. Furthermore, the findings of [29] show how finer time resolutions are necessary to produce realistic results. Those outcomes suggest that, despite the increase in computational effort, considering operational details can be important even when adopting a long-term perspective focused on investments to obtain more relevant results.

Different approaches were presented in the literature aiming to link investments and operational details within ESOMs or power systems models. In this regard, the available options are reported in [30]: unidirectional soft linking; bidirectional soft linking; co-optimization of investments and operations. In the unidirectional soft linking, capacity expansion output constitutes the input for the operational model [31]. This approach has already been applied to Ireland [32], Belgium [26] and North Carolina [14], which highlight how capacity expansion ESOMs with low time granularity are not adequate to consider operational issues. Bidirectional soft-linking iteratively uses unidirectional soft-linking, as discussed in [33]. The co-optimization approach has been adopted so far on simpler models and typically with a focus on the power sector only, either including the storage as in [16] or neglecting it as in [34]. This is due to the substantial computational effort required when considering more complex models.

As the planning and operation problems are strictly correlated, addressing them separately implies approximations in the results. This limitation is even more relevant when dealing with integrated models not only covering the power sector but the entire energy system from primary energy production to final energy consumption and aiming to satisfy a wide set of final energy service demands. Given the complexity of such models, they are usually structured on a limited number of time slices, and few attempts were proposed to refine their time resolution (e.g., [35]), which could, however, still affect the results.

To address this gap, this work introduces a novel methodology to enhance the time scale representation of ESOMs, enabling a more precise simulation of short-term system dynamics with a fine resolution, down to hourly intervals. Within a capacity-expansion-oriented modeling framework extending up to 2050, this study aims to improve the representation of short-term operational details of technologies and the potential role of energy storage in providing flexibility to the overall energy system as the share of VRE grows. The primary innovation involves increasing the time resolution of integrated models representing the entire energy system. This approach not only facilitates the study of storage but also explores potential synergies between storage and technologies in other sectors, including both the supply and demand sides of the system. The developed methodology can be easily extended to any form of energy (e.g., electricity, hydrogen, heat, etc.), as in the adopted ESOM, electricity is only one intermediate commodity among others.

Section 2 presents the methodology adopted to perform the analysis, focusing on the mathematical aspects specifically devoted to representing storage options and the model preprocessing and postprocessing. Section 3 discusses the techno-economic characterization of the modeled energy storage technology options. While Section 4 describes the studied scenarios, the results associated with them are presented and discussed in Section 5. Conclusions and future perspectives are reported in Section 6. TEMOA-Italy, the specific model instance to which the methodology was applied, is presented in the Appendix focusing on the power sector and presenting the specific input data used.

2. Methodology

The main steps of the proposed methodology are depicted in Fig. 1, showing the logical connection between the different phases of data processing and the optimization process. They are:

- Derivation of the representative year through average hourly CFs and demands distribution.
- Association of the months of the year to time seasons and the hours of the day to times of day to define the time slices structure.
- Aggregation of CFs and demand distribution according to the selected time slices.
- Integration of energy storage options, time slices, CFs, and demands distribution in the model input database.
- Optimization.
- Results postprocessing focusing on intra-annual dynamics.

The presented flowchart is general and can be applied to any bottom-up ESOM [20].

Going into the details, Section 2.1 presents the state of the art of how storage technologies are typically modeled in long-term capacity expansion ESOMs. Sections 2.2 and 2.3 present how the methodology summarized in Fig. 1 has been implemented both in the model pre-processing and postprocessing, discussing the main items necessary to improve the time scale representation of an integrated model.

2.1. Time-dependent variables and storage modeling in ESOMs

ESOMs are constituted by tools implementing the mathematical formulation (i.e., the model structure and the set-up of the optimization problem) and a technology database, including the techno-economic characterization of the items constituting the specific energy system under analysis. While the spatial scale of ESOMs may be constituted of one or more interconnected regions, the time scale of the model typically involves a long time horizon of up to several decades, based on the adoption of a set of milestone years to represent the future evolution of the system on a discrete number of time intervals (see [37]).

The structure of the energy system is defined by commodities and technologies. In integrated ESOMs, demand commodities are used to quantify the energy service demands of the region under analysis (buildings end-uses, industrial production, transport needs). The most important techno-economic parameters for technology description are shown in Fig. 2. Firstly, in any ESOM technologies present at least one input and one output commodity, with few exceptions (e.g., mining, import/export, CO2 storage, etc.). The conversion from input to output commodities occurs according to the specified efficiency, representing the output commodity produced per unit of input commodity consumed. The association between commodities and technologies defines the structure of the energy system and the technology chain from primary production to final service demands. Three cost components can be defined, contributing to the objective function of the optimization model [38]: investment cost (M€/cap.), annual fixed O&M cost (M€/cap.), and variable O&M cost (M€/act.). Greenhouse gas (GHGs) emissions are accounted for through emission factors, which may be associated with the consumption of a specific commodity or the activity of a specific technology [39].

In the perspective of modeling the variations of energy production and consumption across time, several expedients are adopted. The first relevant aspect concerns the distinction between baseload and non-

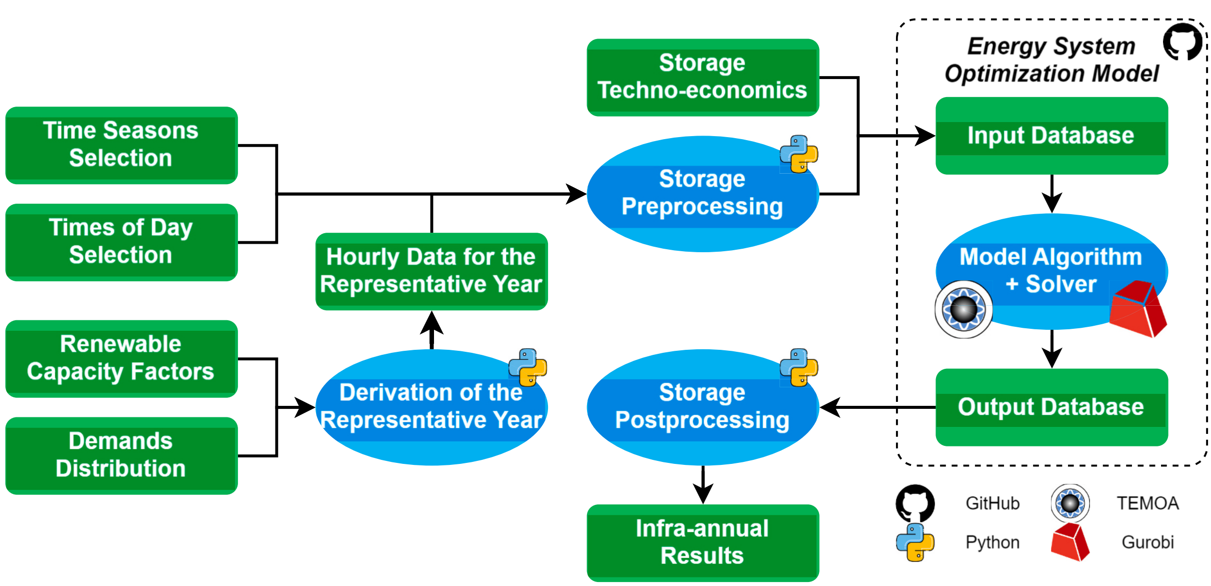

Fig. 1. Computational flowchart representing the data flow and the macro-steps of the proposed methodology. Icons are from [36].

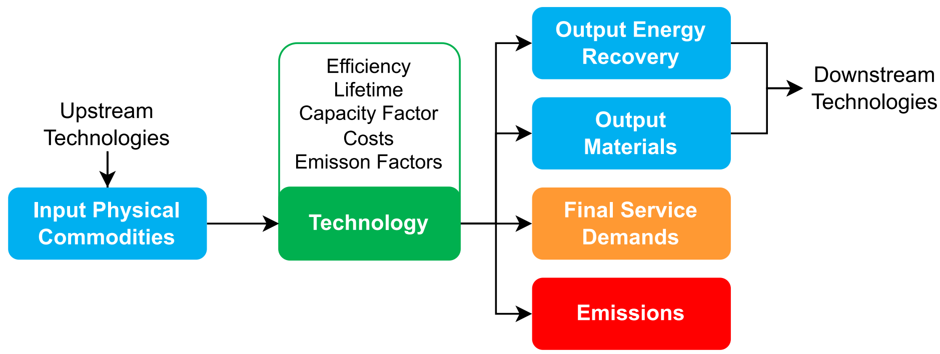

Fig. 2. The main techno-economic parameters of technology in ESOMs and the connection between technologies and physical (energy and material), demand, and emission commodities.

baseload technologies. In the Tools for Energy Modeling Optimization and Analysis (TEMOA) [40] example, baseload processes cannot vary their power across different times of the same day. However, they can vary their power in different seasons of the year. TEMOA also allows the modeler to specify specific limits for ramping rates. Curtailments are allowed for specific technologies when the total production of a specific energy commodity exceeds its total consumption by downstream technologies.

Two parameters are very useful to account for the reliability of power sector technologies, including storage options: the reserve margin and the capacity credit. The reserve margin is a parameter used to quantify the reserve capacity of a power system that is available during the demand peak, and it is necessary to ensure enough backup power to deal with possible contingencies. Each technology can contribute to meeting the minimum reserve capacity according to its capacity credit parameter, which measures the share of the available capacity of a technology that can be considered reliable (see [41] for the mathematical formulation). The capacity credit is typically lower for VREs than for thermoelectric and nuclear power plants due to the intermittency of the first.

Coming to the peculiarities associated with storage technologies, it is necessary to carefully account for the association between the technology rated power (GW) and the available storage capacity (GWh). The several alternatives available in the literature concerning the energy storage modeling in ESOMs can be summarized in two options, one represented by the TIMES Model Generator [42] and the second by TEMOA.

The main difference between the approaches adopted by TIMES and TEMOA consists of the energy storage capacity modeling. As shown in Fig. 3, while the TEMOA formulation includes a dedicated parameter to define the storage duration in hours associated with the rated power of the technology, TIMES exploits an auxiliary commodity to link two technologies devoted to account for the rated power (GW, technology 1 in Fig. 3a) and the storage capacity (GWh, technology 2 in Fig. 3b), respectively. Indeed, each storage option must be assigned in TIMES to a specific time interval (daily, weekly, seasonal), and consequently, the maximum number of storage cycles is endogenously defined (365, 365/7, 1 cycle/year) [38]. On the contrary, the "storage duration" parameter included in TEMOA equations [41] requires identifying the combination between the storage capacity available and the rated power of a technology before the optimization process. Such an approach leaves more flexibility to the modeler, being not constrained by the predefined daily, weekly, and seasonal storage cycles, but requires including in the technology database more versions of the same technology if alternative storage durations should be studied in competition with each other. Consequently, the investment cost associated with any energy storage technologies in TEMOA includes the power and the energy cost components, and it is expressed per unit of technology capacity (e.g., M\$/GW). Note, however, that the relation between power and energy capacity is not only a modeling aspect but it is due to the physical features of the technologies [43].

The TIMES formulation was implemented as an example in the JRC-EU-TIMES Model [44], while the TEMOA storage modeling was extensively tested in [14] using an economic dispatch framework. Given the open-source aspect of the model and data and the flexibility of the abovementioned storage duration definition, TEMOA was selected to carry out the analysis of this work. The main equations included in TEMOA concerning the modeling of storage technologies are presented in detail in Section 2.1. We consider a modified TEMOA version [45]

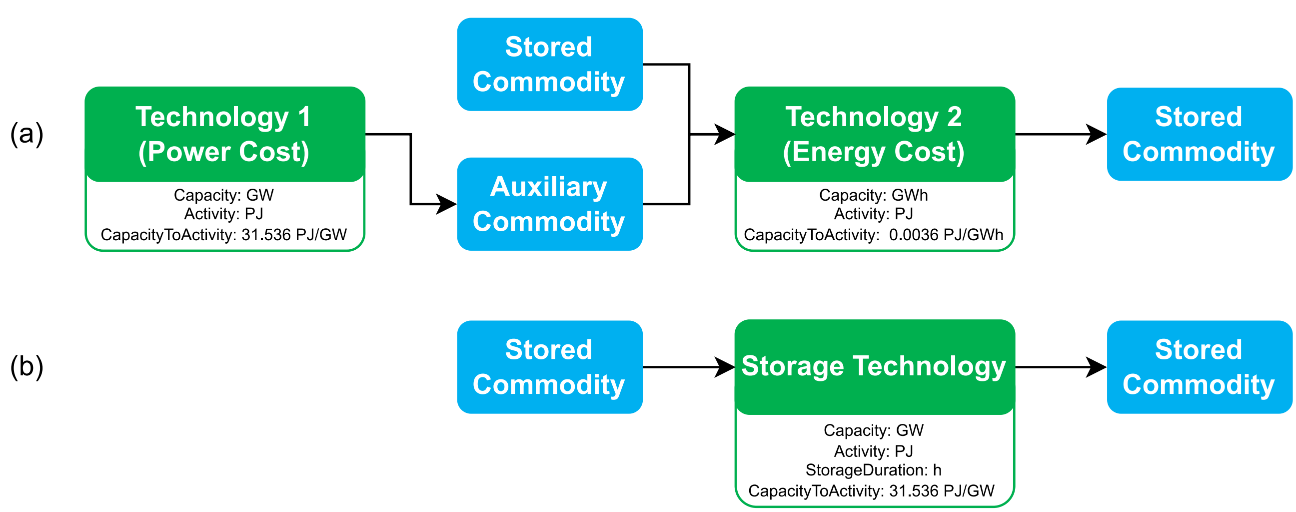

Fig. 3. Graphical representation of the mathematical formulation associated with storage technologies implemented in TIMES Model Generator (a) and TEMOA (b).

from the one presented in [40], including the new parameters and constraints for technology groups from [46].

The specific feature of an energy storage technology in any ESOM consists of the possibility for the input commodity flows to occur in different time slices with respect to the output commodity flows, while for non-storage technologies, they occur simultaneously. This peculiarity enables storage technologies to cover the differences in the time distribution of power supply and consumption. Such discrepancies are typically modeled with devoted parameters which vary across the model time slices. Concerning the supply side, time slice-dependent capacity factors account for the uneven energy production due to the variable availability of VRE resources across time. A similar behavior is associated with the final energy service demand distributions, which may vary with the season of the year (e.g., space heating and cooling) and the hour of the day (e.g., lighting).

The variation of the stored energy $Storage^{Energy}$ by a storage technology in the specific time slice "s,d" is the difference between the total flow of input commodities $Flow^{IN}$ multiplied by the round-trip efficiency and the total flow of output commodities $Flow^{OUT}$ of such technology in the time slice (see Eq. (1) [41]). The round-trip efficiency accounts for both the inlet and the outlet efficiencies, while the self-discharge is neglected. This is due to the modeling approach adopted by ESOMs, typically using lumped parameters to represent technologies. In the example of efficiency, this means using a single value to account for the several energy losses possibly occurring.

$$Storage^{Energy}_{s,d} = \sum_{s,d} Flow^{IN}_{s,d} \cdot Efficiency - \sum_{s,d} Flow^{OUT}_{s,d} \forall s \in S, \forall d \in D \tag{1}$$

The TEMOA formulation evaluates for any time slice the storage level $Storage^{Level}$ of a technology. The storage level measures the energy cumulatively stored in the technology as a function of its values in the previous time slice "p" and the variation of the stored energy (see Eq. (1)), as shown in Eq. (2) [41]. Moreover, the storage level at the end of each milestone years (in the last time slice "s, d_l") must be equal to the storage level at the beginning of the milestone year itself (the first time slice "s, d_f"), see Eq. (3). This constraint is thought to simplify the model formulation by excluding the possibility of exchanging energy between different milestone years. Note that the exclusion of energy exchange between different milestone years does not prevent the possibility of studying seasonal storage within the same year.

$$Storage^{Level}_{s,d} = Storage^{Level}_{s,d_p} + Storage^{Energy}_{s,d} \forall s \in S, \forall d \in D \tag{2}$$

$$Storage^{Level}_{s,d_l} = Storage^{Level}_{s,d_f} \tag{3}$$

The energy storage level at any time slice is also constrained to be lower than, or equal to, the energy storage capacity of the technology, expressed as the maximum $Storage^{Duration}$, measured in hours and provided among the input parameters in the model database, associated with the available technology power capacity Cap, usually measured in GW. The $Storage^{Duration}$ parameter univocally defines the energy capacity of the technology as a multiple of the power capacity. Eq. (4) is the mathematical formulation of such a constraint, also involving the quantification of the number of days associated with the season s through the $SegFrac_{s,d}$ parameter, expresses as a fraction of the total time of the year, multiplied by the number of days within the year. This is done to account for the maximum number of storage cycles, assumed equal to the number of days since the oscillations in the energy supply and demand seen through representative days occur, by definition, on a daily basis. The $CapToAct$ parameter expresses the maximum hypothetical activity of a TEMOA technology per unit of available capacity if constantly operated at full load. It is usually equal to 31.536 PJ/GW for electricity production technologies if the unit of measure for the electricity commodity is PJ (see [46,47]).

$$Storage^{Level}_{s,d} \leq Cap \cdot CapToAct \cdot \frac{Storage^{Duration}}{8760\left(\frac{h}{y}\right)} \cdot \sum_{d} SegFrac_{s,d} \cdot 365\left(\frac{days}{y}\right) \forall s \in S, \forall d \in D \tag{4}$$

The TEMOA code also includes other items devoted to constraining the maximum charging, discharging, and throughput power, which must be within the technology rated power. TEMOA also allows the manual setting of the storage level at the beginning of each milestone year to a specific value [41]. Such items are not discussed here, and the reader should refer to [41,48] for the complete documentation.

2.2. The model preprocessing

Large ESOMs [23] typically include a very simple discretization of the time scale, based on a few time slices per milestone year and representing the system dynamics with typical average days. This model configuration is sufficient to evaluate phenomena well represented by annual average values, and here, it will be used to produce reference results to compare with scenarios with a more refined time scale resolution. In this case, the model time scale refinement is a key factor in precisely assessing intra-day system dynamics associated with the role of energy storage options in long-term capacity planning while addressing operational dispatch challenges [49]. For instance, the availability of renewable sources is strongly dependent on the hour of the day, and some final service demands depend on the season of the year (e.g., heating and cooling in buildings, lighting, office equipment, etc.). In the approach proposed here concerning the slicing method, the adopted time slices are chronological and average. This means that the selected representative days refer to portions of the year that are in the same chronological sequence as in reality, and they represent the average behavior of the represented items, excluding anomalous or extreme events. The choice of chronological time slices is due to the importance attributed to them by the existing literature [26] to retain chronology when dealing with storage technologies, as they aim to meet the energy excess of production and consumption in sequential periods.

The time slices are defined by assigning the months of the year (from January to December) to a specific time season and the hours of the day (from the 1st to the 24th) to a specific time of day. Being based on hourly historical data, the possibility of choosing times of day with a shorter duration than 1 h is not considered. In such a way, the most detailed time resolution that it is possible to explore corresponds to assigning to each month a different season (12) and to each hour of the day a different time of day (24), leading to the maximum possible number of 288 time slices (as also proposed in [34]). The described approach implies two limitations:

1) The minimum duration of a season is one month. This implicitly requires that a single typical day can adequately represent the regular VRE dynamics of all the days within the month. This is an acceptable assumption since ESOMs usually do not consider in detail the variation of final energy service demands across the time (i.e., that would require accounting for different demand profiles associated with working or not working days of the same week and month) [47].
2) Sharing times of day among seasons. Once the times of day are defined, they are shared among seasons without the possibility of setting different assignments for each season. This limitation, shared with several ESOM-based studies that tried to address the same issue [34], is not present in other approaches [49].

According to the desired time slices configuration, the following values should be calculated [41]: the duration of each time slice as a percentage of the total time of the year $SegFrac$; the average CFs for renewable power sector technologies for each time slices *CapacityFactorTech* and the percentage distribution of final energy service demands among the selected time slices *DemandSpecificDistribution*.

Wind and solar CFs follow Eq. (5), where "r" is the spatial region that is considered, "s" is the user-defined season, including one or more months, "d" is the user-defined time of day, including one or more hours of the day, "n_{year}" is the number of years, "$n_{month\in M_s}$" the number of months belonging to the model time season and "$n_{hour\in H_d}$" the number of hours belonging to the model time of day.

$$CapacityFactor_{r,s,d} = \frac{1}{n_{year} \cdot n_{month\in M_s} \cdot n_{hour\in H_d}} \sum_{\forall year\in Y} \sum_{\forall month\in M_s} \sum_{\forall hour\in H_d} CapacityFactor^{Historical}_{r,year,month,hour} \forall r\in R, \forall s\in S, \forall d\in D \tag{5}$$

On the other hand, Eq. (6) is used to evaluate the CFs for hydroelectric plants. The absence of the day and hour indexes for the historical data (right-hand side of Eq. (6)) implies that hydroelectric CF is constant among different times of day within the same time season. This is consistent with the typical data for water availability, as the production from hydropower plants is mainly influenced by dynamics occurring on a seasonal rather than hourly basis.

$$CapacityFactor_{r,s,d} = \frac{1}{n_{year} \cdot n_{month\in M_s}} \sum_{\forall year} \sum_{\forall month\in M_s} CapacityFactor^{Historical}_{r,year,month} \forall r \in R, \forall s\in S, \forall d\in D \tag{6}$$

A specific Python module, named "storage_preprocessing.py" and freely available in the Supplementary material, was developed to address the preprocessing issue, including the computation of the duration of each time slice and the time distribution of non-annual final demands.

2.3. The model postprocessing

At the end of the optimization process and similarly to other ESOMs such as the TIMES modeling framework [42], TEMOA elaborates the decision variables values for the studied scenario, and it saves summary annual results into an Excel file, while detailed results per each time slice are saved into specific tables (devoted to collect results) in SQLite format. As the number of time slices increases, the size of the database does, and manual postprocessing becomes an issue.

Given the focus of this study on intra-annual dynamics with fine time slice resolutions, the postprocessing procedure is focused on deriving the hour-by-hour power of each power sector technology per each time season. Knowing the energy output from each technology in every time slices of the year $Energy_{r,s,d}$, measured in PJ, the average power $Power_{r,s,d}$, measured in GW, for the hours belonging to the time slice is calculated, according to Eq. (7).

$$Power_{r,s,d} = Energy_{r,s,d} \cdot \frac{10^6 \left(\frac{GJ}{PJ}\right)}{SegFrac_{s,d} \cdot 8760 \left(\frac{h}{y}\right) \cdot 3600 \left(\frac{s}{h}\right)} \tag{7}$$

Eq. (7), together with other operations designed for data handling, was implemented in a Python tool named "storage_postprocessing.py" code, freely available in the Supplementary material. The technology groups can be specified by the modeler by assigning to each technology its group. The list of technology groups used to derive results presented in this paper is based on the input energy sources of the power plants with the following classification (also distinguishing CCS-equipped plants): biofuels, CCS, coal, gas, geothermal, hydroelectric, hydrogen, import, nuclear, oil, solar, storage, wind. The tool was used to obtain Figs. 6, 9, and 11.

3. Techno-economic characterization of storage technologies

Several energy storage technology options have been proposed and described in the literature. A complete overview of hydrogen storage options is provided in [50,51], while [52] explores possible strategies to store renewable energy (including chemical and thermal storage) and [53] focuses on utility-scale electricity storage. Moreover, studies providing techno-economic assessments for mature and non-mature technologies are widely available. For example, [54] proposes the life cycle cost of storage and the levelized cost of energy as metrics to make operational decisions for alternative electricity storage options; [55] compares the levelized cost of storage for technologies devoted to primary response; [56] focuses on long-duration energy storage technologies; [57] provides renewables and storage cost projections up to 2030. To limit the effect of uncertainties related to non-mature technologies, this work mainly focuses on technologies with a higher technology readiness level, specifically hydroelectric pumped storage, lithium-ion batteries for electricity storage, and tanks for pressurized gaseous hydrogen storage. Alternative electricity storage options, as described in [14], are also considered in a dedicated scenario (see Section 4), as characterized in [44].

3.1. Electricity storage options

Concerning the techno-economic characterization of electricity storage technologies, the following data sources were selected among institutional data providers and reported in Table 1.

The listed references agree to provide a specific future capital cost evolution per unit of storage capacity (kWh) for utility-scale lithium-ion batteries from ~500 \$/kWh in 2020 to ~200 \$/kWh in 2050. This range is also consistent with data from the JRC-EU-TIMES model [44]. Once validated with the other sources listed, data from the 2022 Annual Technology Baseline by NREL [61] were taken as the main reference for this study since they are the most up-to-date in our knowledge.

Table 1
Examined data sources providing techno-economic data and future projections for energy storage technologies.

Agency	Publication	Year	Reference
International Renewable Energy Agency (IRENA)	Electricity storage and renewables: Costs and markets to 2030	2017	[57]
Lazard	Levelized cost of storage - Version 4.0	2018	[58]
International Energy Agency (IEA) and Nuclear Energy Agency (NEA)	Projected Costs of Generating Electricity	2020	[59]
US Energy Information Administration (EIA)	Capital Cost and Performance Characteristic Estimates for Utility Scale Electric Power Generating Technologies	2020	[60]
National Renewable Energy Laboratory (NREL)	2022 Annual Technology Baseline	2022	[61]

Table 2
Techno-economic characterization of lithium-ion batteries for electricity storage. Values from [61].

Size	Lifetime (years)	Round-trip Efficiency (%)	$Cost^{Power}$ ($\$_{2020}$/kW)		$Cost^{Energy}$ ($\$_{2020}$/kWh)		$Cost^{Constant}$ (k$\$_{2020}$)		Scenario
			2020	2050	2020	2050	2020	2050	
Utility-scale	15	85	249	107	369	82			Advanced
				190		118			Moderate
				199		246			Conservative
Commercial (600 kW)	15	85	205	108	324	77	433.8	131.4	Advanced
				142		82		219.4	Moderate
				249		178		302.3	Conservative
Residential (5 kW)	15	85	655	183	685	237	6.9	2.2	Advanced
				247		320		3.0	Moderate
				257		333		3.1	Conservative

Moreover, that choice guarantees a higher consistency with the techno-economic modeling of new technologies included in the TEMOA-Italy power sector (as presented in Table A3), most of which are from the same source.

As [61] provides three capital cost components for storage technologies (reported in Table 2), namely the power capital cost $Cost^{Power}$, measured in \$/kW, the energy capital cost $Cost^{Energy}$, measured in \$/kWh, and the constant capital cost $Cost^{Constant}$, measured in \$ and only considered for residential and commercial battery storage, while it is assumed to be negligible for utility-scale, the unitary capital cost $Cost^{Invest}$, measured in \$/kW and referred to the rated power of the technology, can be estimated according to Eq. (8).

$$Cost^{Invest} = Cost^{Power} + Cost^{Energy} \cdot Storage^{Duration} + \frac{Cost^{Constant}}{Power^{Rated}} \tag{8}$$

Following the assumption of [61], the rated power $Power^{Rated}$ required in Eq. (8) to estimate the investment cost is assumed to be equal to 5 kW for residential and 600 kW for commercial batteries. According to the TEMOA formulation presented in Section 2.1, alternative technologies with different $Storage^{Duration}$ are considered. The possible storage sizes are assumed to be equal to the options proposed by [61] 2 h, 4 h, 6 h, 8 h, 10 h for utility-scale; 1 h, 2 h, 4 h, 6 h, 8 h for commercial scale; 2.5 h, 4 h for residential scale. This strategy allows competition between different storage configurations. Therefore, it is possible to identify the optimal economic option in terms of storage capacity (kWh) per unity of nominal power (kW) according to the model behavior in the studied scenarios. The fixed O&M costs are set to 2.5 %/year of the total capital cost, as done in [61].

Pumped hydro energy storage is also included among the technologies represented in the model as an existing source. This technology represents the largest energy storage source in several countries, including Italy [62]. However, most of the investments have been made several decades ago. It is challenging to assume an average capital cost for new pumped hydroelectric plants since such data is strongly dependent on the features of the selected sites. In the present study, since the available pumped hydro in Italy has been constant at ~7 GW from 2006 to 2022 and the Italian reservoir hydroelectric capacity, in general, is not expected to increase in the upcoming years, no new investments are allowed in TEMOA-Italy for these technologies and only O&M costs and efficiency improvements are considered. The yearly fixed O&M cost is assumed to be equal to 17.82 M\$/GW, and the variable O&M cost is assumed to be equal to 0.51 M\$/PJ, both from [61]. The round-trip efficiency is assumed to be equal to 67 % in 2006 [63] and to progressively increase up to 80 % in 2050 [61].

In addition to lithium-ion electrochemical batteries and pumped hydro facilities, the other electricity storage options, along with their corresponding efficiencies and costs are sourced from [14]. Specifically, the following technologies are considered: flywheels (0.5 h), compressed air energy storage (CAES, 8.0 h), NaS batteries (6.6 h), lead-acid batteries (2.0 h), flow batteries (4.0 h), superconducting magnetic energy storage (SMES, 1.0 h) and supercapacitors (SCs, 1.0 h). The durations cited are taken from [14]. The first year of availability is assumed to be 2030, except for SMES, which is delayed to 2040 based on [64]. A cost decrease of 25 % for non-mature technologies is assumed from 2030 to 2050, extending the same lithium-ion cost reduction for technology learning to the whole electricity storage sector. This assumption draws on the findings presented in [57], which indicate that the decrease in lithium-ion battery costs should mirror broader trends in the electricity storage sector over the period from 2016 to 2030.

Note that, consistently with standard practices in the ESOMs field, average values have been used to represent different technology categories rather than focusing on data tied to specific processes, applications or conditions. Due to this approach, possible innovative enhancements proposed by the literature in the energy storage field (e.g., [65,66]) are not considered, as well as options characterized by low technology readiness levels.

3.2. Hydrogen storage options

Centralized and decentralized tanks for gaseous hydrogen storage options are considered in the model. The techno-economic parameters are based on the assumptions from the JRC-EU-TIMES model [44]. The related costs are reported in Table 3 and are consistent with [13], which estimates the investment cost of hydrogen tanks at 15 €/kWh (constant from 2021 to 2040) based on [67]. In addition, [68,69] found the cost of tanks for hydrogen storage will be 14.8 \$/kWh and 10.5 \$/kWh, respectively, when the production capacity will reach 500 k units/year. The round-trip efficiency is assumed to be equal to 100 % for such technologies, as the compression losses are already accounted for in the other step of the hydrogen value chain and are dependent on the specific delivery strategy [70]. Availability refers to the uptime of the tank, while the optimal number of operating cycles is evaluated by the model according to the studied scenario, as discussed in Section 2.1.

The JRC-EU-TIMES model also provides the underground storage option with an investment cost equal to 2.7 ÷ 3.5 €/kWh. However, the data validation against other sources resulted in large uncertainties associated with the capital cost of such technology. For instance, the Open Energy Outlook model assumes 0.35 \$/kWh [71]. For this reason, and since precise studies for the underground hydrogen storage potentials are still not available in the literature for the Italian case study, the technology was not included in the study.

Table 3
Techno-economic characterization of tanks for hydrogen storage. Values from [44].

Technology	Investment cost (€$_{2012}$/kWh)		Fixed O&M cost (€$_{2012}$/kWh)		Lifetime	Availability (%)
	2015	2025	2015	2025		
Centralized tank	16.58	12.97	0.76	0.60	22	98
Decentralized tank	9.55	7.47	0.44	0.34	22	98

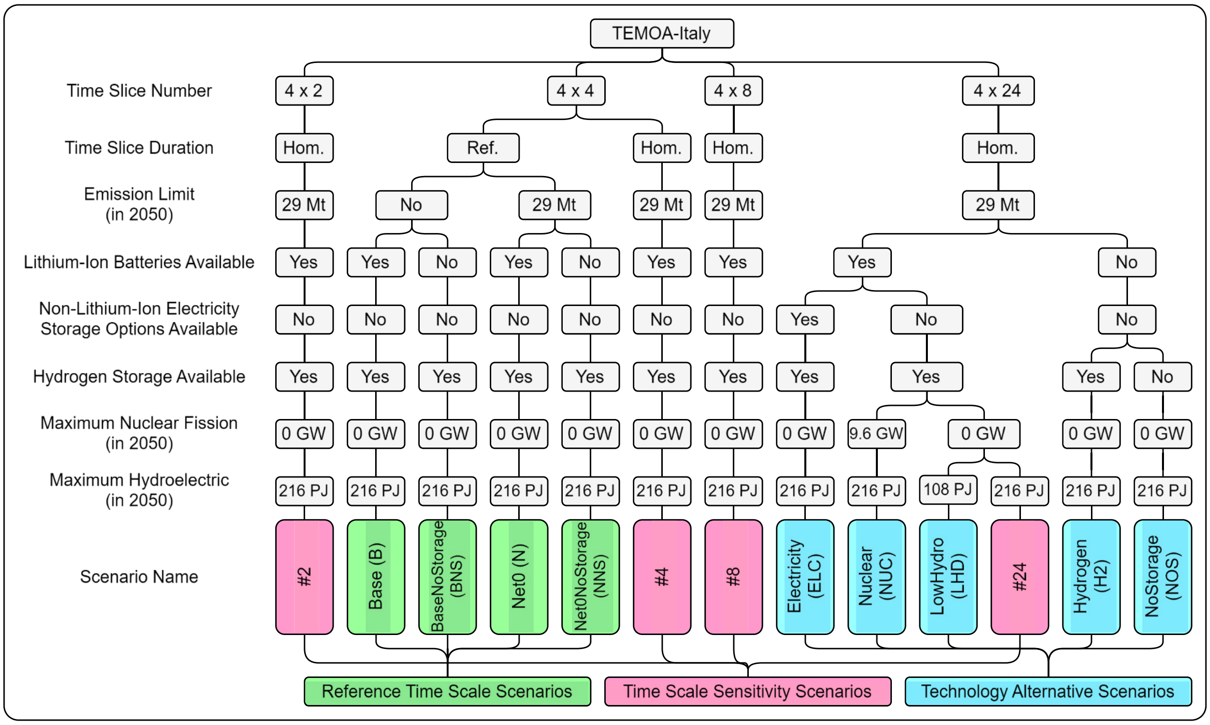

Fig. 4. Set of scenarios analyzed in this work. The time slice number is reported as the product between the time season number (four) and the times of day number. "Ref." stands for reference time slices (as reported in Table A1), and "Hom." for homogeneous (the 24 h of the day are equally prorated among the times of day). (For interpretation of the references to colour in this figure, the reader is referred to the web version of this article.)

4. Scenarios

The results presented in Section 5 are associated with the scenarios shown in Fig. 4. Such scenarios have been implemented in the TEMOA-Italy model, presented in the Appendix. The "reference time scale scenarios", highlighted in green, are used to produce results related to the reference time slices configuration, as detailed in Table A1. The four scenarios differ in terms of the availability of energy storage technologies within the technology portfolio and the application of the emission limits. Concerning the energy storage options, both electricity and hydrogen storage are considered, as discussed in Section 3. More details on how such technologies have been integrated into the TEMOA-Italy energy system are available in the Appendix.

While scenarios B and BNS do not include any emission limit, decarbonization scenarios include a decreasing emission limit starting from 2030. The emission limit is equal to 194 MtCO2 in 2030 [72] and decreases up to 29 MtCO2 in 2050 [10], allowing residual emissions expected to be compensated by land use, land-use change, and forestry (LULUCF) policies, as discussed in [39].

The "time scale sensitivity scenarios" (pink) are used to assess the results' sensitivity to the time steps resolution through the application of the methodology for the required model pre and postprocessing explained in Sections 2.2 and 2.3. Specifically, the time seasons number is constant among such scenarios and equal to four (winter, spring, summer, and fall, as presented in the Appendix), since the most important variations in renewable CFs are associated with solar and wind and they occur on a short term time scale (see Fig. A3), while a variable number of times of day was explored: #2, #4, #8 and #24 (see Fig. 4).

Eventually, "technology alternative scenarios" (light blue in Fig. 4) were studied to assess:

- The power sector evolution without any storage technology available, except for the already existing pumped hydro capacity ("NoStorage"), to evaluate the optimal system evolution in the absence of innovative storage options.
- The possible technology competition among electricity storage technology when including non-lithium-ion options for electricity storage ("Electricity"), as discussed in Section 3.1.
- The hydrogen storage role in a scenario without the availability of electricity storage ("Hydrogen"); to evaluate the possible role of hydrogen production through electrolysis, hydrogen storage, and electricity production with fuel cells in balancing the power sector.
- The effect on the results of a lower hydroelectric production ("LowHydro"); to consider the possible water scarcity in the future due to the impact of climate change [73]. Specifically, this scenario assumes a maximum hydroelectric potential in 2050 that is halved compared to the others (108 PJ versus 216 PJ).
- The possible competition between nuclear and renewables with storage in a dedicated scenario ("Nuclear") allowing the deployment of nuclear fission power plants (light water reactor and small modular reactor [61]), assuming the same electrification level obtained in scenario #24 and a maximum capacity for nuclear power plants in 2050 $\approx$ 10 GW, in accordance with the most ambitious scenario in terms of possible nuclear deployment proposed by [9].

5. Results and discussion

This section presents the results associated with the set of scenarios presented in Fig. 4 (Sections 5.1, 5.2, and 5.3). The main source of uncertainties and remarks are also presented in Section 5.4. More detailed results are discussed in the Appendix.

5.1. Reference time scale scenarios

The time evolution of the available capacity and the electricity production for the power sector in the "reference time scale scenarios" is reported in Fig. 5. Thanks to the model calibration up to 2020, the results for the past milestone years (2010 and 2020) are common for all

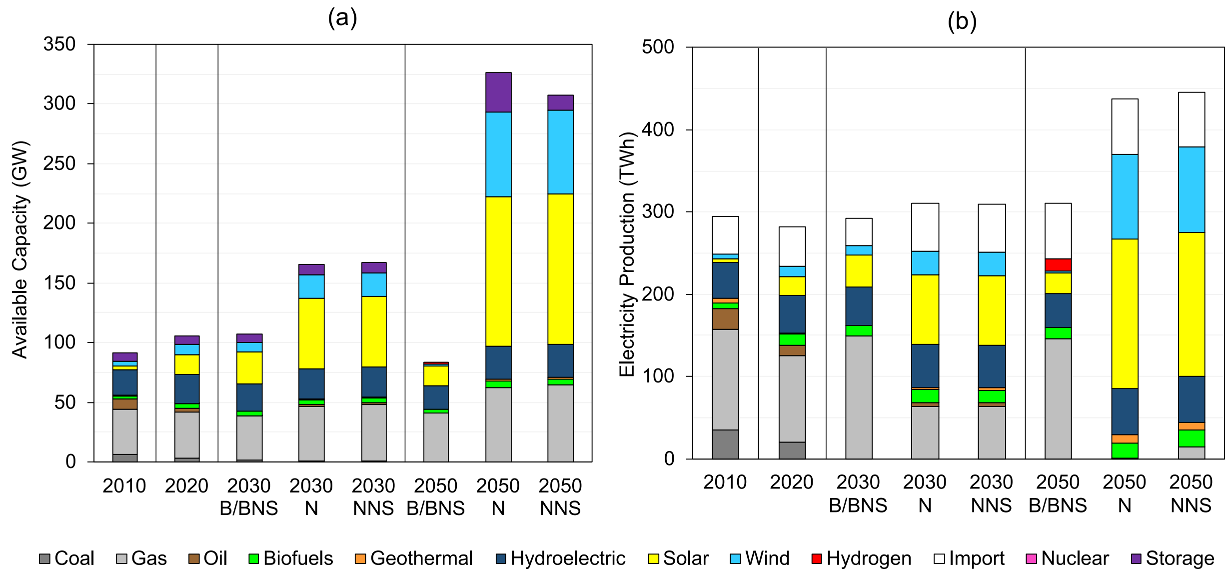

Fig. 5. Available capacity (a) and electricity production (b) in 2010, 2020, 2030, and 2050 for the "reference time scale scenarios".

the scenarios and correspond to historical data by the Eurostat Energy Balances [74]. An increase in solar and wind capacity and electricity production is shown from 2010 to 2020, to the detriment of coal and oil plants. Base (B) and BaseNoStorage (BNS) scenarios only differ regarding the availability of storage options in the future. However, as the results suggest that storage is not competitive in the absence of a decarbonization target, the results do not vary between such scenarios, and a single column is reported in Fig. 5a and b for both of them.

The differences between B/BNS, Net0 (N), and Net0NoStorage (NNS) occur in the future time periods. Fig. 5 shows results for 2030 and 2050.

Firstly, Fig. 5a shows a huge increase in the available capacity associated with N (+290 %) and NNS (+267 %) with respect to B/BNS, mainly due to the high penetration of renewable power plants, characterized by a much lower CF with respect to fossil-fueled plants (see Table A3). The main difference between N and NNS is due to the different deployment of electricity storage capacity. The deployment is lower in the NNS, as the only available storage technology is the existing pumped hydro. Moreover, in the absence of storage (NNS), residual electricity production from natural gas is still required in 2050. This is due to the need to balance the solar unavailability during the night, as more precisely shown in Fig. 6. The storage label in Fig. 5 only represents lithium-ion batteries and the existing pumped hydroelectric storage capacity since other electricity storage options are not available in the considered scenarios, as shown in Fig. 4. Note that no hydrogen storage options were deployed in the optimal system configuration, although they are available for installation in such scenarios.

Secondly, higher electricity production is computed for the N and NNS scenarios, namely +41 ÷ 44 %, with respect to the base scenarios in 2050 (Fig. 5b). This outcome is due to the higher electrification of the end-uses, evaluated as electricity share in the final energy consumption, consequent from the necessity of respecting the emission limit (see Fig. 4) and within the constraints applied to the power sector (see the Appendix).

Fig. 6 shows, for winter and summer, the electricity mix hour by hour

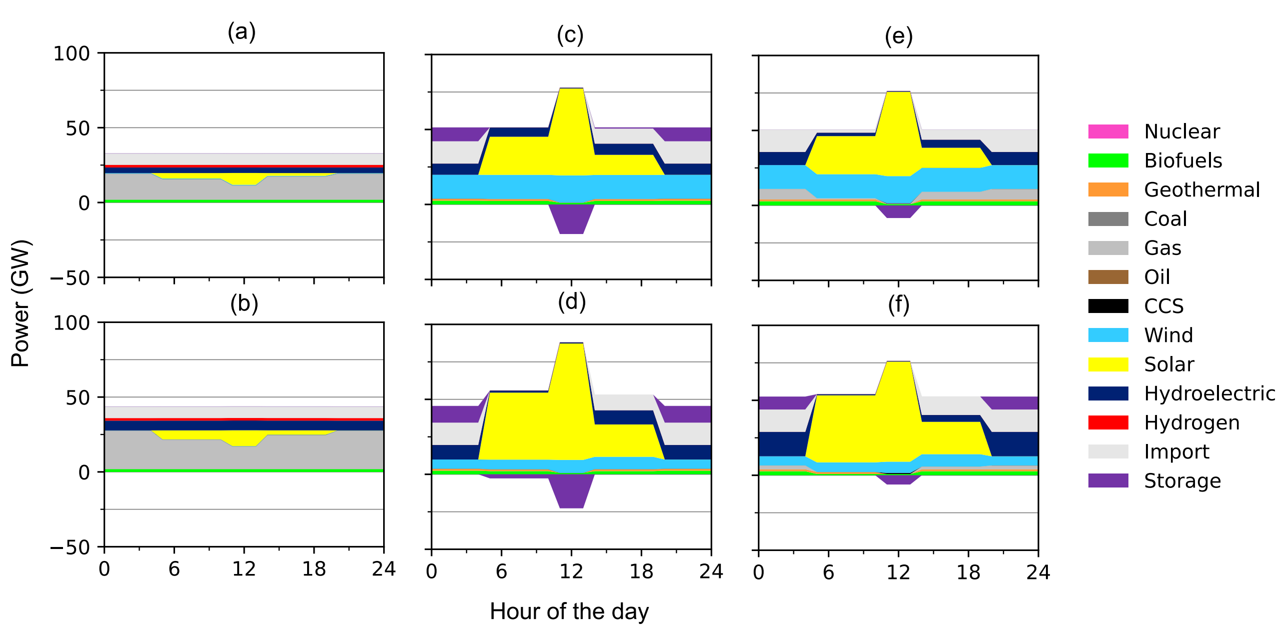

Fig. 6. Intra-annual electricity production and energy storage charge and discharge, hour by hour in winter (a, c, e) and summer (b, d, f) for the "reference time scale scenarios" B/BNS (a, b), N (c, d) and NNS (e, f).

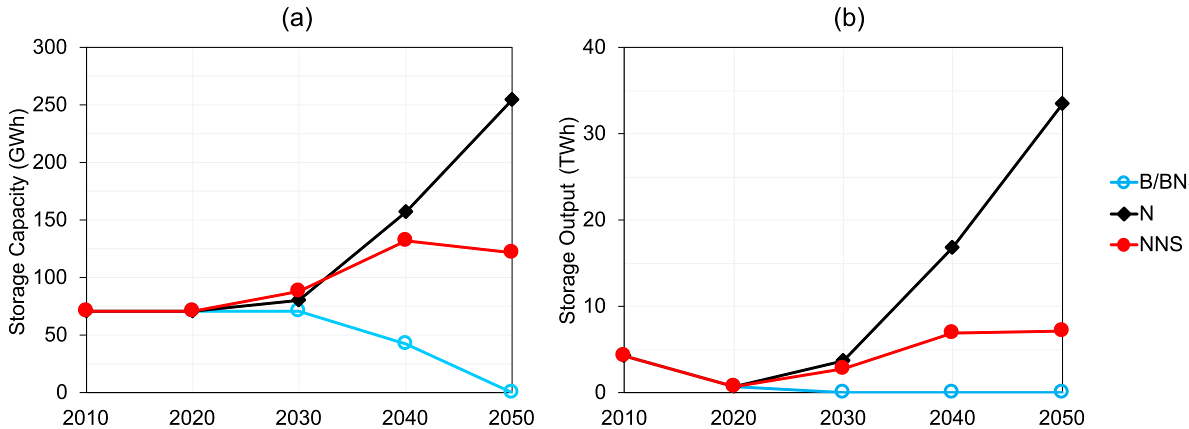

Fig. 7. Electricity output from storage technologies (a) and installed storage capacity (b) for the "reference time scale scenarios".

in the typical day used to model the season, including the electricity production evolution by technology group and the storage charge and discharge phases. The same differences in terms of natural gas and renewable penetration in the mix have already been observed in Fig. 5 and are also evident in Fig. 6. Specifically, the role played by pumped hydroelectric in the NNS scenario is much lower with respect to the penetration of pumped hydro and lithium-ion batteries in the N scenario, and the electricity production from natural gas is necessary during the night and to a larger extent during the winter than during the summer, due to the lower solar availability.

Focusing now on the evolution of the penetration of storage technologies across the time horizon, Fig. 7 shows the evolution of energy storage capacity and electricity output from 2010 to 2050 for the "reference time scale scenarios". The first interesting result is that the three curves associated with the B/BNS, N, and NNS scenarios are relatively close one each other up to 2030, and they remain on values comparable to the historical evolution of the existing pumped hydroelectric facilities both in terms of storage capacity and electricity output, suggesting that the massive deployment of energy storage option is not necessary to satisfy the Fitfor55 decarbonization targets for 2030 [72]. Coming to 2040 and 2050, as also highlighted by Fig. 5, the existing storage capacity is completely disposed of in the B/BNS scenarios, while a relevant difference emerges between N and NNS, due to the lithium-ion penetration in scenario N that is not possible in NNS, only including pumped hydroelectric plants. While in terms of storage capacity, the deployment of pumped hydroelectric and lithium-ion batteries is comparable (≈13 GW/134 GWh and ≈20 GW/120 GWh, respectively), in terms of annual electricity output, lithium-ion batteries contributed more than pumped hydroelectric (≈26 TWh with respect to ≈7 TWh, respectively), due to the higher efficiency and CF of that technology. The cost associated with lithium-ion battery deployment is 4.2 B€ throughout the time horizon.

5.2. *Time-scale sensitivity scenarios*

In this section, results related to the "time-scale sensitivity scenarios" are presented. As discussed in Section 4, such scenarios only differ for the times-of-day number: 2, 4, 8, and 24.

Fig. 8 reports the storage deployment in 2050 (lithium-ion batteries and pumped hydroelectric plants) according to the studied scenario. The name of the scenario corresponds to the number of times of day. From 8 to 24 times of day, both the capacity and the activity do not significantly vary, suggesting that 8 times of day are necessary and sufficient for the convergence of the results. Moreover, the deployed capacity oscillates around the optimal value also suggested by the N scenario (≈39 GW/254 GWh, see Fig. 7a).

Concerning the storage electricity output, a clear increasing trend

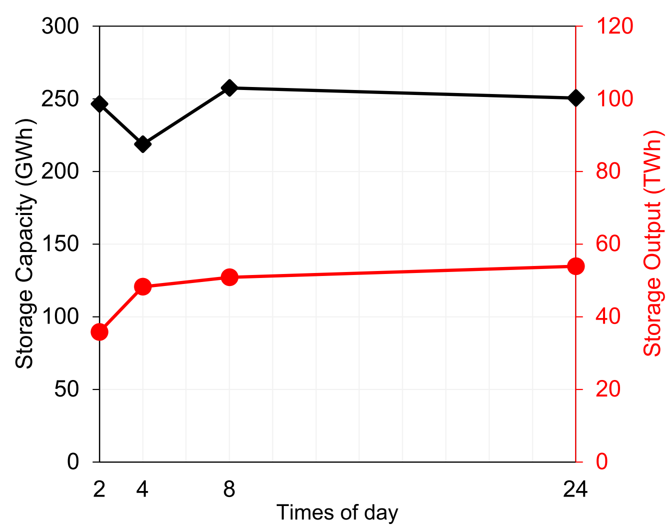

Fig. 8. Electricity output from storage technologies and installed storage capacity for the "time scale sensitivity scenarios" (#2, #4, #8, and #24 as reported in the horizontal axis) in 2050. Storage capacity is depicted as a black line, and storage output as a red line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

with the times of day number can be observed in Fig. 8. Since this is not associated with a variation in the renewables' penetration among the different scenarios, this behavior suggests that a fine time scale is useful to properly model the storage contribution to balancing renewables intermittency, as it is confirmed by the higher CF emerging by Fig. 8.

The storage capacity reported in Fig. 8, ranging from 28 to 39 GW in terms of rated power, helps to meet the planning reserve margin constraints. This capacity, shown as peak charge/discharge power during the summer in Fig. 9, aligns with the Italian government's target to deploy 30 to 40 GW of storage by 2050, as mentioned in [10]. Furthermore, this result is consistent with findings from studies [75,76], which used clustered representative days in their analyses. The similarity in results, despite using average representative days, confirms the reliability of this approach in estimating the necessary storage deployment, even when accounting for anomalous and extreme events.

The cumulative cost of technology installation rises from 2.1 B€ in scenario #2 to 6.1 B€ in scenario #24. This increase is due to the selection of technologies with shorter storage durations in scenario #24. Specifically, the average storage duration decreases from 8.0 h in scenario #2 to 6.7 h in scenario #24 as the time scale is refined, leading to higher per-unit investment costs. The choice of storage durations, which

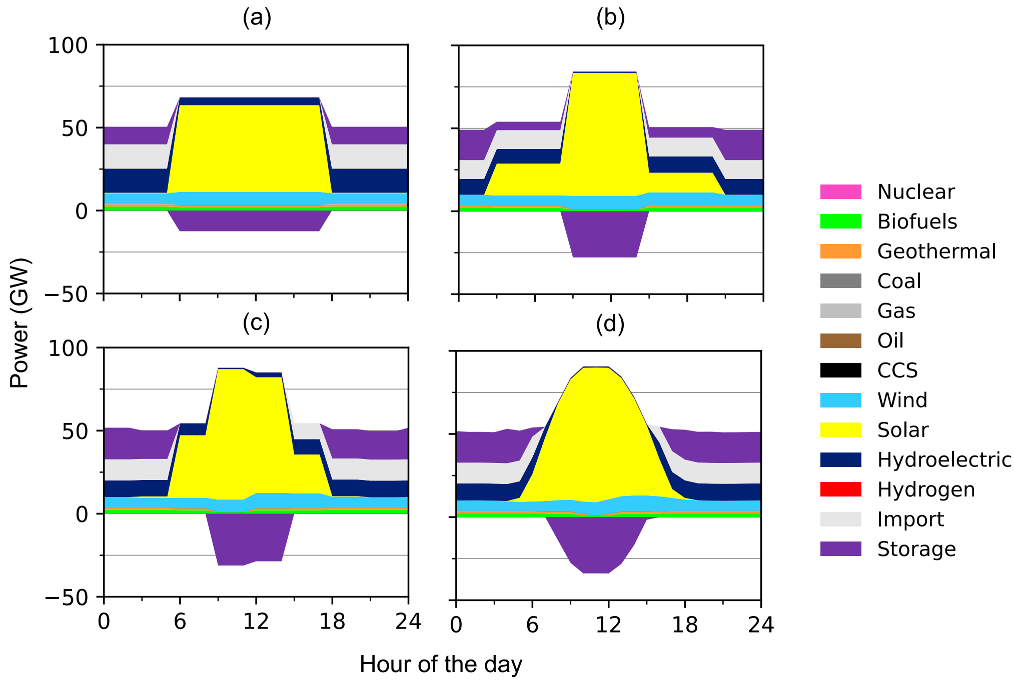

Fig. 9. Intra-annual electricity production and storage charge and discharge, hour by hour in summer for the "time scale sensitivity scenarios" #2 (a), #4 (b), #8 (c), and #24 (d).

are shorter than the maximum available options, indicates that long-duration storage configurations, including seasonal storage, are not competitive within the Italian energy system and the scenarios studied.

As far as the computational burden of increasing the number of time-of-day is concerned, the computational time associated with each of the time scale sensitivity scenarios spans from 147 s for scenario #2 to 1451s for scenario #24, tested on a machine equipped with an Intel Xeon Gold 6248R CPU and 256 GB of RAM. The increased number of time slices directly affects the computational cost: the time required to perform the four phases of a TEMOA deterministic optimization: reading the input database, creating the optimization problem, solving the problem, and calculating output variables. By linearly interpolating the total time as a function of the times of day number, the proportionality coefficient can be estimated at 59.6 s per time of day, with a correlation coefficient higher than 0.99. The approximately linear dependency of the computational time on the number of time slices is also consistent with the results of [76].

5.3. Technology alternative scenarios

In this section, results associated with the "technology alternative scenarios" are reported. The aim of studying such scenarios is to explore the results' dependency on the model structure and the availability of key technologies for the competition with storage options in balancing the VRE intermittency. Scenario #24, belonging to the "time scale sensitivity scenarios", is used here as a reference, and common features of all the scenarios are the decarbonization target and the adoption of 24 times of day: the most refined time scale.

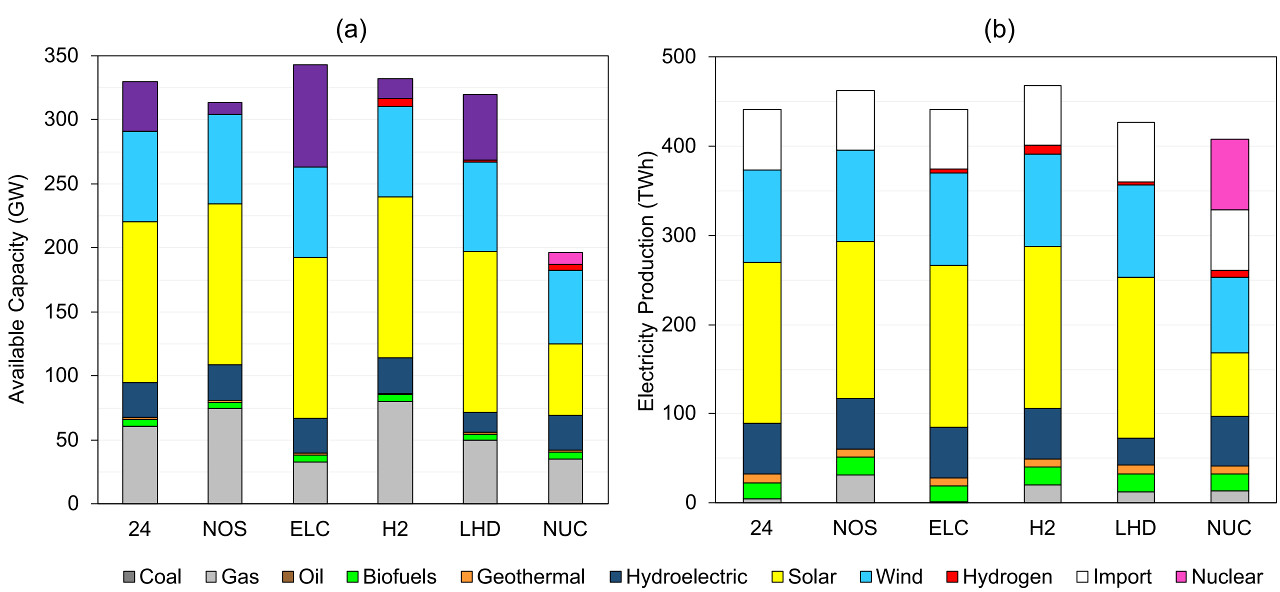

Fig. 10. Available capacity (a) and electricity production (b) in 2050 for the "technology alternative scenarios".

In terms of capacity, in Fig. 10a, an emerging competition between storage and natural gas in satisfying the planning reserve margin can be observed, whereas the VRES installed capacity does not significantly vary among the alternative scenarios (except for NUC). With respect to scenario #24, the scenarios ELC and LHD, which include more electricity storage options and boosting the storage role due to low hydroelectric resources, respectively, deploy more storage power, while scenarios NOS and H2, which do not include any electricity storage technologies, require increasing the available backup capacity based on natural gas.

The first difference among the scenarios concerns the role of natural gas power plants in Fig. 10b. Although the electricity production by natural gas is marginal in all the scenarios, the maximum value corresponds to NOS, where neither electricity nor hydrogen new storage options are available in the system, and in H2, where only hydrogen storage options are available. Since the emission limit is applied to the overall emissions of the system, minor changes in the other sectors compensate for the slightly higher emissions in the power and hydrogen sectors.

In the H2 scenario, centralized tanks are deployed only with an annual activity of ~120 PJ in 2050, equal to ~65 % of the total hydrogen production through electrolysis. Natural gas is necessary to guarantee electricity production during the night, as well as the deployment of a small CCS capacity. Note that H2 is the only scenario in which such plants are selected, as shown in Fig. 11d.

When nuclear power plants participate in the technology competition, they are deployed up to the maximum capacity constraint assumed (≈10 GW), to the detriment of both solar and wind. Indeed, in terms of nominal power deployed, solar decreases from ≈126 GW in scenario #24 to ≈56 GW in NUC, and wind decreases from ≈70 GW in scenario #24 to 57 GW in NUC. In the presence of the nuclear baseload, storage is not necessary anymore and even the existing pumped hydroelectric storage capacity is progressively disposed of (see Fig. 11f). This discovery indicates that the decision to utilize nuclear power or not could significantly influence the role of renewables and energy storage in the Italian energy system. This aspect surely warrants further investigation. Note that the net hourly electricity distributions shown in Fig. 11 for the six scenarios are not necessarily representative of the actual one. Indeed, for ESOMs in general, as well as for TEMOA-Italy, electricity is an intermediate commodity for which both production and consumption across the time slices are defined by the model without considering detailed operational constraints.

Looking at the energy output from storage technologies, the four scenarios also including alternative electricity storage technologies show a good agreement in estimating ≈50 TWh in 2050 through storage, similar to scenario #24. In the ELC scenario, where non-lithium electricity storage technologies are available, a higher storage capacity is installed in 2050 with respect to the other scenarios, as shown in Figs. 10a and 11c. The breakdown of such capacity by technology is reported in Fig. 12a, highlighting that CAES and NaS batteries may be economically competitive even if with a lower penetration with respect to lithium-ion batteries, despite the lower round-trip efficiency associated with CAES, while more expensive technologies are not selected. Although this analysis focuses on short-term storage, the outcome related to the competitiveness of CAES aligns with the findings of [77] for long-term storage in the UK case study. Moreover, the necessity of combining the deployment of lithium-ion batteries with technologies presenting better performances in specific applications (e.g., primary response and seasonal storage), such as CAES and NaS batteries, is an outcome of [78] as well.

In conclusion, to assess the variability of the results among scenarios considering the availability of at least one new electricity storage option, Fig. 12b illustrates the electricity routed through storage relative to the total electricity production by the power sector. The deviation from the average trend is relatively small: the minimum to maximum range for the listed scenarios indicates that storage contributes less than 3 % in 2030 and between 8 and 13 % in 2050 with respect to the total electricity production in the Italian system. Thus, at least for the scenarios examined in this study and without nuclear options, the results show limited divergence due to perturbations in the model structure.

5.4. Sources of uncertainties and remarks

The construction of an ESOM is a complex task that involves data sources, assumptions, and modeling choices, all of which can be subject to discussion. This complexity is compounded by uncertainties associated with future projections for socio-techno-economic input data. Although this study does not address a precise uncertainty analysis, this section highlights some key concerns related to that.

Firstly, considerable uncertainties surround the techno-economic

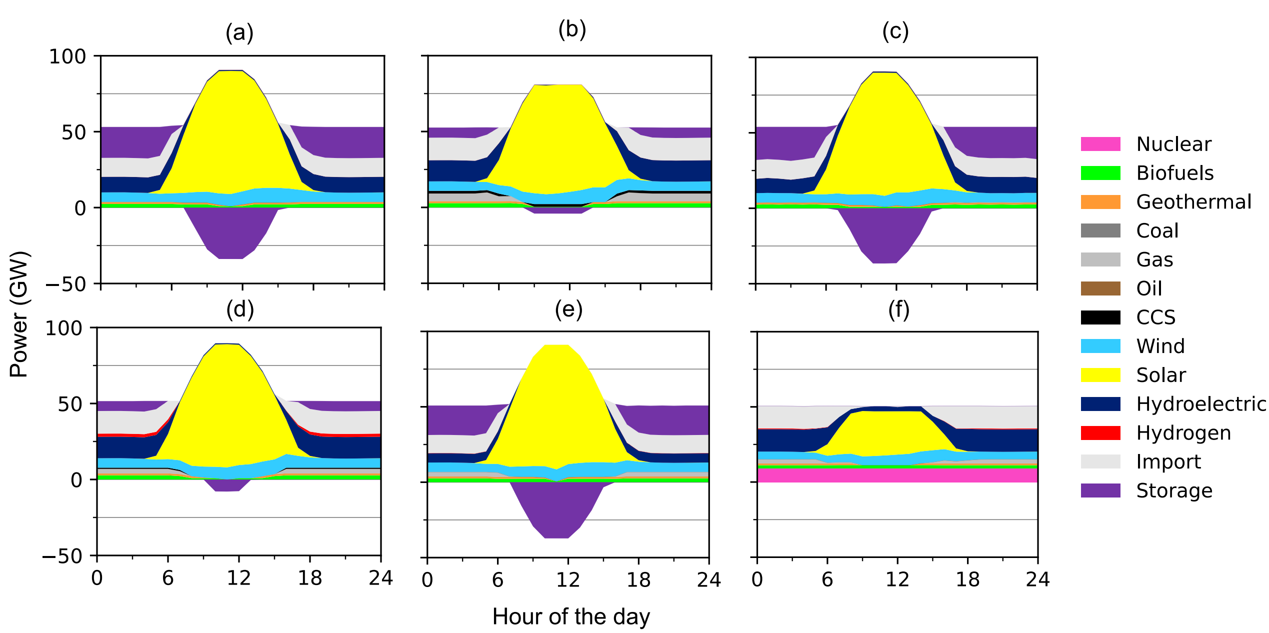

Fig. 11. Intra-annual electricity production and storage charge and discharge, hour by hour in summer for the "technology alternative scenarios" #24 (a), NOS (b), ELC (c), H2 (d), LHD (e) and NUC (f).

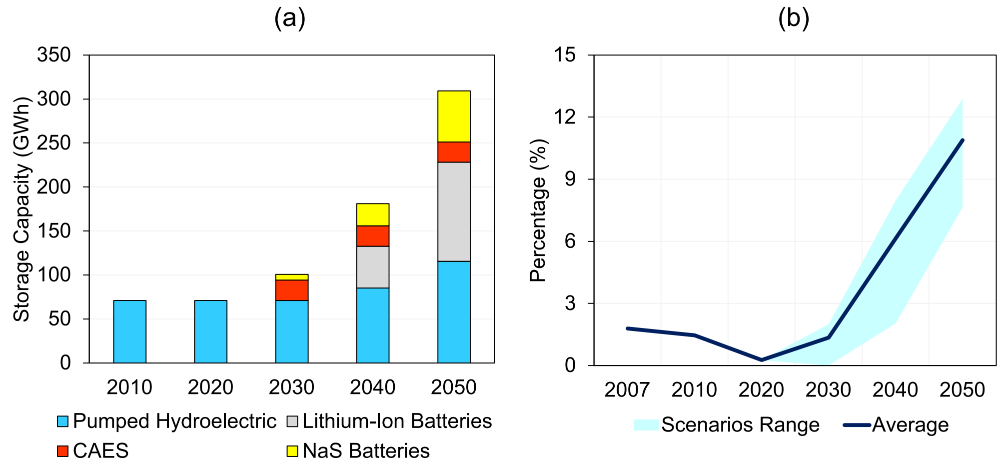

Fig. 12. Time evolution and breakdown by technology of the storage capacity deployed in the ELC scenario (a). Average evolution across the time horizon of the percentage electricity through storage technologies with respect to the total electricity production (dark blue line) and minimum to maximum range (light blue area) for scenarios N, #2, #4, #8, #24, ELC, LHD (b). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

parameters used to model non-lithium-ion electricity storage technologies, particularly those with a low technology readiness level, like SMES and supercapacitors. Those uncertainties led to the specific focus on lithium-ion batteries in the main analysis due to their more reliable data. Conducting a detailed parametric analysis, incorporating both advanced and conservative improvements due to technology learning, could yield different outcomes in technology competition. Such an analysis should be conducted to enhance the reliability of the results.

Secondly, the modeling of the electric load profile in TEMOA-Italy is indirect, as it considers the distribution of final service demands in buildings, the transport sector, and industry. While this approach allows for the joint optimization of supply and demand sectors, it does not allow for precisely modeling the electricity consumption profile. Although results proposed in this paper have been compared and validated with similar studies using different methodologies to highlight the capability of capacity expansion models to properly estimate the order of magnitude of the necessary storage capacity, the intrinsic time slice structure of ESOMs inevitably neglects some aspects. For instance, extreme events and fluctuations in the very short term are not considered at all. To address these limitations, it is worth exploring the possibility of soft-linking TEMOA-Italy with an alternative model instance specifically focused on the operational challenges of the power sector. This linkage could help to reproduce and validate the results using a different modeling strategy. Moreover, applying the study to a different spatial region (e.g., Europe) may lead to different results, including seasonal energy storage, as higher variability in the renewables within the year is associated with higher latitudes.

Finally, despite their contribution to reducing emissions and energy import dependency, renewables and storage technologies pose challenges due to their raw materials intensity. Fluctuations in market prices or issues in the availability of these commodities could arise in the future, especially considering the growing demand for renewables and potential international crises. To account for such uncertainties in energy planning, stochastic optimization could be a valuable tool. It enables the exploration of alternative scenarios and their specific probabilities, providing a more robust perspective on the system's resilience to uncertainties.

6. Conclusions

This study presented an innovative methodology for integrating short-term energy storage technologies into capacity-expansion-oriented ESOMs. The approach allows enhancing the time scale refinement of integrated ESOMs, incorporating higher granularity in time slice structure, renewable CFs, and specific demand distribution. The paper proposes a comprehensive techno-economic characterization of various electricity and hydrogen storage options applied to the Italian energy system using the open-source and open-data TEMOA-Italy model. A model database preprocessing and postprocessing strategy to deal with infra-annual input and output data is proposed.

The results highlighted how ESOMs could be used to catch the expected role of energy storage in future scenarios, provided a sufficient number of time slices are considered. This was demonstrated by investigating the results' sensitivity to the model time resolution and comparing them with those obtained with models focused on the operational dispatchment, in the case of electricity storage.

The findings reveal the crucial role of storage technologies in power sector dynamics within capacity expansion models. The results emphasize the sensitivity of these models to both time scale and the inclusion of diverse available technologies. With a decarbonization target, storage technologies are projected to handle 8 ÷ 13 % of the Italian total electricity production by 2050. However, in the absence of emission constraints, the different storage solutions are not competitive. The optimal deployed storage capacity when considering new electricity storage options is ≈250GWh and ≈40GW, corresponding to an average storage duration of ≈6 h.

This research could be extended by applying it to a power sector model or considering a soft coupling with operational dispatching models. This extension would enable a more detailed analysis of electricity dynamics, considering factors such as ramp-up and ramp-down constraints represented in unit commitment models. Moreover, the proposed methodology could be extended by considering not only chronological average time slices but also time slices representing clustered typical days as proposed, for instance, in [76]. This would enable the consideration of extreme weather conditions impacting both energy production and consumption, for instance.

Notably, the availability of nuclear power plants significantly impacts the results, rendering storage non-optimal and reducing renewables penetration due to the deployment of nuclear power for baseload generation. Future investigations should explore the competition between renewables/storage and nuclear power within the Italian energy system and other countries or regions in the world, providing valuable insights for strategic decision-making.

CRediT authorship contribution statement

Matteo Nicoli: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Victor Augusto Duraes Faria:** Writing – review & editing, Methodology, Conceptualization. **Anderson Rodrigo de Queiroz:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization. **Laura Savoldi:** Writing – review & editing, Supervision, Resources, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

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

Data availability

The release 3.0 of TEMOA-Italy is available at [47]. The release 1.0 of the MAHTEP version of TEMOA is available at [45]. The "storage_preprocessing.py" and "storage_postprocessing.py" tools and the set of results related to this paper are available in the Supplementary material.

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Appendix

TEMOA-Italy is a model instance focused on the Italian energy system and based on energy statistics provided by the International Energy Agency (IEA) for the year 2006 (the "base year" of the time horizon for the analyses) [79], as extensively described in [63]. It allows the exploration of future energy scenarios on a time scale up to the year 2050, subdivided into several time periods. The model is fully calibrated (i.e., matches actual energy statistics) from the base year up to 2020. The model includes the techno-economic characterization of the typical energy sector included in any ESOM (upstream, power sector, industry, transport sector, and buildings), together with technology modules devoted to hydrogen production (as described in [70,80]) and CCUS options (carbon capture technologies, synfuels production processes, and carbon dioxide storage, from [44]), as shown in Fig. A1. Internal production of hydrocarbons is based on [81], while i86mport and export prices are elaborate from [82,83]. The projection of final demands in the industrial sector is performed according to [84]. More details on the model structure are available in [85,86].

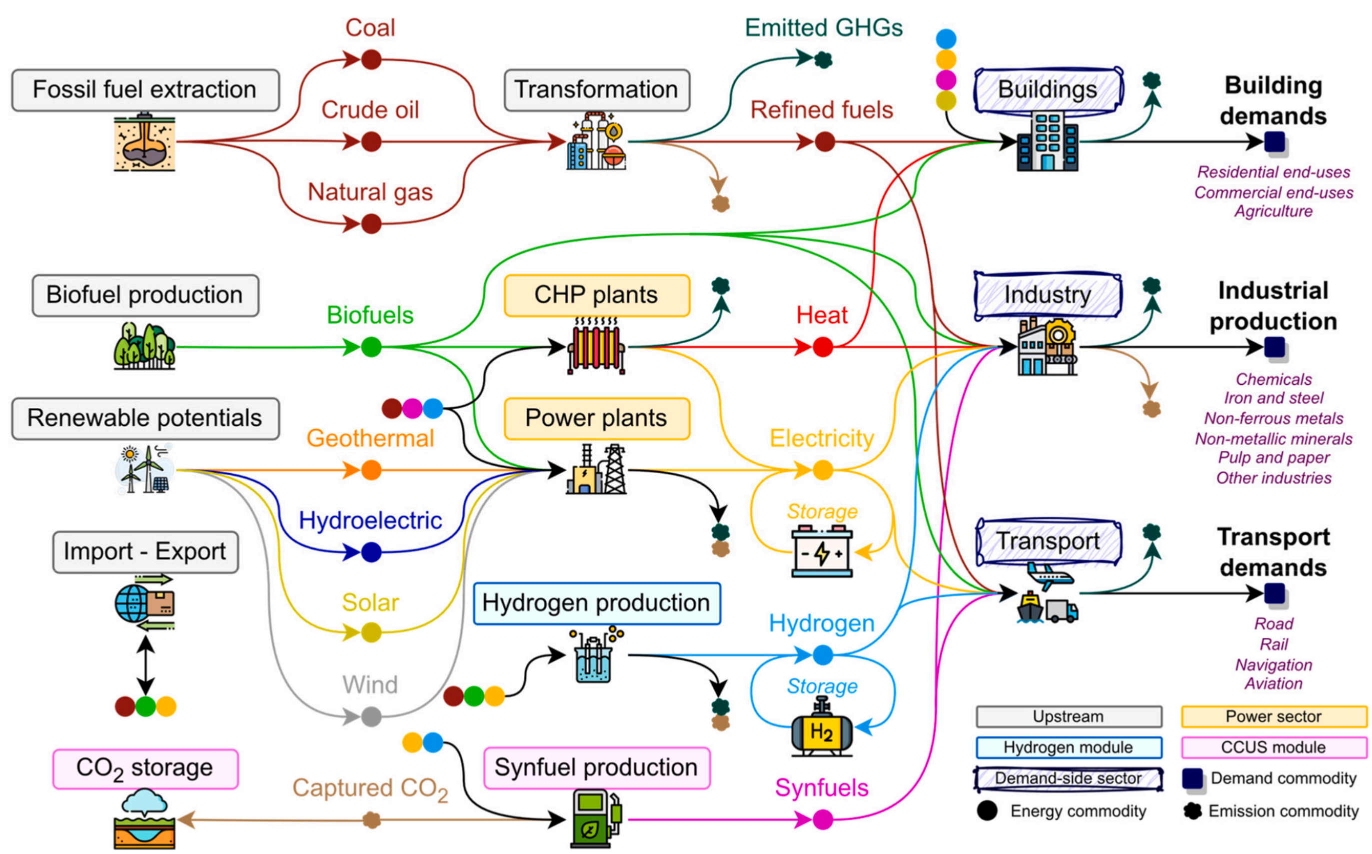

Fig. A1. The whole TEMOA-Italy energy system [47], including electricity and hydrogen storage options. Icons are from [36].

As discussed in Section 2.1, TEMOA includes technology sets to distinguish between baseload and non-baseload technologies, to account for curtailments, and to respect the reserve margin constraint at the sectorial level. In the model, curtailment is enabled only for solar and wind power plants (non-dispatchable).

Given that TEMOA-Italy is currently optimized with a maximum time resolution of 1 h and that, even for coal-based plants (the least flexible), the typical ramping rates are in the order of 1 ÷ 4 % per minute [87], the average hourly ramping rate would be higher than 100 %, having no relevant effects on the optimization process. For this reason, coal- and oil-fueled plants in TEMOA-Italy are assumed to have a constant output within the day (as a simplification to model their lower flexibility), while gas-fueled plants are free to vary the output power hour by hour.

All the technologies producing electricity are involved in the computation of the reserve margin, which is set to 35 %, equal to the maximum value registered by TERNA (the Italian transmission system operator) in the 2007–2016 period [88]. A 35 % planning reserve margin is also set by the Open Energy Outlook [89], a TEMOA model instance developed for the US energy system. The capacity credits used to express the technologies' reliability are reported in Table A3.

For this work, the TEMOA-Italy power sector was updated to the most recently available techno-economic data. Fig. A2 highlights the main technology groups (power, CHP, and heat plants), the input as well as the output commodities (electricity and heat), and the connection with the other technology modules of the model (regarding electricity and heat consumption). The technology-specific discount rates shown in Table A3 are from [90,91]. The different currencies used to express the costs according to the cited references are converted to €$_{2020}$ (the reference currency for TEMOA-Italy) through the exchange rates from [92].

Regarding the model time scale, the standard model time slices are shown in Table A1. They consist of a combination of four seasons (winter, spring, summer, and fall) and four times of day (night, morning, noon, and afternoon), corresponding to sixteen time slices. The allocation of the total time of the year among the time slices is also reported in Table A1, assuming a non-leap year.

Table A1
Reference TEMOA-Italy time slices structure and duration of each time slice as a fraction of the total time of the year.

	Hour of the day	20:00–04:59	05:00–10:59	11:00–13:59	14:00–19:59
Month of the year	Time season	Time of the day			
		Night	Morning	Noon	Afternoon
January–March	Winter	9.25 %	6.17 %	3.08 %	6.17 %
April–June	Spring	9.35 %	6.23 %	3.12 %	6.23 %
July–September	Summer	9.45 %	6.30 %	3.15 %	6.30 %
October–December	Fall	9.45 %	6.30 %	3.15 %	6.30 %

Table A2
Association of the stored commodity to each storage technology implemented in the TEMOA-Italy database.

Storage category	Storage technology	Associated commodity
Electricity	Lithium-ion batteries – Utility-scale	Centralized electricity
	Lithium-ion batteries – Commercial	Distributed electricity
		Commercial electricity
		Industrial electricity
	Lithium-ion batteries – Residential	Residential electricity
	Flywheels	Centralized electricity
	CAES	Centralized electricity
	NaS batteries	Distributed electricity
	Lead-acid batteries	Distributed electricity
	Flow batteries	Centralized electricity
	SMES	Centralized electricity
	Super capacitors	Centralized electricity
Hydrogen	Centralized tank	Centralized hydrogen
	Decentralized tank	Distributed hydrogen

Other time slice options with respect to those presented in Table A1 are possible, and alternative configurations to assess the sensitivity of the model results to the time scale modeling are presented in Section 4. The time slice variation is possible through the storage preprocessing tool presented in Section 2.2.

Electricity and hydrogen storage options presented in Section 3 were introduced in the model by assigning to each technology a specific stored commodity, as shown in Fig. A1. The model presents a distinction between centralized and distributed electricity and hydrogen. For instance, centralized electricity is produced by ground photovoltaic plants, while rooftop plants are devoted to distributed electricity production. Moreover, lithium-ion batteries are also associated with the sectorial electricity delivered to the industrial, commercial, and residential sectors (the final commodity representing sectorial consumption and produced mixing centralized and distributed electricity). The choice between centralized and distributed electricity for non-lithium-ion electricity options is performed according to [14]. The commodity associated with each storage technology is provided in Table A2.

The complete techno-economic characterization of new technologies included in the TEMOA-Italy power sector is available in Table A3. The overall technology categories are power plants (devoted to electricity production), CHP and micro-CHP plants (devoted to combined electricity and heat production), and plants devoted to heat production, including several technology options. More specifically, the possible energy inputs for the power sector are fossil fuels (including the synfuels blending options, as discussed in [39,93]), biofuels, renewables, and hydrogen.

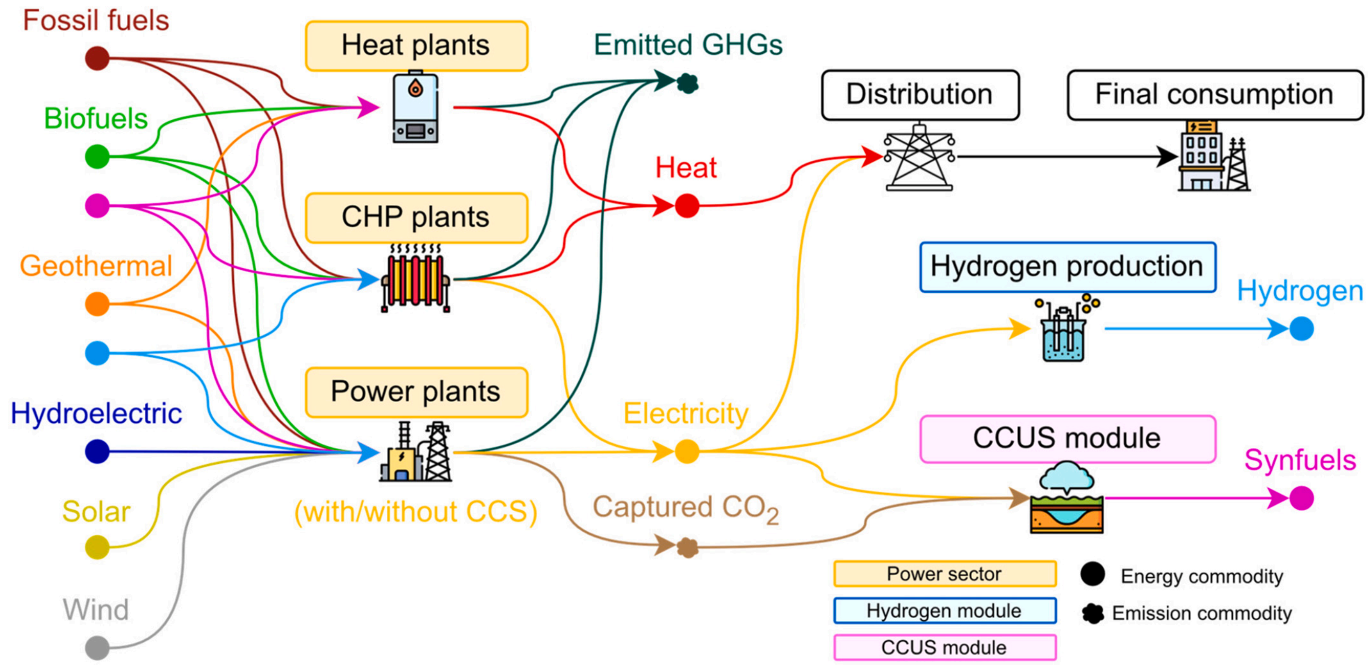

Fig. A2. Scheme of the TEMOA-Italy power sector and its connection with the other technology modules composing the energy system. Icons are from [36].

Table A3 also includes the data sources. Concerning CHP, micro-CHP, and heat plants, the source is the TIMES-Italy model (another model instance for Italy developed by ENEA and recently extensively updated in collaboration with the MAHTEP Group) in its original version [94], except for CHP fuel cells, modeled according to the JRC-EU-TIMES Model [95]. Only the average value for the Combined Heat to Power Ratio (CHPR) is reported in Table A3 for brevity.

Regarding the power plants, several sources were combined for their characterization. Indeed, being discount rates and capacity credits strongly dependent on the Italian system's specificity and peculiarities, the TIMES-Italy values were adopted [94]. The average CFs of hydroelectric, solar, and wind technologies are only reported in Table A3, but they are non-constant and dependent on the specific intra-annual time slice, as discussed in Section 2.2. The techno-economic parameters of hydroelectric, geothermal, and biogas plants are from TIMES-Italy, while the power plants with CCS and the hydrogen fuel cell are from the JRC-EU-TIMES Model [95]. Concerning fossil fuels, solid biomass, solar, and wind power plants, their costs and efficiencies are from the 2022 Annual Technology Baseline (by the NREL, [61]), while the lifetimes are from [96]. Concerning the future projection for the efficiency of fossil-fueled plants, a general 10 % efficiency improvement was applied to such facilities as an assumption based on the TIMES-Italy projections.

The techno-economic data associated with nuclear options (light water reactor and small modular reactor) are from [61] and the basic model structure excludes their deployment through a capacity constraint constant and equal to zero due to the Italian nuclear power plants phase-out [97]. This constraint is increased in a dedicated scenario (as discussed in Section 4) specifically devoted to studying the effect of a possible nuclear penetration in the system starting from 2040.

Possible new investments in the electricity import/export capacity are considered, assuming an investment cost of 1000 M€/GW (based on recent projects [98]) and assuming a capacity in 2050 up to ~15GW for import a ~9GW for export (based on the past growth trend from [99]).

Coming to the model constraints (detailed in [47]), the main sources of data are:

- TERNA Statistics [100], Eurostat Energy Balances [74] and GSE Statistics [101] for the calibration of the historical period 2006–2020.
- National Integrated Plan for Energy and Climate (PNIEC) [102], Long-term Italian strategy for GHG emission reduction (LTS) [103], Fit for 55 [104] concerning stated future policies implemented in the model. This includes the phase-out of coal power plants no later than 2030.
- Elaboration from ENSPRESO Database [105], for renewable future potentials.

Concerning the CFs computation, the algorithm requires historical data for solar, wind, and hydroelectric resources as an input. For the Italian case study and considering solar and wind, the data source is the EMHIRES dataset [106] by the Joint Research Center (JRC) of the European Commission. It provides historical hourly CFs from January 1st, 1986, to December 31st, 2015. Data are aggregated according to three different spatial layers, following the nomenclature of territorial units for statistics (NUTS) by Eurostat [107]: countries, NUTS1 (macro-regions), and NUTS2 (administrative regions). For this study, country and macro-regional data were selected, as explained in the following.

Table A3
Techno-economic characterization of new technologies in the TEMOA-Italy power sector (release 3.0 [47]).

Category	Resource	Technology	Efficiency (%)	Lifetime	Investment cost		Fixed O&M cost		Variable O&M cost		Discount rate (%)	Capacity to activity	Capacity factor (%)	Capacity credit (%)	CHPR	Source
Power plants	Natural gas	Gas cycle	35 ÷ 49	30	703 ÷ 922	$\mathrm{M\$}_{2020}$/GW	21	$\mathrm{M\$}_{2020}$/GW	1.39	$\mathrm{M\$}_{2020}$/PJ	2.7	31.536 PJ/GW	95	100		[94] [61]
		Combined cycle	54 ÷ 59	30	838 ÷ 1038	$\mathrm{M\$}_{2020}$/GW	28	$\mathrm{M\$}_{2020}$/GW	0.56	$\mathrm{M\$}_{2020}$/PJ			90			[96]
		95 % CCS	55	30	1330	M€$_{2010}$/GW	38	M€$_{2010}$/GW	0.34	M€$_{2010}$/PJ	10.0		90			
	Coal	Steam cycle	40 ÷ 44	30	2240 ÷ 3075	$\mathrm{M\$}_{2020}$/GW	74	$\mathrm{M\$}_{2020}$/GW	2.22	$\mathrm{M\$}_{2020}$/PJ	6.2		76			
		79 ÷ 84 % CCS	41 ÷ 48	15 ÷ 30	2757 ÷ 3758	M€$_{2010}$/GW	69 ÷ 88	M€$_{2010}$/GW	0.64 ÷ 1.62	M€$_{2010}$/PJ	10.0		90			
	Oil products	Steam cycle	40 ÷ 44	30	2240 ÷ 3075	$\mathrm{M\$}_{2020}$/GW	74	$\mathrm{M\$}_{2020}$/GW	2.22	$\mathrm{M\$}_{2020}$/PJ	6.2		85			
	Biofuels	Biodiesel plant	35 ÷ 39	15	3626 ÷ 4416	$\mathrm{M\$}_{2020}$/GW	151	$\mathrm{M\$}_{2020}$/GW	1.61	$\mathrm{M\$}_{2020}$/PJ	6.7		70			
		Biomass plant	25 ÷ 28	15	3626 ÷ 4416	$\mathrm{M\$}_{2020}$/GW	151	$\mathrm{M\$}_{2020}$/GW	1.61	$\mathrm{M\$}_{2020}$/PJ			57			
		Agriculture and farming biogas plant	32 ÷ 40	9	2025 ÷ 3500	M€$_{2009}$/GW							58 ÷ 65	70		[94]
		Landfill biogas plant			900 ÷ 1100	M€$_{2009}$/GW	40 ÷ 75	M€$_{2009}$/GW	1.61	M€$_{2009}$/PJ			49 ÷ 60	50		
	Hydroelectric	Micro-hydroelectric		30	4500	M€$_{2009}$/GW	78	M€$_{2009}$/GW			5.2		≈23	30		[94]
		Mini-hydroelectric			2250	M€$_{2009}$/GW	33	M€$_{2009}$/GW						30		
	Geothermal	High enthalpy plant	10	15	3200 ÷ 4000	M€$_{2009}$/GW	60 ÷ 86	M€$_{2009}$/GW			10.0		86	100		[94]
		Low enthalpy plant			4480 ÷ 6000	M€$_{2009}$/GW							88 ÷ 90	100		
	Solar	Ground photovoltaic		30	620 ÷ 6000	$\mathrm{M\$}_{2020}$/GW	13 ÷ 43	$\mathrm{M\$}_{2020}$/GW			5.7		≈14	20		[94] [61]
		Rooftop photovoltaic			751 ÷ 8000	$\mathrm{M\$}_{2020}$/GW	10 ÷ 48	$\mathrm{M\$}_{2020}$/GW						15		[96]
	Wind	Onshore		20	765 ÷ 2532	$\mathrm{M\$}_{2020}$/GW	33 ÷ 49	$\mathrm{M\$}_{2020}$/GW			7.6		≈17	25		[94] [61]
		Offshore (fixed)			2343 ÷ 5000	$\mathrm{M\$}_{2020}$/GW	70 ÷ 111	$\mathrm{M\$}_{2020}$/GW			8.6			30		[96]
		Offshore (floating)			3467 ÷ 4049	$\mathrm{M\$}_{2020}$/GW	57 ÷ 69	$\mathrm{M\$}_{2020}$/GW						35		
	Hydrogen	PEM fuel cell	45 ÷ 47	15	1000 ÷ 3000	M€$_{2013}$/GW	56 ÷ 61	M€$_{2013}$/GW	8.33 ÷ 29.17	M€$_{2013}$/PJ	8.0		90	100		[95]
	Nuclear	Light water reactor		60	5000 ÷ 5600	$\mathrm{M\$}_{2020}$/GW	146.96	$\mathrm{M\$}_{2020}$/GW	2.92	$\mathrm{M\$}_{2020}$/PJ	10.0		94	100		[61]
		Small modular reactor		60	5500 ÷ 6200	$\mathrm{M\$}_{2020}$/GW	114.00	$\mathrm{M\$}_{2020}$/GW	3.13	$\mathrm{M\$}_{2020}$/PJ						
CHP plants	Natural gas	Gas cycle	77 ÷ 86	25	960	M€$_{2009}$/GW			1.11 ÷ 1.67	M€$_{2009}$/PJ	3.3	31.536 PJ/GW	57	70	≈1.3	[94]
		Combined cycle	90	30	720	M€$_{2009}$/GW			0.33 ÷ 0.50	M€$_{2009}$/PJ			34		≈0.6	
		Cycle in counter pressure	84	35	702	M€$_{2009}$/GW			1.39	M€$_{2009}$/PJ			74		≈4.0	
		Cycle with steam tapping	82	35											≈2.5	

(continued on next page)

Table A3 (*continued*)

Category	Resource	Technology	Efficiency (%)	Lifetime	Investment cost		Fixed O&M cost		Variable O&M cost		Discount rate (%)	Capacity to activity	Capacity factor (%)	Capacity credit (%)	CHPR	Source
	Municipal waste	Municipal waste cycle	38	20	2059 ÷ 4000	M€$_{2009}$/GW			9.50 ÷ 12.50	M€$_{2009}$/PJ			70 ÷ 80		≈0.5	
Micro-CHP plants	Natural gas	Internal combustion engine (commercial)	80 ÷ 88	15	900 ÷ 1100	M€$_{2009}$/GW			4.17	M€$_{2009}$/PJ	10.0	31.536 PJ/GW	34	20	≈1.1	[94]
		Microturbine (commercial)	80 ÷ 88	12 ÷ 20	1000 ÷ 1500	M€$_{2009}$/GW			2.78	M€$_{2009}$/PJ			34		≈0.4	
		Combined cycle (commercial)	80	15 ÷ 20	1300	M€$_{2009}$/GW			5.00	M€$_{2009}$/PJ			34		≈0.4	
		Solid oxide fuel cell (commercial)	90 ÷ 96	20	2250 ÷ 10,000	M€$_{2020}$/GW			4.86 ÷ 30.56	M€$_{2020}$/PJ			90		≈0.4	[95]
	Biofuels	Internal combustion engine (commercial)	80	15	1350 ÷ 1870	M€$_{2009}$/GW			4.17	M€$_{2009}$/PJ			34		≈0.4	[94]
	Hydrogen	PEM fuel cell (commercial)	94 ÷ 96	20	1050 ÷ 1500	M€$_{2020}$/GW			6.94 ÷ 13.89	M€$_{2020}$/PJ			90		≈0.8	[95]
	Natural gas	Internal combustion engine (residential)	80 ÷ 88	15	900 ÷ 1100	M€$_{2009}$/GW			2.78 ÷ 4.17	M€$_{2009}$/PJ			34	20	≈1.1	[94]
		Microturbine (residential)	80 ÷ 92	12 ÷ 20	1000 ÷ 1500	M€$_{2009}$/GW			1.67 ÷ 2.78	M€$_{2009}$/PJ			34		≈1.5	
		Combined cycle (residential)	80	15 ÷ 20	1300	M€$_{2009}$/GW			0.42 ÷ 0.50	M€$_{2009}$/PJ			34		≈0.4	
		Stirling engine (residential)	80 ÷ 90	15	2100 ÷ 2180	M€$_{2009}$/GW			2.78 ÷ 5.00	M€$_{2009}$/PJ			34		≈0.2	
		Solid oxide fuel cell (residential)	90	20	3500 ÷ 10,000	M€$_{2020}$/GW			6.97 ÷ 27.78	M€$_{2020}$/PJ			90		≈0.5	[95]
	Hydrogen	PEM fuel cell (residential)	92 ÷ 96	20	4000 ÷ 6000	M€$_{2020}$/GW			6.94 ÷ 20.89	M€$_{2020}$/PJ			90		≈0.5	
	Natural gas	Internal combustion engine (industry)	80 ÷ 91	15	1030 ÷ 1100	M€$_{2009}$/GW			2.78 ÷ 4.17	M€$_{2009}$/PJ			57	100	≈1.1	[94]
		Gas turbine (industry)	74 ÷ 80	20 ÷ 25	800	M€$_{2009}$/GW			1.39 ÷ 1.67	M€$_{2009}$/PJ			74		≈1.2	
		Steam turbine (industry)	75 ÷ 79	30	1500	M€$_{2009}$/GW							63		≈0.3	
	Biofuels	Internal combustion engine (industry)	85 ÷ 93	15	1800 ÷ 2100	M€$_{2009}$/GW			2.50 ÷ 3.75	M€$_{2009}$/PJ			57		≈0.2	
Heat plants	Natural gas	Natural gas plant	80	60	4	M€$_{2009}$/PJ	2.4	M€$_{2009}$/PJ			5.0	1.00 PJ/PJ	60	100		[94]
	Coal	Coal plant			6	M€$_{2009}$/PJ	2.8	M€$_{2009}$/PJ								
	Oil products	Oil products plant			5	M€$_{2009}$/PJ	2.5	M€$_{2009}$/PJ								
	Biofuels	Biofuels plant			6	M€$_{2009}$/PJ	2.8	M€$_{2009}$/PJ								
	Geothermal	High enthalpy plant	10		12	M€$_{2009}$/PJ	2.5	M€$_{2009}$/PJ								
		Low enthalpy plant			12	M€$_{2009}$/PJ	2.5	M€$_{2009}$/PJ								

For the hydroelectric CFs, the data sources are the 2006–2022 monthly reports on the electricity system by TERNA [100] (corresponding to the existing years of TEMOA-Italy). Solar technologies are modeled with a macro-regional based distinction of CFs and future potentials (as explained in Section 2.2). The selected macro-regions correspond to the NUTS1 Eurostat nomenclature, and they are north-west (ITC), north-east (ITH), center (ITI), south (ITF), and islands (ITG). Five ground and five rooftop technologies are then included in the TEMOA-Italy database: characterized by the same economic parameters shown in Table A3, but with different CFs according to the specific region of each technology.

While the detailed results, both for wind and solar, evaluated with a time resolution made of 4 seasons and 24 times of day, are shown in Fig. A3 (at the country level), the annual average CFs are estimated at 14 % for solar and 17 % for wind (also reported in Table A3).

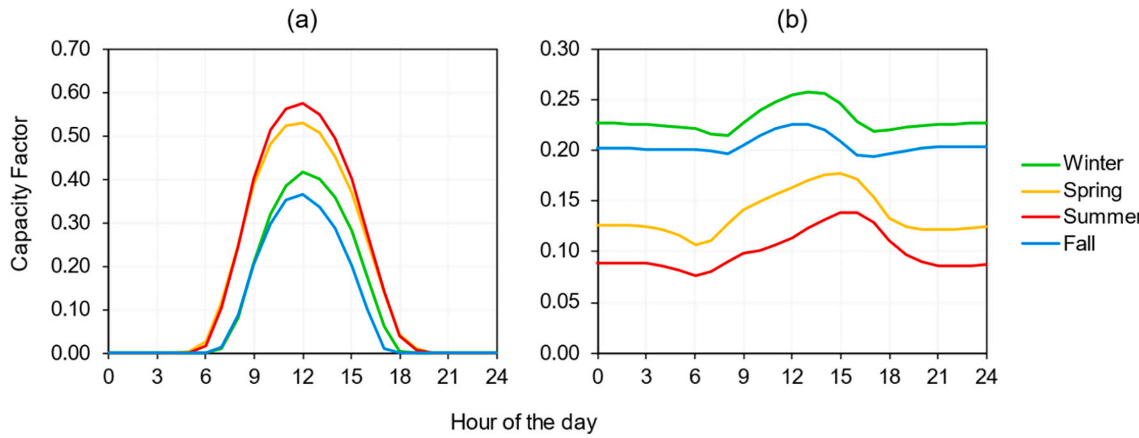

Fig. A3. Solar (a) and wind (b) average CF by season and hour of the day estimated using data from 1986 to 2015 for Italy.

The resulting annual average CF for hydroelectric is approximately 23 % (as also reported in Table A3). Concerning the long-term trend for hydroelectric energy production, Fig. A4 shows both yearly data and the linear trendline from 2006 to 2022, highlighting a slightly decreasing trend in that period for hydroelectric production. Despite this behavior (due to the Italian water scarcity in the last years and particularly in 2022 [73]), the future CFs are kept equal to the 2006–2022 average values, assuming improvements in the facility's efficiency could compensate for this declining trend.

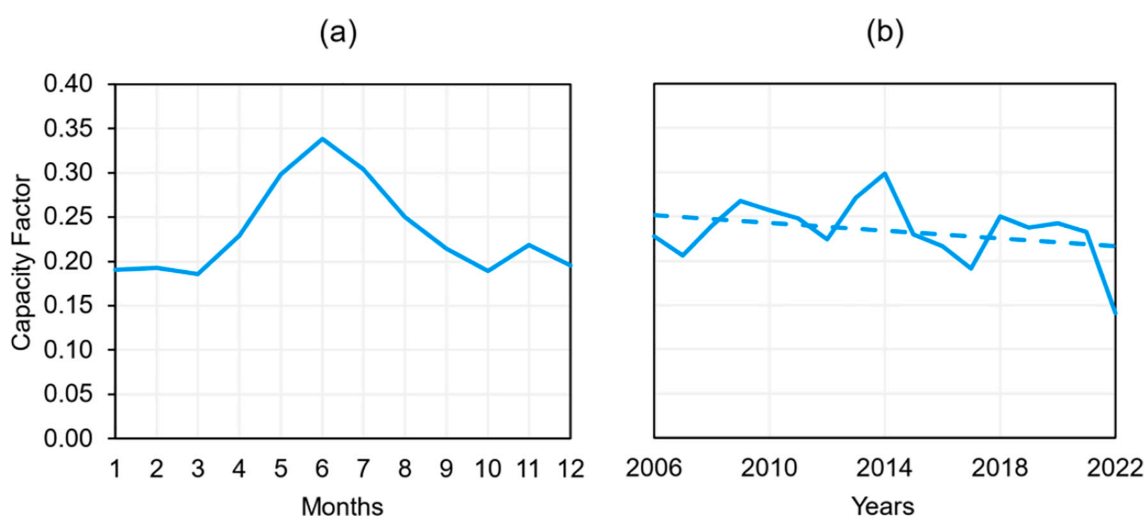

Fig. A4. Annual Italian CF for hydroelectric plants from 2006 to 2022 [100]. The solid line represents the annual data, and the dashed line is the trendline.

Supplementary material

Supplementary material to this article can be found online at https://doi.org/10.1016/j.est.2024.113814.

References

[1] B. Yu, D. Fang, K. Xiao, Y. Pan, Drivers of renewable energy penetration and its role in power sector's deep decarbonization towards carbon peak, Renew. Sustain. Energy Rev. 178 (May 2023) 113247, https://doi.org/10.1016/J.RSER.2023.113247.

[2] Energy Information Administration (EIA), Electric power monthly, Accessed: Oct. 28, 2023. [Online]. Available: https://www.eia.gov/electricity/monthly/.

[3] T. Levin, et al., Energy storage solutions to decarbonize electricity through enhanced capacity expansion modelling, Nature Research (2023), https://doi.org/10.1038/s41560-023-01340-6.

[4] U.S. Internal Revenue Service, Residential clean energy credit, Accessed: Oct. 28, 2023. [Online]. Available: https://www.irs.gov/credits-deductions/residential-clean-energy-credit.

[5] European Commission, Report from the Commission to the European Parliament, the Council, the European Economic and Social Committee, the Committee of the Regions and the European Investment Bank on the implementation of the strategic action plan on batteries: building a strategic battery value chain in

Europe, Accessed: Oct. 28, 2023. [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM:2019:176:FIN.
[6] European Commission, Commission Recommendation of 14 March 2023 on Energy Storage - underpinning a decarbonised and secure EU energy system, Accessed: Oct. 28, 2023. [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32023H0320%2801%29&qid=1679302898964.
[7] European Commission, A European green deal, Accessed: Jun. 27, 2022. [Online]. Available: https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en.
[8] European Commission, REPowerEU, Accessed: Jul. 27, 2023. [Online]. Available: https://ec.europa.eu/commission/presscorner/detail/en/IP_22_3131.
[9] Ministry of the Environment and Energy Security, Integrated national energy and climate plan 2023, Accessed: Jul. 27, 2023. [Online]. Available: https://commission.europa.eu/publications/italy-final-updated-necp-2021-2030-submitted-2024_en, 2023.
[10] Ministry of the Environment and Land and Sea Protection, Ministry of Economic Development, Ministry of Infrastructure and Transport, and F. and F. P. Ministry of Agricultural, Italian long-term strategy of greenhouse gases emissions reduction, Accessed: Aug. 30, 2023. [Online]. Available: https://www.mase.gov.it/sites/default/files/lts_gennaio_2021.pdf, 2021.
[11] A.R. de Queiroz, et al., Repurposing an energy system optimization model for seasonal power generation planning, Energy 181 (Aug. 2019) 1321–1330, https://doi.org/10.1016/J.ENERGY.2019.05.126.
[12] G. Ma, J. Li, X.-P. Zhang, Energy storage capacity optimization for improving the autonomy of grid-connected microgrid, IEEE Trans Smart Grid (2023) 1, https://doi.org/10.1109/TSG.2022.3233910.
[13] P. Marocco, R. Novo, A. Lanzini, G. Mattiazzo, M. Santarelli, Towards 100% renewable energy systems: the role of hydrogen and batteries, J Energy Storage 57 (Jan. 2023) 106306, https://doi.org/10.1016/J.EST.2022.106306.
[14] NC State Energy Storage Team, Energy storage options for North Carolina, Accessed: Dec. 22, 2022. [Online]. Available: https://energy.ncsu.edu/storage/wp-content/uploads/sites/2/2019/02/NC-Storage-Study-FINAL.pdf, 2019.
[15] D. Sodano, J. DeCarolis, A. Rodrigo de Queiroz, J.X. Johnson, The symbiotic relationship of solar power and energy storage in providing capacity value, Renew. Energy 177 (Nov. 2021) 823–832, https://doi.org/10.1016/J.RENENE.2021.05.122.
[16] E. Hale, B. Stoll, T. Mai, Capturing the impact of storage and other flexible technologies on electric system planning, Accessed: Jan. 08, 2023. [Online]. Available: https://www.nrel.gov/docs/fy16osti/65726.pdf, 2016.
[17] A. Farnsworth, E. Gençer, Highlighting regional decarbonization challenges with novel capacity expansion model, Cleaner Energy Systems 5 (100078) (2023), https://doi.org/10.1016/j.cles.2023.100078.
[18] J. Bistline, G. Blanford, T. Mai, J. Merrick, Modeling variable renewable energy and storage in the power sector, Energy Policy 156 (Sep. 2021) 112424, https://doi.org/10.1016/j.enpol.2021.112424.
[19] R. Golombek, A. Lind, H.K. Ringkjøb, P. Seljom, The role of transmission and energy storage in European decarbonization towards 2050, Energy 239 (Jan. 2022), https://doi.org/10.1016/j.energy.2021.122159.
[20] M.G. Prina, G. Manzolini, D. Moser, B. Nastasi, W. Sparber, Classification and challenges of bottom-up energy system models - a review, Renew. Sustain. Energy Rev. 129 (Sep. 2020) 109917, https://doi.org/10.1016/J.RSER.2020.109917.
[21] A.S.R. Subramanian, T. Gundersen, T.A. Adams, Modeling and simulation of energy systems: a review, Processes 6 (12) (Dec. 2018), https://doi.org/10.3390/PR6120238.
[22] S. Pfenninger, A. Hawkes, J. Keirstead, Energy Systems Modeling for Twenty-First Century Energy Challenges, Elsevier Ltd., 2014, https://doi.org/10.1016/j.rser.2014.02.003.
[23] National Renewable Energy Laboratory (NREL), Power system planning: advancements in capacity expansion modeling, Accessed: Jul. 12, 2023. [Online]. Available: https://www.nrel.gov/docs/fy21osti/80192.pdf, 2021.
[24] T. Brown, J. Hörsch, D. Schlachtberger, PyPSA: python for power system analysis, J Open Res Softw 6 (1) (2018), https://doi.org/10.5334/JORS.188.
[25] J. Johnston, R. Henriquez-Auba, B. Maluenda, M. Fripp, Switch 2.0: a modern platform for planning high-renewable power systems, SoftwareX 10 (Jul. 2019) 100251, https://doi.org/10.1016/J.SOFTX.2019.100251.
[26] K. Poncelet, E. Delarue, D. Six, J. Duerinck, W. D'haeseleer, Impact of the level of temporal and operational detail in energy-system planning models, Appl. Energy 162 (Jan. 2016) 631–643, https://doi.org/10.1016/j.apenergy.2015.10.100.
[27] C. Marcy, T. Goforth, D. Nock, M. Brown, Comparison of temporal resolution selection approaches in energy systems models, Energy 251 (Jul. 2022), https://doi.org/10.1016/j.energy.2022.123969.
[28] H. Teichgraeber, A.R. Brandt, Clustering methods to find representative periods for the optimization of energy systems: an initial framework and comparison, Appl Energy 239 (August 2018) (2019) 1283–1293, https://doi.org/10.1016/j.apenergy.2019.02.012.
[29] J.H. Merrick, On representation of temporal variability in electricity capacity planning models, Energy Econ. 59 (Sep. 2016) 261–274, https://doi.org/10.1016/J.ENECO.2016.08.001.
[30] N. Helistö, J. Kiviluoma, H. Holttinen, J.D. Lara, B.M. Hodge, Including operational aspects in the planning of power systems with large amounts of variable generation: a review of modeling approaches, Wiley Interdiscip Rev Energy Environ 8 (5) (Sep. 2019) e341, https://doi.org/10.1002/WENE.341.
[31] S. Collins, et al., Integrating Short Term Variations of the Power System into Integrated Energy System Models: A Methodological Review, Elsevier Ltd., 2017, https://doi.org/10.1016/j.rser.2017.03.090.
[32] J.P. Deane, A. Chiodi, M. Gargiulo, B.P.Ó. Gallachóir, Soft-linking of a power systems model to an energy systems model, Energy 42 (1) (Jun. 2012) 303–312, https://doi.org/10.1016/j.energy.2012.03.052.
[33] R.C. Pietzcker, et al., System integration of wind and solar power in integrated assessment models: a cross-model evaluation of new approaches, Energy Econ. 64 (May 2017) 583–599, https://doi.org/10.1016/J.ENECO.2016.11.018.
[34] T. Barnes, A. Shivakumar, M. Brinkerink, T. Niet, OSeMOSYS Global, an open-source, open data global electricity system model generator, Sci Data 9 (1) (Dec. 2022), https://doi.org/10.1038/S41597-022-01737-0.
[35] M. Sánchez Diéguez, A. Fattahi, J. Sijm, G. Morales España, A. Faaij, Modelling of decarbonisation transition in national integrated energy system with hourly operational resolution, Adv. Appl. Energy 3 (Aug. 2021), https://doi.org/10.1016/j.adapen.2021.100043.
[36] flaticon, Accessed: Dec. 05, 2023. [Online]. Available: https://www.flaticon.com/.
[37] R. Loulou, G. Goldstein, A. Kanudia, A. Lettila, U. Remme, Documentation for the TIMES model: part I, Accessed: Oct. 17, 2022. [Online]. Available: https://iea-etsap.org/docs/Documentation_for_the_TIMES_Model-Part-I_July-2016.pdf, 2016.
[38] R. Loulou, A. Lehtilä, A. Kanudia, U. Remme, G. Goldstein, Documentation for the TIMES model: part II [Online]. Available: http://www.iea-etsap.org/web/Documentation.asp, 2016.
[39] G. Colucci, D. Lerede, M. Nicoli, L. Savoldi, A dynamic accounting method for CO2 emissions to assess the penetration of low-carbon fuels: application to the TEMOA-Italy energy system optimization model, Appl. Energy 352 (121951) (Dec. 2023), https://doi.org/10.1016/j.apenergy.2023.121951.
[40] TemoaProject, GitHub - TemoaProject/temoa, GitHub. . Accessed: Feb. 11, 2023. [Online]. Available: https://github.com/TemoaProject/temoa.
[41] TemoaProject, Temoa project documentation, Accessed: Jul. 12, 2023. [Online]. Available: https://temoacloud.com/temoaproject/index.html.
[42] IEA-ETSAP, TIMES, Accessed: Jun. 25, 2022. [Online]. Available: https://iea-etsap.org/index.php/etsap-tools/model-generators/times.
[43] M. Li, R. Shan, A. Abdulla, J. Tian, S. Gao, High energy capacity or high power rating: which is the more important performance metric for battery energy storage systems at different penetrations of variable renewables? J Energy Storage 59 (Mar. 2023) 106560 https://doi.org/10.1016/J.EST.2022.106560.
[44] W. Nijs, P. Ruiz, JRC-EU-TIMES Full Model, European Commission, Joint Research Centre (JRC), May 09, 2022 [Online]. Available: http://data.europa.eu/89h/8141a398-41a8-42fa-81a4-5b825a51761b.
[45] MAHTEP Group, MAHTEP/TEMOA - Release 1.0, GitHub, Jul. 06, 2023 [Online]. Available: https://github.com/MAHTEP/TEMOA/releases/tag/1.0.
[46] M. Nicoli, F. Gracceva, D. Lerede, L. Savoldi, Can we rely on open-source energy system optimization models? The TEMOA-Italy case study, Energies (Basel) 15 (18) (Sep. 2022) 6505, https://doi.org/10.3390/en15186505.
[47] MAHTEP Group, MAHTEP/TEMOA-Italy - Release 3.0, GitHub, Oct. 28, 2023 [Online]. Available: https://github.com/MAHTEP/TEMOA-Italy/releases/tag/3.0.
[48] K. Hunter, S. Sreepathi, J.F. DeCarolis, Modeling for insight using Tools for Energy Model Optimization and Analysis (Temoa), Energy Econ. 40 (Nov. 2013) 339–349, https://doi.org/10.1016/j.eneco.2013.07.014.
[49] S. Buchholz, M. Gamst, D. Pisinger, Sensitivity analysis of time aggregation techniques applied to capacity expansion energy system models, Appl. Energy 269 (Jul. 2020) 114938, https://doi.org/10.1016/J.APENERGY.2020.114938.
[50] Z. Abdin, K. Khalilpour, K. Catchpole, Projecting the levelized cost of large scale hydrogen storage for stationary applications, Energ. Conver. Manage. 270 (2022) 116241, https://doi.org/10.1016/j.enconman.2022.116241.
[51] G. Kubilay Karayel, N. Javani, I. Dincer, A comprehensive assessment of energy storage options for green hydrogen, Energ. Conver. Manage. 291 (Sep. 2023) 117311, https://doi.org/10.1016/J.ENCONMAN.2023.117311.
[52] Leonard Wagner, Overview of Energy Storage Technologies, 2014, https://doi.org/10.1016/B978-012370624-9/50005-0.
[53] K. Mongird, V. Viswanathan, J. Alam, C. Vartanian, V. Sprenkle, R. Baxter, 2020 Grid Energy Storage Technology Cost and Performance Assessment, Accessed: Jun. 28, 2023. [Online]. Available: https://www.pnnl.gov/sites/default/files/media/file/Final%20-%20ESGC%20Cost%20Performance%20Report%2012-11-2020.pdf, 2020.
[54] M.H. Mostafa, S.H.E. Abdel Aleem, S.G. Ali, Z.M. Ali, A.Y. Abdelaziz, Techno-economic assessment of energy storage systems using annualized life cycle cost of storage (LCCOS) and levelized cost of energy (LCOE) metrics, J Energy Storage 29 (December 2019) (2020) 101345, https://doi.org/10.1016/j.est.2020.101345.
[55] M. Mugyema, C.D. Botha, M.J. Kamper, R.J. Wang, A.B. Sebitosi, Levelised cost of storage comparison of energy storage systems for use in primary response application, J Energy Storage 59 (January) (2023) 106573, https://doi.org/10.1016/j.est.2022.106573.
[56] C.A. Hunter, M.M. Penev, E.P. Reznicek, J. Eichman, N. Rustagi, S.F. Baldwin, Techno-economic analysis of long-duration energy storage and flexible power generation technologies to support high-variable renewable energy grids, Joule 5 (8) (Aug. 2021) 2077–2101, https://doi.org/10.1016/J.JOULE.2021.06.018.
[57] International Renewable Energy Agency (IRENA), Electricity Storage and Renewables: Costs and Markets to 2030, International Renewable Energy Agency, 2017, p. 132. Accessed: Jun. 26, 2023. [Online]. Available: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2017/Oct/IRENA_Electricity_Storage_Costs_2017.pdf (no. October).
[58] Lazard, Levelized cost of storage - version 4.0 [Online]. Available: https://www.lazard.com/media/42dnsswd/lazards-levelized-cost-of-storage-version-70-vf.pdf, 2018.

[59] International Energy Agency (IEA), Nuclear Energy Agency (NEA), Projected costs of generating electricity, Accessed: Aug. 23, 2023. [Online]. Available: https://www.iea.org/reports/projected-costs-of-generating-electricity-2020, 2020.

[60] Energy Information Administration (EIA), Capital cost and performance characteristic estimates for utility scale electric power generating technologies, Accessed: Aug. 22, 2023. [Online]. Available: https://www.eia.gov/analysis/studies/powerplants/capitalcost/pdf/capital_cost_AEO2020.pdf, 2020.

[61] National Renewable Energy Laboratory (NREL), 2022 Annual Technology Baseline (ATB) Cost and Performance Data for Electricity Generation Technologies, National Renewable Energy Laboratory, Golden, CO, Jul. 06, 2023 [Online]. Available: https://atb.nrel.gov/electricity/2022/about.

[62] Joint Research Centre (JRC), Hydropower and hydropower storage in the European Union, Accessed: Nov. 13, 2023. [Online]. Available: https://setis.ec.europa.eu/hydropower-and-pumped-hydropower-storage-european-union-0_en, 2023.

[63] M. Nicoli, A TIMES-Like Open-Source Model for the Italian Energy System, Politecnico di Torino, Turin, 2021. Accessed: Jul. 04, 2022. [Online]. Available: https://webthesis.biblio.polito.it/18850/.

[64] B.B. Adetokun, O. Oghorada, S.J. afar Abubakar, Superconducting Magnetic Energy Storage Systems: Prospects and Challenges for Renewable Energy Applications, Elsevier Ltd., Nov. 25, 2022, https://doi.org/10.1016/j.est.2022.105663.

[65] W. Yang, et al., Honeycomb-like nitrogen-doped porous carbon decorated with Co3O4 nanoparticles for superior electrochemical performance pseudo-capacitive lithium storage and supercapacitors, Adv. Compos. Hybrid Mater. 5 (4) (Dec. 2022) 3146–3157, https://doi.org/10.1007/S42114-022-00556-6/FIGURES/5.

[66] H. Jiang, et al., Advanced ferroferric oxide-based composites for lithium-ion battery: recent developments and future perspectives, Prog. Nat. Sci.: Mater. Int. 33 (6) (Dec. 2023) 743–753, https://doi.org/10.1016/J.PNSC.2023.12.017.

[67] M. Reuß, T. Grube, M. Robinius, P. Preuster, P. Wasserscheid, D. Stolten, Seasonal storage and alternative carriers: a flexible hydrogen supply chain model, Appl. Energy 200 (Aug. 2017) 290–302, https://doi.org/10.1016/J.APENERGY.2017.05.050.

[68] M. Zhang, H. Lv, H. Kang, W. Zhou, C. Zhang, A literature review of failure prediction and analysis methods for composite high-pressure hydrogen storage tanks, Int. J. Hydrogen Energy 44 (47) (Oct. 2019) 25777–25799, https://doi.org/10.1016/j.ijhydene.2019.08.001.

[69] B.D. James, C. Houchins, J.M. Huya-Kouadio, D.A. Desantis, Final Report: Hydrogen Storage System Cost Analysis, 2016, https://doi.org/10.2172/1343975.

[70] A. Balbo, G. Colucci, M. Nicoli, L. Savoldi, Exploring the role of hydrogen to achieve the Italian decarbonization targets using an open-source energy system optimization model, in: International Journal of Energy and Power Engineering, E. and T. World Academy of Science, Ed, Mar. 2023, pp. 89–100. Accessed: Apr. 25, 2023. [Online]. Available: https://publications.waset.org/10013040/exploring-the-role-of-hydrogen-to-achieve-the-italian-decarbonization-targets-using-an-open-source-energy-system-optimization-model.

[71] Wilton E. Scott Institute for Energy Innovation - Carnegie Mellon University, Open energy outlook, Accessed: Dec. 22, 2022. [Online]. Available: https://www.cmu.edu/energy/key-initiatives/open-energy-outlook/index.html.

[72] G. Erbach, L. Jensen, S. Chahri, E. Claros, European Council, Fit for 55 Package, Accessed: Jan. 30, 2023. [Online]. Available: https://www.consilium.europa.eu/en/policies/green-deal/fit-for-55-the-eu-plan-for-a-green-transition/, 2022.

[73] C. Cirelli, I. La Jeunesse, Adaptation of water management to face drought and water scarcity, in: Facing Hydrometeorological Extreme Events: A Governance Issue, Sep. 2019, pp. 245–259, https://doi.org/10.1002/9781119383567.CH17.

[74] Eurostat, Energy balances - energy - Eurostat, Accessed: Aug. 19, 2022. [Online]. Available: https://ec.europa.eu/eurostat/web/energy/data/energy-balances.

[75] ENEL Foundation, Politecnico di Torino, Energy Security Transition (EST), Massachusetts Institute of Technology (MIT), Electrify Italy, Accessed: Jan. 30, 2024. [Online]. Available: https://www.enelfoundation.org/topics/articles/2019/11/electrify-italy, 2020.

[76] C. Carà, P. Marocco, R. Novo, M. Koivisto, M. Santarelli, G. Mattiazzo, Modeling the long-term evolution of the Italian power sector: the role of renewable resources and energy storage facilities, Int. J. Hydrogen Energy 59 (Mar. 2024) 1183–1195, https://doi.org/10.1016/J.IJHYDENE.2024.01.358.

[77] B. Cárdenas, R. Ibanez, J. Rouse, L. Swinfen-Styles, S. Garvey, The effect of a nuclear baseload in a zero-carbon electricity system: an analysis for the UK, Renew. Energy 205 (Mar. 2023) 256–272, https://doi.org/10.1016/J.RENENE.2023.01.028.

[78] O. Schmidt, S. Melchior, A. Hawkes, I. Staffell, Projecting the Future Levelized Cost of Electricity Storage Technologies, 2019, https://doi.org/10.1016/j.joule.2018.12.008.

[79] International Energy Agency (IEA), Energy Balances of OECD Countries 2009, 2009, https://doi.org/10.1787/energy_bal_oecd-2009-en-fr (Paris).

[80] T. Pillon, Sensitivity Analysis for Hydrogen End-Use Technologies Through Energy System Optimization Models: An Application to TEMOA-Italy, Politecnico di Torino, 2023. Accessed: Jan. 22, 2024. [Online]. Available: https://webthesis.biblio.polito.it/29219/.

[81] Ministero dell''ambiente e della sicurezza energetica, Bollettino petrolifero - Statistiche energetiche e minerarie - Ministero dell'ambiente e della sicurezza energetica, Accessed: Jan. 08, 2024. [Online]. Available: https://dgsaie.mise.gov.it/bollettino-petrolifero.

[82] World Bank, World Bank commodities price forecast (nominal US dollars)-2022, Accessed: Aug. 04, 2023. [Online]. Available: https://thedocs.worldbank.org/en/doc/d8730a829c869c7aeaba547eb72d6b3f-0350012022/related/CMO-October-2022-forecasts.pdf, 2022.

[83] International Energy Agency (IEA), World energy outlook 2022, Accessed: Dec. 22, 2022. [Online]. Available: https://www.iea.org/reports/world-energy-outlook-2022, 2022.

[84] A. Oliva, F. Gracceva, D. Lerede, M. Nicoli, L. Savoldi, Projection of post-pandemic Italian industrial production through Vector AutoRegressive models, Energies 14 (17) (Sep. 2021) 5458, https://doi.org/10.3390/EN14175458.

[85] M. Nicoli, et al., Enabling coherence between energy policies and SDGs through open energy models: the TEMOA-Italy example, in: M. Labriet, K. Espegren, G. Giannakidis, B. O'Gallachoir (Eds.), Aligning the Energy Transition With the Sustainable Development Goals: Key Insights From Energy System Modelling, Springer, 2024, pp. 97–118, https://doi.org/10.1007/978-3-031-58897-6_5.

[86] D. Mosso, G. Colucci, D. Lerede, M. Nicoli, M.S. Piscitelli, L. Savoldi, How much do carbon emission reduction strategies comply with a sustainable development of the power sector? Energy Rep. 11 (Jun. 2024) 3064–3087, https://doi.org/10.1016/J.EGYR.2024.02.056.

[87] M. Joshi, D. Palchak, S. Rehman, S. Soonee, S. Saxena, S. Narasimhan, Ramping up the ramping capability-India's power system transition, Accessed: Aug. 01, 2023. [Online]. Available: https://www.nrel.gov/docs/fy20osti/77639.pdf, 2020.

[88] Terna, Monthly report on the electricity system - May 2017 [Online]. Available: https://download.terna.it/terna/0000/0959/79.PDF, 2017.

[89] Carnegie Mellon University, North Carolina State University, An open energy outlook: decarbonization pathways for the USA, Accessed: Mar. 09, 2023. [Online]. Available: https://www.cmu.edu/energy/key-initiatives/open-energy-outlook/oeo-report-2022.html, Sep. 2022.

[90] S. Laera, G. Colucci, V. Di Cosmo, D. Lerede, M. Nicoli, L. Savoldi, Technology-specific hurdle rates for Energy System Optimization Models, Energy Proceedings 39 (2024), https://doi.org/10.46855/energy-proceedings-10911.

[91] M. Nicoli, G. Colucci, V. Di Cosmo, D. Lerede, L. Savoldi, Evaluating the impact of hurdle rates on the Italian energy transition through TEMOA, in: Under Review for Publication in Applied Energy, 2024.

[92] World Bank, Exchange rates, Euro per domestic currency, period average, rate, Accessed: May 08, 2024. [Online]. Available: https://prosperitydata360.worldbank.org/en/indicator/IMF+IFS+EENA_EUR_XDC_RATE.

[93] G. Colucci, D. Lerede, M. Nicoli, L. Savoldi, Dynamic accounting for end-use CO2 emissions from low-carbon fuels in energy system optimization models, Energy Proceedings 29 (2022), https://doi.org/10.46855/energy-proceedings-10294.

[94] National Agency for New Technologies Energy and Sustainable Economic Development (ENEA), The TIMES-Italy energy model structure and data 2010 version, Accessed: Sep. 02, 2022. [Online]. Available: https://biblioteca.bologna.enea.it/RT/2011/2011_9_ENEA.pdf, 2011 (Rome).

[95] Sofia Simoes, et al., The JRC-EU-TIMES Model - Assessing the Long-Term Role of the SET Plan Energy Technologies, 2013, p. 376, https://doi.org/10.2790/97799.

[96] National Renewable Energy Laboratory (NREL), Useful life|energy analysis|NREL, Accessed: Jul. 06, 2023. [Online]. Available: https://www.nrel.gov/analysis/tech-footprint.html.

[97] World Nuclear Association, Nuclear power in Italy, Accessed: Nov. 01, 2023. [Online]. Available: https://world-nuclear.org/information-library/country-profiles/countries-g-n/italy.aspx.

[98] Terna, 'Italy-France' electrical connection, Accessed: Nov. 01, 2023. [Online]. Available: https://www.terna.it/en/projects/projects-common-interest/italy-france-electrical-interconnection.

[99] Terna, Cross-border capacity, Accessed: Nov. 01, 2023. [Online]. Available: https://www.terna.it/en/electric-system/electricity-market/capacity-interconnection-abroad.

[100] Terna, Electric system, Accessed: Jul. 10, 2023. [Online]. Available: https://www.terna.it/en/electric-system.

[101] Gestore Servizi Energetici (GSE), Statistiche, Accessed: Jul. 17, 2023. [Online]. Available: https://www.gse.it/dati-e-scenari/statistiche.

[102] Ministry of Economic Development, Ministry of the Environment and Land and Sea Protection, Ministry of Infrastructure and Transport, Integrated national energy and climate plan 2019, Accessed: Aug. 19, 2022. [Online]. Available: https://commission.europa.eu/energy-climate-change-environment/implementation-eu-countries/energy-and-climate-governance-and-reporting/national-energy-and-climate-plans_en, 2019.

[103] Ministry of Economic Development, Long term Italian strategy for greenhouse gas emission reduction, Accessed: Jun. 20, 2022. [Online]. Available: https://ec.europa.eu/clima/sites/lts/lts_it_it.pdf, 2021.

[104] European Council, Fit for 55 - the EU's plan for a green transition, Accessed: Jan. 29, 2023. [Online]. Available: https://www.consilium.europa.eu/en/policies/green-deal/fit-for-55-the-eu-plan-for-a-green-transition/.

[105] P. Ruiz, et al., ENSPRESO - an open, EU-28 wide, transparent and coherent database of wind, solar and biomass energy potentials, Energ. Strat. Rev. 26 (Nov. 2019) 100379, https://doi.org/10.1016/J.ESR.2019.100379.

[106] Joint Research Center (JRC), European Meteorological derived High Resolution RES generation time series for present and future scenarios (EMHIRES), Accessed: Jul. 12, 2023. [Online]. Available: https://data.jrc.ec.europa.eu/collection/id-0055, 2021.

[107] Eurostat, NUTS - nomenclature of territorial units for statistics, Accessed: Jul. 12, 2023. [Online]. Available: https://ec.europa.eu/eurostat/web/nuts/background.