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Optimal decarbonisation pathways for the Italian energy system: Modelling a long-term energy transition to achieve zero emission by 2050

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HIGHLIGHTS

- H2RES model to identify a cost-optimal decarbonisation pathway.
- Long-term optimisation based on linear programming.
- Technical and economic feasibility of a 100% renewable Italian energy system.
- Power-to-X technologies play a pivotal role in balancing intermittent generation.
- Integration of cost sensitivity analysis into the energy planning process.

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ABSTRACT

The goal of achieving a zero-emission energy system by 2050 requires accurate energy planning to minimise the overall cost of the energy transition. Long-term energy models based on cost-optimal solutions are extremely dependent on the cost forecasts of different technologies. However, such forecasts are inherently uncertain. The aim of the present work is to identify a cost-optimal pathway for the Italian energy system decarbonisation and assess how renewable cost scenarios can affect the optimal solution. The analysis has been carried out with the H2RES model, a single-objective optimisation algorithm based on Linear Programming. Different cost scenarios for photovoltaics, on-shore and off-shore wind power, and lithium-ion batteries are simulated. Results indicate that a 100% renewable energy system in Italy is technically feasible. Power-to-X technologies are crucial for balancing purposes, enabling a share of non-dispatchable generation higher than 90%. Renewable cost scenarios affect the energy mix, however, both on-shore and off-shore wind saturate the maximum capacity potential in almost all scenarios. Cost forecasts for lithium-ion batteries have a significant impact on their optimal capacity and the role of hydrogen. Indeed, as battery costs rise, fuel cells emerge as the main solution for balancing services. This study emphasises the importance of conducting cost sensitivity analyses in long-term energy planning. Such analyses can help to determine how changes in cost forecasts may affect the optimal strategies for decarbonising national energy systems.

1. Introduction

Growing awareness of the risks associated with human-induced climate change has prompted several countries to set net-zero emission targets and develop strategies for the complete decarbonisation of energy systems [1]. Research on 100% renewable energy systems has grown considerably in recent years. Various energy planning tools have been developed in order to analyse different aspects of the energy transition [2]. Several studies show that it is possible to decarbonise not only the electricity sector, but all energy sectors [3]. However, the complexity of the energy system presents characteristics and barriers that must be taken into account in the planning process.

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The large-scale integration of renewable energy sources (RES), poses challenges in terms of system flexibility [4]. Indeed, a high share of non-dispatchable generation requires several energy storage and balancing systems [5]. Addressing such an issue only by means of electric batteries (EBs) are considered insufficient and expensive [6,7].

In the last decade, the need for a holistic approach has emerged in literature. For this reason, the concept of Smart Energy Systems has been established in the literature in order to transcend singular sector-focused strategies and emphasise cross-sector interconnections [8]. Consequently, the literature regarding the sector coupling technologies and their role in the energy transition has grown significantly in the last years [9]. Such systems allow the conversion of electricity into different energy carriers in order to exploit the characteristics of diverse sectors [10]. For instance, it is widely demonstrated how the integration of heat and electricity networks can provide better solutions than electricity storage systems on different scales [11]. Furthermore, in recent years the role of hydrogen as a key vector for the flexibility of future energy systems is emerging [12].

In Kachirayil et al. [13], more than 100 studies have been analysed in order to identify the main solutions applied to provide flexibility in energy system models. As a result, sector coupling systems are the most commonly applied solution, playing a more important role than demand side management and supply-side flexibility. Moreover, the integration of the heating sector is generally considered more than the transport sector.

These sector coupling systems are often identified in the literature as "Power-to-X technologies". The concept of "Power-to-X" has been introduced precisely to identify the general conversion of renewable electricity into different energy carriers [14]. Power-to-X technologies, especially Power-to-Heat (PtH) [15] and Power-to-Gas (PtG) [16] systems, have been explored as a means to efficiently use non-electrochemical energy storage technologies.

Besides, also the integration with the transport sector has been analysed for this purpose [17]. Electric vehicles can assume a pivotal role in grid balancing by means of both smart charging [18] and bidirectional energy flow (vehicle-to-grid systems) [19]. Additionally, this electricity-transport integration paradigm extends to the synthesis of hydrogen [20]. Thus, hydrogen can be applied in the transport sector in a direct manner [21], in co-combustion with compressed natural gas [22] and through further synthesis in electro-fuels [23].

Future renewable energy systems cannot rely on a single strategy, but will need to interconnect numerous Power-to-X systems with intermittent renewable generation [24].

In order to assess the future role of different technologies and to identify the best allocation of different decarbonisation options, computational energy models are key tools to support energy planning processes [25]. Bottom-up energy models allow to analyse different options for the energy system decarbonisation by investigating the role of different renewable and Power-to-X technologies [26].

The main distinction between energy modelling approaches is between simulation and optimisation [27]. Simulation models involve an analytical simulation of alternative strategies and scenarios. In this approach, modelling involves running scenarios and comparing the results, leaving the choice of best scenarios to the interpretation of alternatives and subsequent discussion.

On the contrary, optimisation models seek optimal solutions through mathematical analysis prior to the decision-making process [28]. The objective function must be decided beforehand, and the definition of the best scenario takes place within the model itself. Different optimisation approaches, such as linear programming, mixed integer linear programming and non-linear programming, can be applied to solve the optimisation problem [29].

In Lund et al. [30], the authors have compared and discussed the two approaches. Accordingly, simulation models aim to compare various options and scenarios, allowing for qualitative analysis, while optimisation models seek the optimal solution based on quantitative analysis.

Furthermore, it is important to distinguish between static and long-term approaches.

Static energy models are used to analyse the configuration of an energy system in a specific year [31]. Such systems are suitable for both optimising and simulating energy system configurations. The simulation then takes place on the target year by analysing the behaviour of the energy system. For example, the EnergyPLAN software [32] falls into this category. Indeed, it simulates the energy system in hourly steps over an entire year [33].

Long-term models, on the other hand, take into account the evolution of the energy system up to the target year, considering the time when the different technologies are installed and analysing how this affects the allocation of the different installable technologies [34].

Two approaches for long-term optimisation can be applied: myopic optimisation or perfect foresight. In the first approach, the model makes decisions by not knowing in advance the information about the future. In this way the optimization problem is divided into several steps where the output of one is the input of the other. This approach realistically describes the decision-making process, but does not identify the optimal scenario throughout the period, as it does not analyse in advance the possible evolution of technology costs.

In perfect forecasting models, future information on costs and demand developments is known in advance. In this way, the model faces a single optimisation problem considering the whole system and its evolution over time and optimising all the simulation steps together.

Several energy long-term energy modelling tools have been developed and applied to the national energy system planning. In Feijoo et al. [35], such tools have been reviewed highlighting different characteristics and modelling approaches. Few of these models provide both a methodological approach based on system optimisation and hourly resolution for simulation. For instance, PLEXOS [36] focuses on unit commitment and capacity planning, OSeMOSYS [37,38] on open-source modelling for minimum energy system cost, and GenX on power system optimisation to minimise costs and meet constraints [39]. Other models such as LUT Energy System Transition [40] consider long-term capacity optimisation with hourly energy dispatch. Moreover, PyPSA (PyPSA-Eur-Sec-30) [41] allows to optimise the operation and investments of an energy system, taking in consideration cross-border trade of electricity and cross-sector integration.

However, as pointed out by Feijoo et al. [35], there is a gap in existing energy modelling tools. Indeed, there is no open-source optimisation model for assessing entire energy systems with both hourly resolution and long-term, multi-year investment operational planning for capacities, including Power-to-X technologies and other sectors like industry and transport.

H2RES model stands as a tool to bridge that gap. Such model is a single-objective optimisation algorithm based on Linear Programming. H2RES allows to plan an energy system over short-to-long horizons, optimising capacity additions for technologies, including variable RES and Power-to-X technologies, with hourly scale resolutions for energy dispatch.

In the present work, such model has been applied to the Italian energy system for the first time. Some works in the recent years have addressed the issue of national energy planning in Italy.

In the study conducted by Bellocchi et al. [42], the role of electric vehicles in the energy transition toward low-carbon systems has been analysed by using the EnergyPLAN software. Furthermore, the same model has been applied to explore the impact of electrifying transport and residential heating in Italy, assessing their contributions to improve energy system flexibility [43]. Prina et al. [34] have coupled EnergyPLAN with a multi-objective evolutionary algorithm in order to develop a long-term optimisation model and apply it to the Italian energy system. In Gaeta et al. [44], roadmaps toward net zero emissions in Italy have been developed by means of TIMES model and represents one of the few studies in the literature analysing the decarbonisation of the Italian energy system. Nevertheless, such model optimises the system without considering hourly variations and the RES availability. The authors proposed integration with a stochastic medium-term simulator, however this solution does not solve the optimisation of the different sectors and does not identify the optimal capacity of Power-to-X technologies.

Some of the authors of the present work have proposed a method for improving the Italian energy strategy in order to achieve the target of at least 55% greenhouse gases GHG (greenhouse gases) emission reductions by 2030 [45], by applying the EnergyPLAN software.

While some works have analysed specific sectors within the Italian context, there is a lack of national energy planning studies in Italy. Some studies have investigated the Italian context to identify decarbonisation pathways, but mainly through static simulation energy models or long-term energy models with computational or system limitations.

This work applies for the first time H2RES software to elaborate an optimal decarbonisation pathway for the Italian energy system. To the best of the authors' knowledge, there are no works investigating the Italian energy system decarbonisation by means of a model that considers hourly resolution in a long-term energy planning optimisation setting, integrating all energy sectors and several Power-to-X technologies. Moreover, this tool has been applied for a country extremely reliant on the solar resource and with limited wind power potential, both in terms of full load hours and installable capacity.

The aim of the present work is to identify cost-optimal pathways for the Italian energy system decarbonisation, by modelling a long-term energy transition to achieve zero emission by 2050.

In long-term energy planning, the optimal configuration for each step is dependent on the previous one. Hence, variations in renewable and Power-to-X technology costs change the optimal configurations during the simulation period. A potential limitation of these models is therefore the goodness of cost forecasts. Thus, it is necessary to extend the analysis to different cost scenarios in order to identify how the optimisation results are dependent on the input data.

The present paper aims to discuss such issue by investigating how different renewable cost scenarios can affect the optimal solution in long-term energy modelling tools.

This is one of the main novelties of this article. Indeed, most optimisation studies do not analyse the variation of outputs as cost inputs vary. Thus, there is often a lack of information on how changes in the cost of a single key technology, like wind or solar, affect the overall capacity of the other technologies included in a complex system such as the national energy system. To the best of the authors' knowledge, there are no studies that analyse the reciprocal interaction of technology allocations due to cost scenarios and the effects on the system using a long-term optimisation tool based on a perfect foresight approach.

In Section 2, material and methods applied in the present work have been described. In detail, the H2RES software has been introduced, data regarding the Italian energy system model have been outlined, cost scenarios have been presented and the main technical and economic assumptions have been described. In Section 3, the outcomes of the work have been presented and discussed. Finally, in Section 4, the main findings have been summarised.

2. Material and methods

The aim of this paper is to identify a cost-optimal path for the decarbonisation of the Italian energy system and to assess how renewable cost forecasts may influence the optimal solution.

In long-term energy planning, the optimal configuration for each step depends on the previous one. Therefore, different cost scenarios of renewable technologies change the optimal configurations during the simulation period. The analysis has been conducted with the H2RES model, a single-objective optimisation algorithm based on linear programming. Starting with 2020 as the reference year, the model identifies with a foresight approach the optimal energy mix with a 5-year step from 2025 to the horizon year of 2050. Each year is simulated with hourly resolution.

In order to analyse how the cost forecasts of the main technologies affect this analysis, different capital expenditure (CAPEX) scenarios have been developed for photovoltaics (PV), wind power and lithium-ion batteries.

In detail, an optimistic and a pessimistic CAPEX scenario for each of these technologies has been considered on the basis of major international reports.

As an initial analysis, a reference scenario considering the average values of cost forecasts has been simulated. Afterwards, further eight cost scenarios, combining the different CAPEX scenarios, have been simulated and analysed.

In Fig. 1, the methodology workflow has been depicted.

2.1. H2RES software

In the present work, H2RES software has been applied to model the energy transition of the Italian energy system. H2RES is a long-term linear optimisation-based model that integrates sector coupling solutions with a high temporal resolution (on an hourly basis), and technological resolution. The model systematically considers interactions among power, heat, industry, and transport sectors, aiming to optimise capacity investments for each zone, output of generators and storage, storage levels while adhering to predefined Critical Excess of Energy Production (CEEP) thresholds.

The general structure of the model, highlighting the main energy sectors, the most significant technologies that can be used and the links between them, has been illustrated in Fig. 2.

The model considers a variety of technologies, from conventional power generators to renewable energy sources like solar, both on-shore and off-shore wind, and hydro-river. It allows users to define hourly profiles, capital costs, and capacity levels.

The model addresses the heating sector by considering both centralised (i.e. district heating) and decentralised production, and including various options for heat generation, such as conventional boilers or Heat Pumps (HPs). In so doing, the model allows for the modelling of different technologies within the same category. It allows for the analysis of Power-to-X technologies with varying technical characteristics, capacity potentials, and cost structures.

This versatility extends to the hydrogen (H_2) demand, where H2RES incorporates hourly profiles distributed across sectors like transport, building, industry, and others. It optimises the size of electrolyser and H_2 storage to meet demand levels, offering optimal generation and storage levels at hourly resolutions. This functionality is extended to the fuel-cell (FC) technologies, with the model allowing for the optimisation of dispatch and sizes for different electrolysers and FCs with distinct technical and cost characteristics.

The H2RES model involves three distinct types of decision variables. Firstly, there are yearly investment capacities allocated to each technology for each year. The model assumes that the additional installed capacity resulting from these investments is immediately available at the beginning of each year. Secondly, variables representing the output of generators and storage are optimized for each hour of each simulated year, specifically for technologies with an installed capacity greater than zero. Lastly, there is a set of variables corresponding to storage levels (hydro, heat, H_2), modelled at an hourly resolution for each technology and each year in the planning horizon.

The main objective of the H2RES model is to minimise yearly operation and capacity costs across all years in the planning horizon. Given that the model allows for long-term planning, it considers the net present value of future operation and capacity costs. The general mathematical representation of the model's objective is expressed in Eq. 1. This equation includes various terms, such as dispatching costs, annualized capital costs, costs associated with ramping up or down operations, costs of importing electricity, and costs per unit of carbon dioxide (CO_2) emissions. The goal is to identify the optimal combination of these

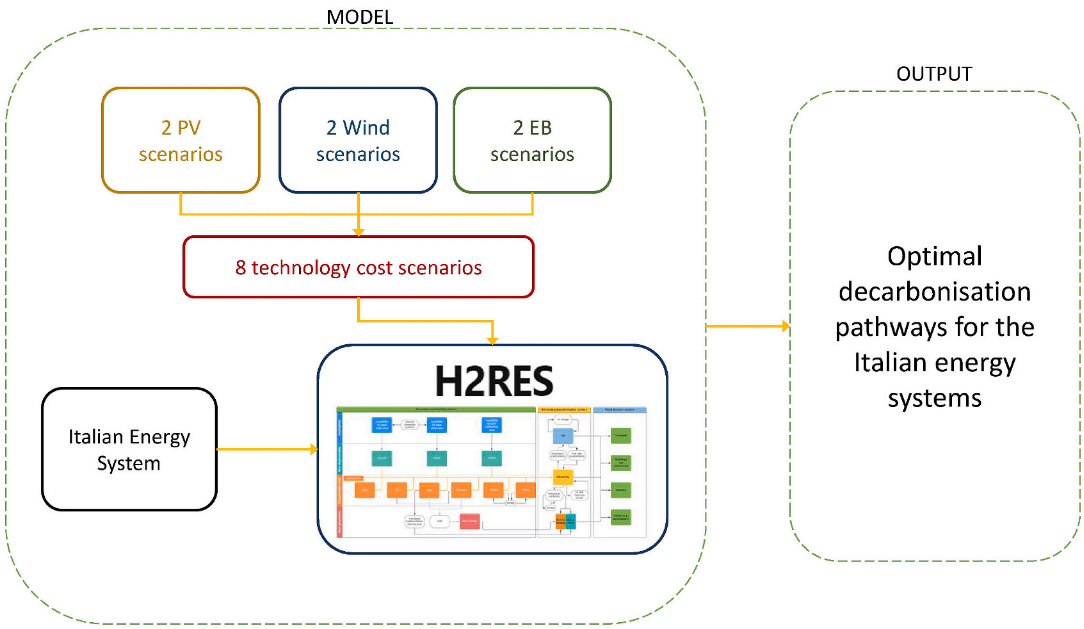

Fig. 1. Graphical methodology.

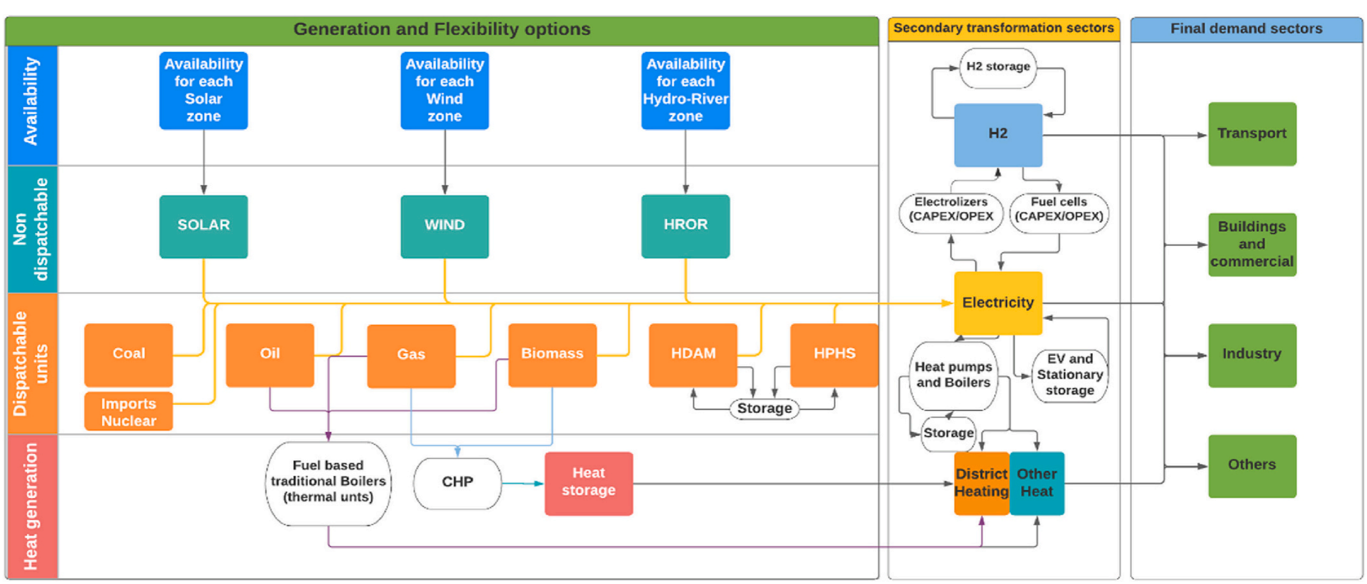

Fig. 2. Graphical representation of the H2RES model [35].

variables that results in the lowest overall cost throughout the planning horizon.

$$\sum_y\sum_p\sum_t df_y\left[vC_{t,p,y}D_{t,p,y}+C_{t,y}K_tInv_{t,y}+R_{t,p,y}Ramp_{t,p,y}\right.$$
$$\left.+I_{p,y}Imp_{p,y}+CO_2Price_yCO_2Levels_{t,p,y}\right] \tag{1}$$

Within Eq. 1, the first term encompasses the dispatched energy $D_{t,p,y}$ associated with each technology t, during hour p, in year y. The variable cost ($C_{t,p,y}$) is a function determined by the interplay of fuel costs and non-fuel costs, as outlined in Eq. 2. This structural approach enables the modelling of cost structures for various types of technologies. In other words, it allows for the differentiation and representation of costs associated with different technology types, taking into account both fuel-related and non-fuel-related expenses.

$$vC_{t,p,y}=\left[\frac{FuelCost_{t,p,y}}{eff_{t,p,y}}+NonFuelCost_{t,p,y}\right] \tag{2}$$

The second term within the objective function pertains to the annualized capital cost (K_t) of technology t that is multiplied to the invested capacity ($Inv_{t,y}$) of each technology t in each year y and the capital cost ($C_{t,y}$) of each given technology, which may fluctuate in various modelled years to simulate changes in technology costs, such as those following a learning curve that reduces capital costs over time.

This aspect is a user-defined input.

The third and fourth terms of the objective function correspond to the costs associated with ramping up or down operations and importing electricity, respectively. Hence, they both encompass the cost of ramping up/down and import per unit of power/energy and the amount of power/energy that is involved in such process in each hour (p) of each year (y) (the ramping up and down cost is also defined for each

Table 1
Electricity demand by sector.

Sector	Electricity consumption (TWh)
Households and Services	154.8
Industry	119.5
Transport	11.5
Consumption of the energy branch	19.8
Distribution and transmission losses	17.8
Import	43.9
Export	5.8

Table 2
Heating demand by technology.

Technology	Fuel consumption (TWh)
Natural Gas boilers	247.5
Oil boilers	29.03
Biomass boilers	73.3
Heat pump	29.0 (Ambient heat)
Thermal solar	2.5

Table 3
District Heating demand.

DH	Heat demand (TWh)
Households and Services supplied by boilers	4.0
Households and Services supplied by CHPs	10.1
Industry supplied by CHP	50.1

technology while import is not). It is important to note that the present iteration of H2RES permits the consideration of electricity imports exclusively, with the import price being a user-specified input expressed at an hourly granularity for each year in the model. Additionally, the model takes into account the cost per unit of CO_2 emissions for each of the technologies, typically measured in euros per metric ton of CO_2 emissions (EUR/tCO_2).

H2RES places several constraints on technology sizes and dispatch levels to ensure the minimisation of costs as defined by the objective function. The main constraints encompass disaggregating demand levels across various sectors, setting upper bounds on technology output based on installed capacity, considering technical constraints, and managing storage state-of-charge.

Furthermore, H2RES accounts for three policy dimensions: maximum CEEP levels, renewable energy penetration targets, and yearly limits on CO_2 emissions levels, allowing for comprehensive analysis of low-carbon economy transitions.

The model has been implemented in order to consider the constraint on overall biomass consumption. Indeed, biomass is largely used in hard-to-abate sectors and the potential for electricity generation should be implemented considering the actual biomass availability in the system.

H2RES is open-source [46], fostering accessibility, and further details about its functionality are available in the provided references, allowing researchers and practitioners to explore and contribute to the model's development [35,47,48].

2.2. Case study - Italian energy system

As a case study, the decarbonisation of the Italian energy system has been analysed.

The inputs for the H2RES model have been considered by converting the EnergyPLAN model developed in Ref. [49] and also applied in Ref. [50].

Such model has been built on the basis of the Eurostat data and those

Table 4
Transport demand.

Fuel	Annual consumption (TWh)
Diesel	224.0
Petrol	115.1
LPG	27.3
NG	13.3
Jet Fuel	10.5
Biofuels	14.8
Electricity	11.5

Table 5
Industry fuels demand.

Industry	Annual consumption (TWh)
Coal	6.9
Oil	115.1
Natural Gas	99.3
Biomass	4.9

Table 6
Renewable electricity capacity and annual generation.

Technology	Capacity (GW)	Electricity generation (TWh)
Hydroelectric	22.8	46.3
PV	20.1	23.7
Wind	10.9	20.2
Bioenergy	4.2	19.5
Geothermal	0.8	6.0

Table 7
Central power plants capacity and national average efficiencies.

Technology	Capacity (GW)	Electrical efficiency (–)	Thermal efficiency (–)
NG - Electricity only	24.1	0.532	–
Oil - Electricity only	0.5	0.401	–
Coal - Electricity only	8.3	0.376	–
Biomass - Electricity only	1.9	0.413	–
NG - Combined Heat and Power	17.1	0.436	0.238
Oil - Combined Heat and Power	2.5	0.325	0.219
Biomass - Combined Heat and Power	2.2	0.287	0.316

provided in national documentation [51–54].

The simulation period starts in 2020, however 2019 has been considered as the reference year, since 2020 is characterised by the first COVID lockdown and the data are not representative of the country's real energy consumption.

Tables 1–7 summarise data used for modelling the Italian Energy System.

Some assumptions regarding decarbonisation scenarios have been made, as the model optimises the mix of renewable generation, heating systems and Power-to-X technologies, however, the demand for energy carriers related to other energy sectors is considered as an input.

In detail, assumptions regarding transport and industry influence the overall electricity and hydrogen demand of the energy system and thus the ability of the system to provide flexibility and balance variable RES generation.

For the transport sector, the first solution concerns the conversion of 90% of light duty vehicles to electric vehicles. The deployment of electric vehicles has been considered linear until 2050. A decarbonisation scenario based on Synthetic Liquid Fuels (SLFs) has been developed for fuel demand in the remaining part of light duty vehicles and for all heavy duty vehicles.

Hydrogen can be combined with biomass-derived syngas to produce SLFs [55]. In detail, the power-to-liquid option involves the production of Dimethyl Ether (DME) replacing diesel consumption.

The SLF production based on the biomass hydrogenation has been considered. Indeed, as demonstrated by Korberg et al. [56], this solution allows the biomass supply chain to be better managed and the hydrogen supply chain to be optimized. The deployment of SLFs in the transport sector was assumed to be linear from 2035 onwards, leading to the complete replacement of fossil fuels by 2050.

Industry represents a hard-to-abate sector as a large part of the thermal demand is at high temperatures. A portion of the low-temperature industrial demand can be electrified. This demand has a maximum potential of 13 TWh/yr and a linear trend for its electrification has been considered.

Hydrogen consumption in industry already exists in Italy, which is supplied by natural gas by the Steam Methane Reforming (SMR) process. This demand amounts to 0.5 Mt_{H2}/yr and can instead be supplied by green hydrogen produced by water electrolysis [57]. Finally, bio-electrofuels are introduced to replace the industrial demand provided by fossil fuels. Also in this sector, the hydrogenation chain is chosen to minimise the biomass consumption. Thus, hydrogen is combined with biogas to produce SNG or is used for the hydrogenation of syngas to produce SNG or SLF [58]. The substitution of grey hydrogen from SMR with green hydrogen is considered as a linear process from 2030 onwards. While the deployment of SNGs and SLFs in the industrial sector is assumed to be linear from 2035 onwards to full replacement of fossil fuels in 2050. Finally, according to the above-mentioned assumptions, the evolution of both electricity and hydrogen demand has been computed and depicted in Fig. 3.

2.3. Renewable technology cost scenarios

Different cost scenarios have been developed in order to investigate the effect of technology cost forecasts on the optimal generation mix. For renewable technologies, scenarios have been developed on the basis of Ref. [59, 60]. Accordingly, renewable generation costs will sharply decrease in the medium and long term.

In Fig. 4, CAPEX range forecasts for photovoltaics, onshore and offshore wind are shown.

Based on these forecasts, a cost path of renewable technologies has been assumed for the next 30 years. A high-cost and low-cost scenario has been developed for each technology. The CAPEX scenarios for PV and Wind are shown in Fig. 5.

Furthermore, CAPEX scenarios for EBs have been considered in accordance with Ref. [61] and depicted in Fig. 6.

Therefore, by combining those technology CAPEX scenarios, a reference scenario plus further eight cost scenarios have been simulated and analysed. In the reference scenario, the average values for each technology have been taken into account for the simulation, while the combination of low-cost and high-cost scenarios leads to 8 different cost scenarios.

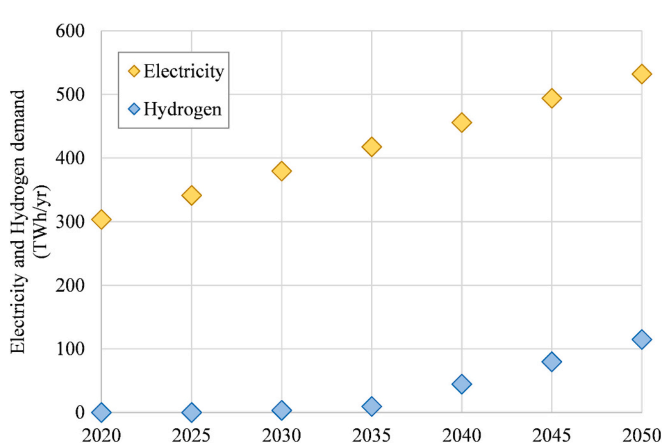

Fig. 3. Evolution of electricity and hydrogen demand from 2020 until 2050.

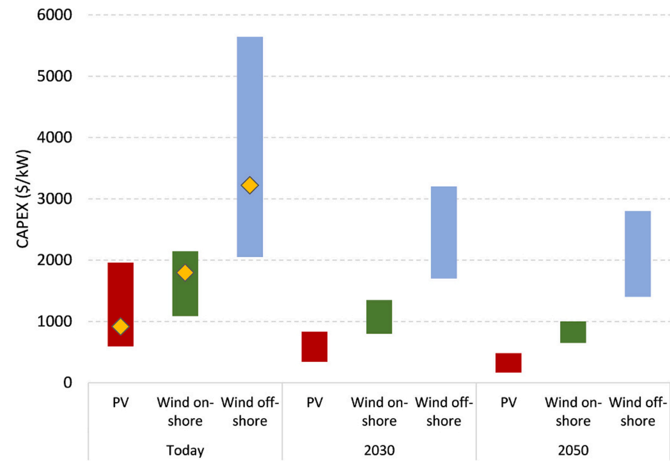

Fig. 4. CAPEX range forecasts for photovoltaics, onshore and offshore wind (the yellow indicator shows the current average costs for Italy). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.4. Technical and economic assumptions

Techno-economic inputs for H2RES model assumed in the present work have been summarised in Table 8. The fuel prices (coal, gas, oil, biomass) have been assumed to increase by an average of 1% per year compared to the historical levels of 2020. For hydro units, inflows, and the availability factors of wind and solar, it is anticipated that they will remain consistent with the levels observed in 2020 throughout subsequent years. The biomass potential has been considered equal to 108 TWh/yr, in accordance with Ref. [62]. Furthermore, the RES capacity installation potential in Italy has been assumed according to Ref. [63] and summarised in Table 9. Hourly RES profile has been considered in accordance with the model developed in Ref. [49].

3. Results and discussion

The target of achieving complete decarbonization of the energy system by 2050 has been established for the simulation. Furthermore, a CEEP limit has been imposed, capped at 10%. However, this threshold is not reached in the reference scenario.

Fig. 7 illustrates the electricity generation mix and the percentage of renewable electricity in the reference decarbonisation scenario from 2020 to 2050. Furthermore, the cumulated RES capacity installation and the cumulated capacity installation of both lithium-ion batteries and electrolysers have been represented in Figs. 8 and 9, respectively.

Nowadays, the Italian generation mix is extremely natural gas-based. The share of renewables in electricity production experiences a rapid increase during the initial stages of the simulation. In 2020, the share is slightly below 40%, however, already by 2035, it surpasses 70%. By 2040, the share reaches values above 90%. At this step, gas-fired electricity generation mainly serves as a balancing component in the power system, alongside biomass. In 2045, electricity generation is nearly entirely renewable; however, to attain full decarbonization of the national energy system, demand for hydrogen and electricity continues to rise in hard-to-abate sectors. Consequently, a total renewable capacity exceeding 100 GW, primarily PV, is installed in the final phase.

During the initial stages, onshore wind capacity experiences a more

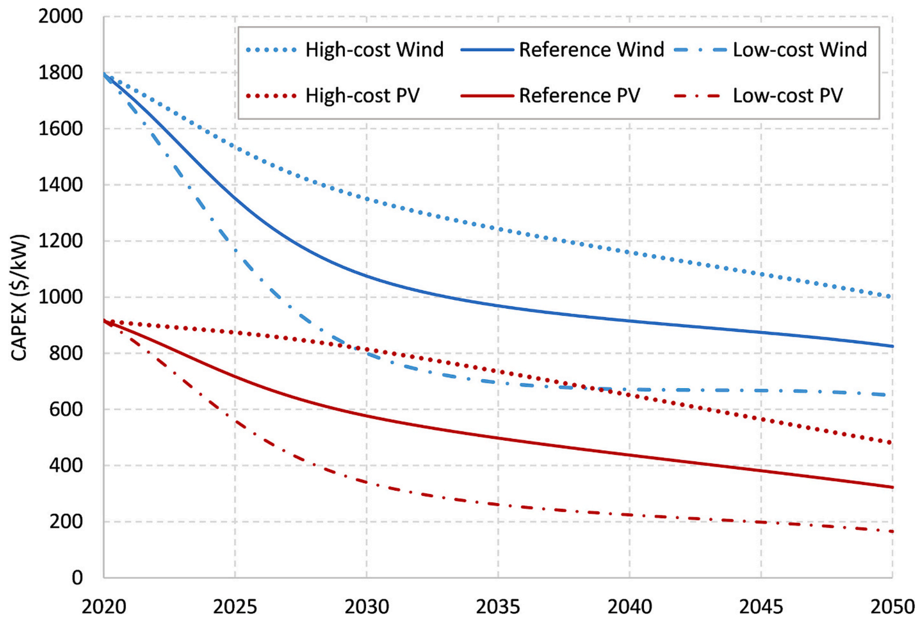

Fig. 5. RES CAPEX scenarios.

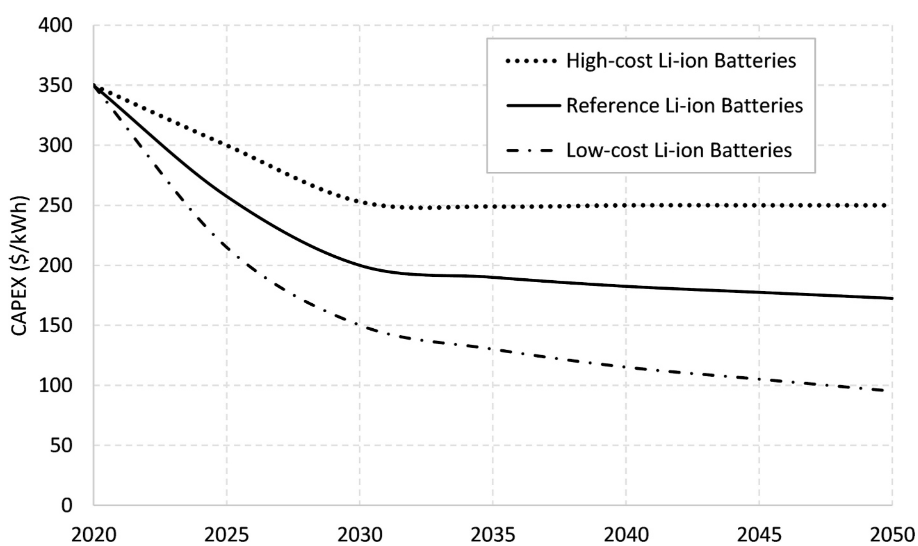

Fig. 6. CAPEX scenarios of lithium-ion batteries [61].

Table 8
Input data for H2RES model.

Technology	Units	INV 2020 (M€/unit)	INV 2030 (M€/unit)	INV 2040 (M€/unit)	INV 2050 (M€/unit)	Efficiency	Source
PEMFC CHP	MW	1.3	1.1	0.9	0.8	50%	[64]
SOFC CHP	MW	3.3	2	1.3	0.8	60%	[64]
Alkaline Electrolyser	MW	0.65	0.45	0.3	0.25	66.5–78	[64]
SOEC Electrolyser	MW	4.5	1.9	1.3	0.78	77–83.5%	[64]
PEM Electrolyser	MW	0.92	0.65	0.45	0.4	58–70.5%	[64]
H2 storage (tanks)	MWh	0.057	0.045	0.027	0.021	–	[64]
biomass boiler	MW_{th}	0.47	0.447	0.425	0.404	79–85%	[64]
gas boiler	MW_{th}	0.278	0.265	0.252	0.24	90%	[64]
air-to-water HPs	MW_{th}	1.2	1.076	1.016	0.956	3.282 (SCOP evaluated)	[64]
geothermal HP	MW_{th}	1.932	1.836	1.74	1.566	4.621 (SCOP evaluated)	[64]
Electric boilers	MW_{th}	0.89	0.85	0.81	0.77	100%	[64]

substantial increase than PV systems. However, starting from 2040, PV installation surpasses that of onshore wind. Furthermore, offshore wind begins to be installed by 2030. By 2050 the total installable wind potential is saturated, so the optimal mix is affected by this limit.

The optimal energy system configuration by 2050 envisages an overall share of electricity generation from PV systems approximately

Table 9
VRES capacity installation potential in Italy [63,65,66].

RES	Capacity potential (GW)	Full load hours (h/yr)
PV	357.4	1517
Wind onshore	115.4	2418
Wind offshore	55.7	2759

equal to that from wind power. In 2050, electricity generation is almost twice as high as the total electricity demand. The integrable electricity excess is converted into hydrogen and used in hard-to-abate sectors and to balance electricity system through the hydrogen conversion into electricity by means of fuel cells.

Such an increase in PV and wind generation includes a growth in energy storage systems. Lithium-ion batteries and fuel cell provide dispatchable generation, avoiding large use of biomass in the power sector. Nevertheless, non-dispatchable generation will account for 92% of total electricity generation by 2050.

Lithium-ion batteries have significant capacities as of 2035. In the same step, a small capacity of electrolysers is considered in the optimal configuration. The installed capacity of electrolysers increases substantially in 2040, when the RES penetration surpasses 90% and high shares of non-dispatchable renewables are integrated in the system.

EBs have a faster deployment, however, the installed capacity in the 100% renewable energy system is lower than the electrolyser one.

3.1. Renewable technology cost scenarios

In this section, the issue about how variations in cost forecasts can affect optimisation study for long-term energy planning has been addressed and discussed.

To this end, the optimal decarbonisation path of the Italian energy system has been simulated across the eight different cost scenarios for

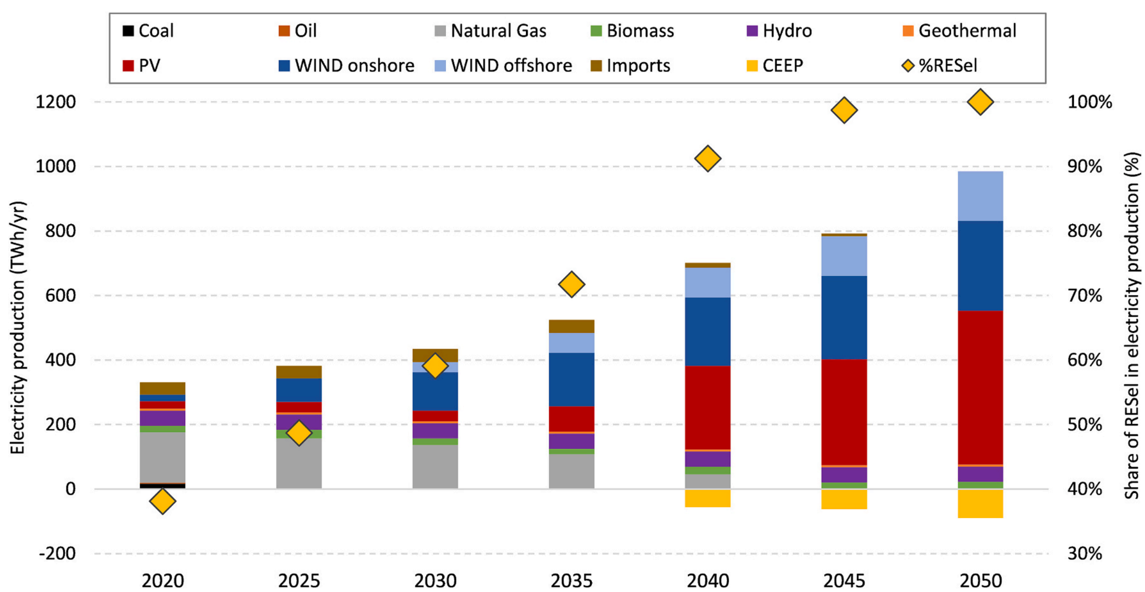

Fig. 7. Electricity generation by fuel and RES share for the reference decarbonisation scenario.

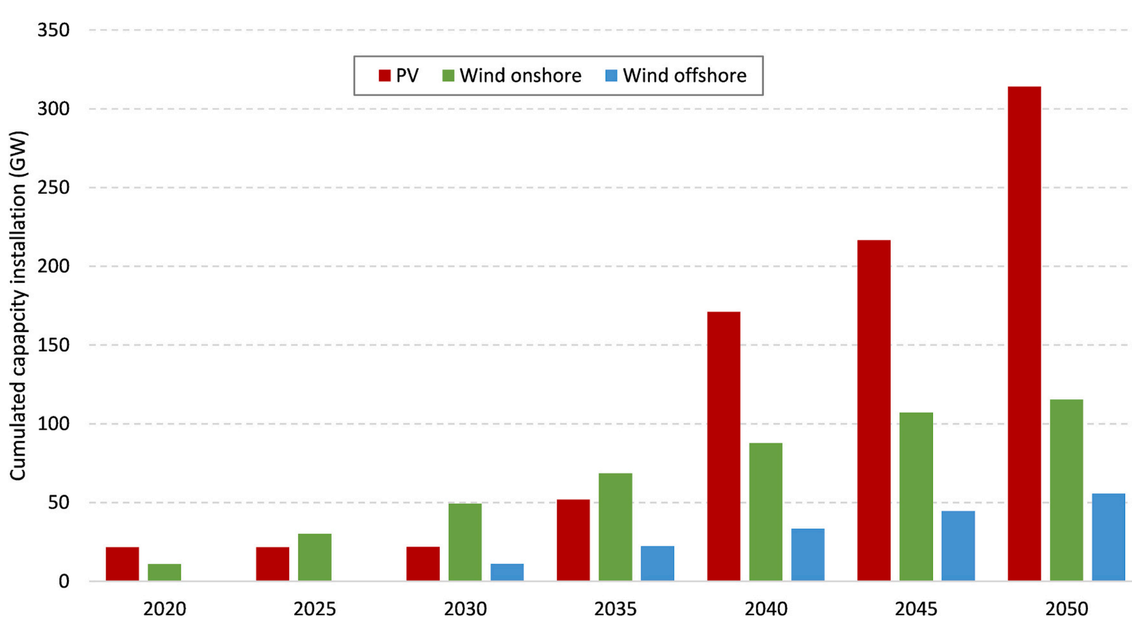

Fig. 8. Cumulated RES capacity installation for the reference decarbonisation scenario.

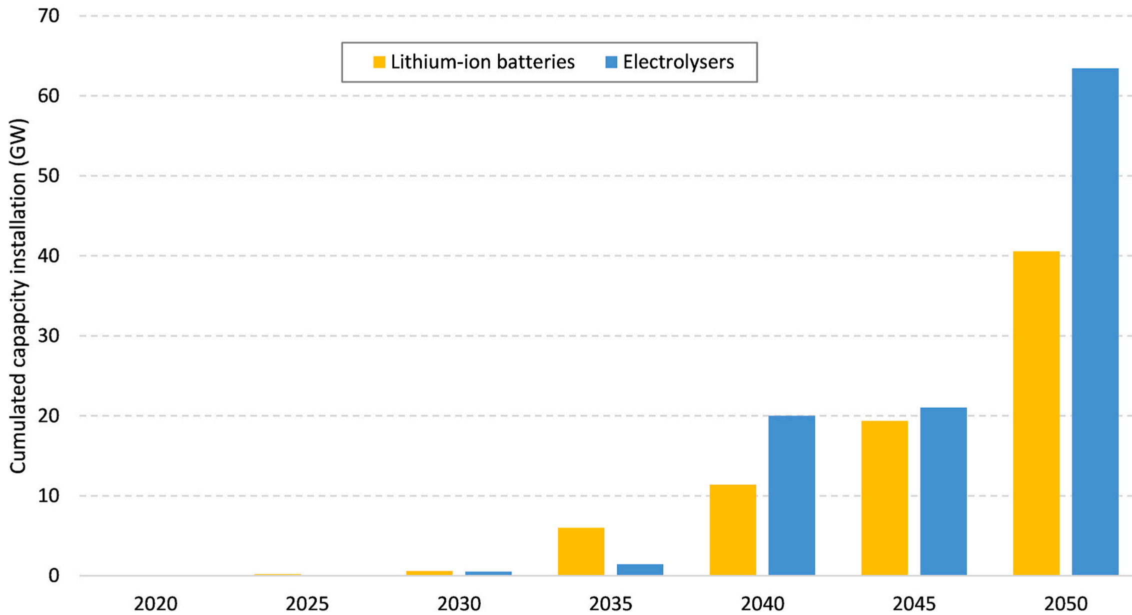

Fig. 9. Cumulated capacity installation of lithium-ion batteries and electrolysers for the reference decarbonisation scenario.

renewable technologies. In Fig. 10, the optimal configurations of RES capacity and lithium-ion battery capacity by 2050 in the different cost scenarios have been depicted.

A minimum of 260 GW of PV consistently required across all cost scenarios. However, Low PV - High EB cost scenarios necessitate around 350 GW of PV in the optimal configuration. In detail, the Low PV – High Wind cost scenarios are the only ones where the installed capacity of PV reaches its maximum potential.

The maximum potential of both onshore and offshore wind capacity is almost always saturated except in the scenario where PV installs the maximum available capacity. This shows that in general wind generation is cheaper and easier to integrate into the system than photovoltaics. Furthermore, in High PV cost, the change in the cost of wind turbines does not substantially affect installed capacities. This is due to the fact that even as the cost of wind power increases, this technology remains a priority and installation is only limited by the depletion of potential capacity.

Forecasts of lithium-ion battery costs exert a substantial influence on the optimal electric battery capacity. For the same renewables cost scenarios, the battery capacity in Low EB cost is up to three times the installed capacity in the High EB cost scenario. Furthermore, in High EB cost, the increase in RES capacity installation leads to increased stationary storage capacity. Indeed, in those scenarios, the overall increase in renewable generation requires more storage capacity to handle the increased renewable capacity and integrate the critical excess.

EB cost scenarios barely change the optimal electricity generation mix. The VRES capacity remains essentially the same by changing EB costs. In contrast, by changing the VRES costs, the overall EB capacity

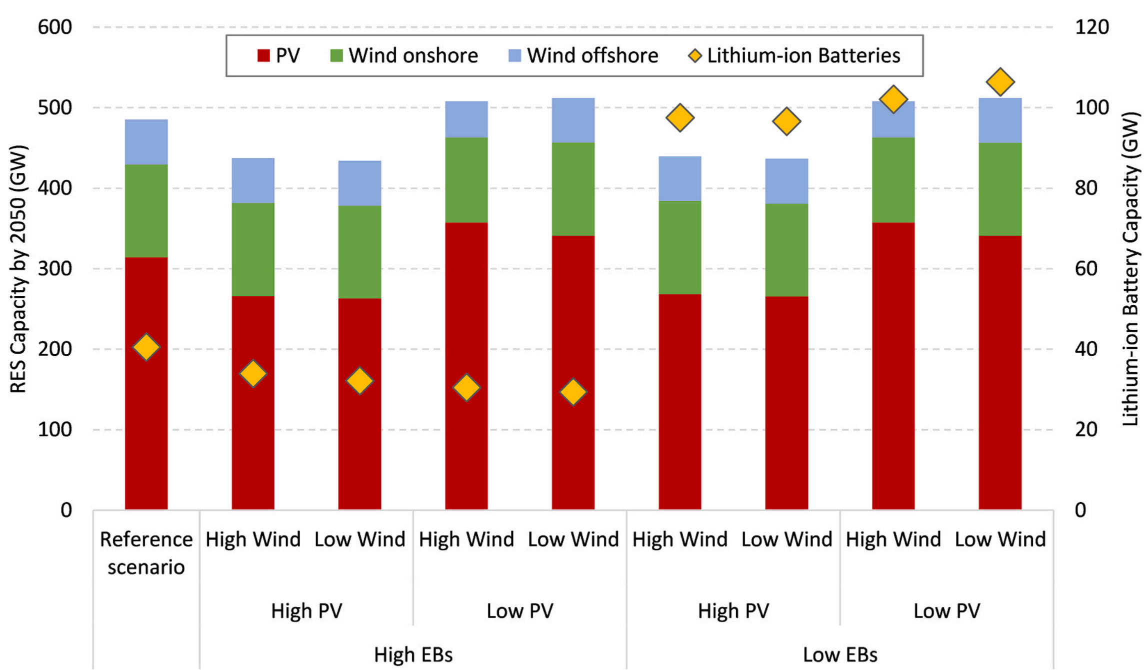

Fig. 10. Optimal configuration of RES capacity and lithium-ion battery capacity by 2050 in the different cost scenarios.

varies. This is because as the costs of renewables vary, their installed capacity varies and the generation mix affects the use of energy storage systems.

These capacity allocations also correlate with the role of dispatchable generation in the energy system.

In Fig. 11, the electricity mix generation and CEEP by 2050 in the different cost scenarios have been depicted.

Biomass plays a marginal role in renewable generation and is only used to provide dispatchable generation. Especially in Low EB cost scenarios, generation from biomass is very low, as fuel cells and lithium-ion batteries, along with hydroelectric power, provide sufficient dispatchable generation. The constraint on biomass availability affects the results in some scenarios. Indeed, without such constraint, biomass consumption would be higher. Higher biomass consumption is considered where stationary storage systems and fuel cells are less installed and used. Indeed, as VRES generation increases, it is preferable to provide dispatchable generation by means of electrochemical storage systems or hydrogen instead of using biomass.

Hydroelectric power generation is approximately constant across all scenarios and is not affected by cost variations in the considered technologies. All the scenarios exhibit very high shares of non-dispatchable generation, ranging between 90% and 93%.

CEEP values vary between 8.4% and 9.6%. As the cost of electric batteries decreases, the capacity increases and this is reflected in a reduction of CEEP. The increase in electrical generation causes an increase in the excess in absolute terms. However, the increase in CEEP is less proportional to the increase in generation, reducing the percentage values.

The overall annual electricity demand of the energy system is about 500 TWh. In some scenarios, electricity generation nearly doubles the demand, leading to the conversion of excess electricity into hydrogen. The latter serves various purposes, including further synthesis into alternative fuels, utilisation in hard-to-abate sectors, and balancing through conversion into electricity by means of fuel cells. The role of hydrogen is tied to the considered cost scenario.

In Fig. 12, the electrolyser and hydrogen storage capacity by 2050 in the different cost scenarios have been depicted. In Fig. 13, the breakdown of hydrogen production by consumption item by 2050 in the different cost scenarios. Furthermore, in Fig. 14, the fuel cell capacity and electricity fuel cell generation by 2050 in the different cost scenarios have been represented.

High electric battery costs result in a slight increase in electrolyser capacity in all the scenarios, reaching up to around 70 GW. EB cost scenarios have a greater impact on overall hydrogen production, which varies between 240 TWh/yr and 370 TWh/yr. Moreover, the total fuel cell capacity increases significantly, almost doubling, in High EB cost scenarios.

Hydrogen plays a crucial role in power grid balancing and providing a significant portion of dispatchable electricity in all configurations. Moreover, this hydrogen application is also significant compared to other direct and indirect usages in the hard-to-abate sectors.

Specifically, in High EB cost, hydrogen generation through fuel cells is the preferred method for storage and balancing, resulting in a decrease in EB capacity and utilisation. In contrast, in low-cost scenarios for lithium-ion batteries, a significant increase in EB capacity emerges as the primary method for enhancing storage services.

The overall electrolyser capacity is slightly linked to the amount of VRES generation and is mainly provided by alkaline electrolysers. The FC capacity varies little as the cost scenario of renewables changes, while their utilisation varies greatly. Indeed, FC generation of electricity increases as renewable generation increases, thus creating a substantial share of dispatchable energy in the system. This causes a slight reduction in CEEP in such scenarios. Furthermore, it can be seen that the installed capacities of EB and FC do not vary, but the choice of storage system utilisation mainly changes according to the need for short-term or long-term storage.

Although hydrogen production rises as renewable generation increases, there is a slight reduction in overall hydrogen storage capacity. This is because frequent FC use can discharge the storage, reducing the residence time of hydrogen in the storage system and thus its size.

In Fig. 15, the share of H_2 in final energy consumption versus the share of VRES in primary energy supply has been depicted.

Depending on the cost scenario, the hydrogen penetration in energy end-uses changes. Such issue can be partially correlated with the VRES penetration. In High EB cost, the increase of VRES share in primary energy supply significantly increases the hydrogen penetration in energy end-uses. Conversely, the increase in the hydrogen share, as the VRES share increases, is much reduced in Low EB cost scenarios, since lithium-ion batteries provide the necessary dispatchable generation.

A decrease in PV costs has a greater impact on the VRES penetration than a decrease in wind costs. Additionally, when PV costs are high, changes in wind costs do not affect the VRES share due to the saturation

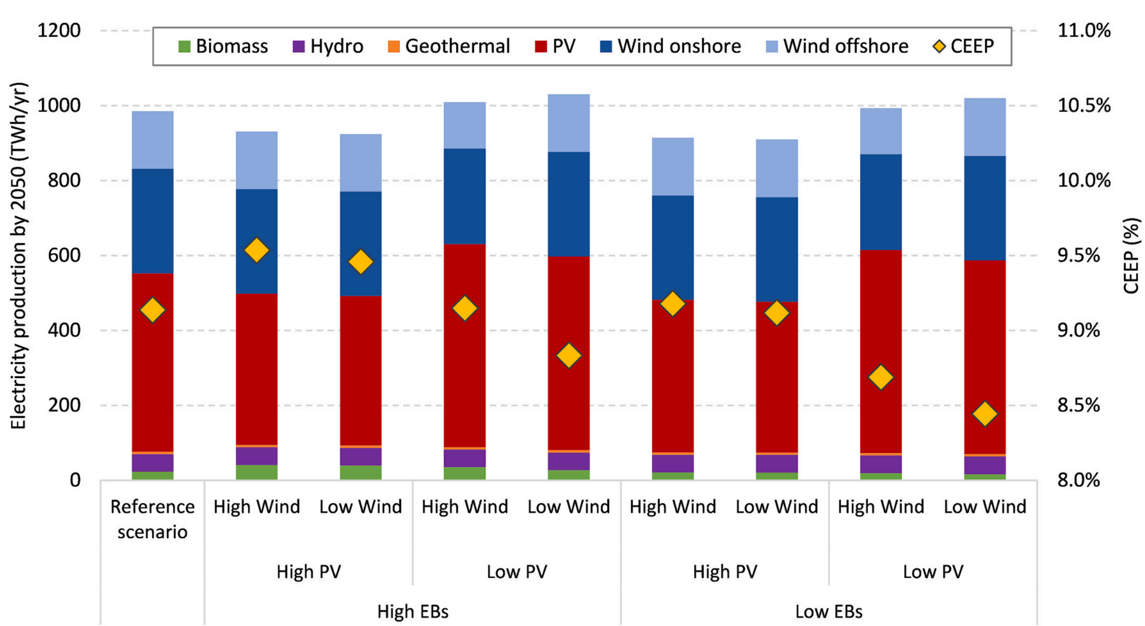

Fig. 11. Electricity production and CEEP by 2050 in the different cost scenarios.

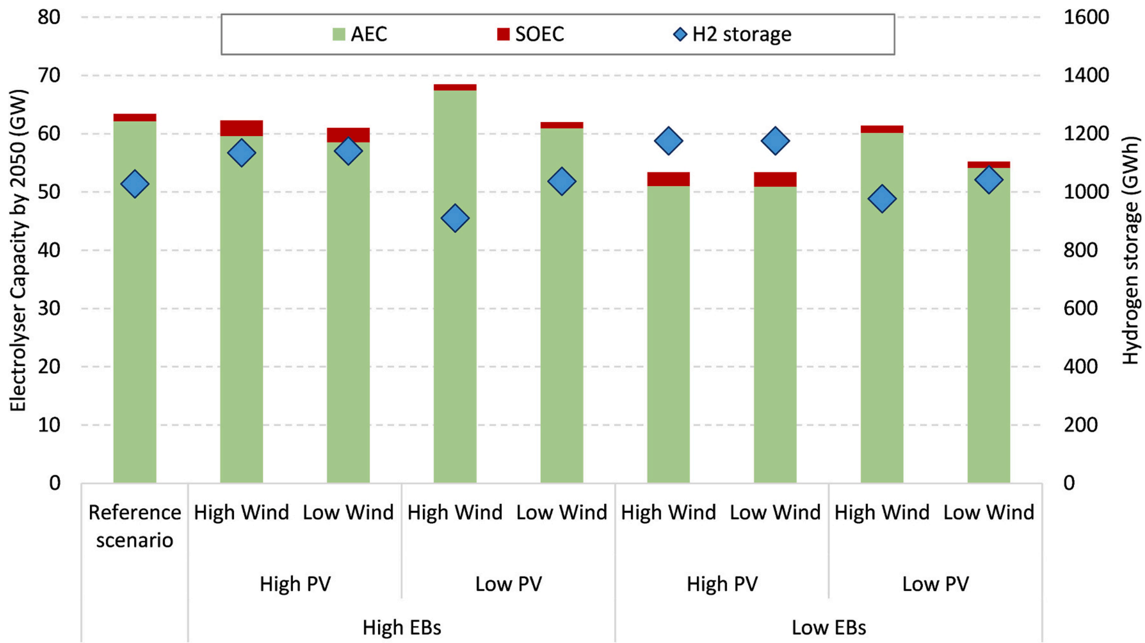

Fig. 12. Electrolyser capacity and hydrogen storage by 2050 in the different cost scenarios.

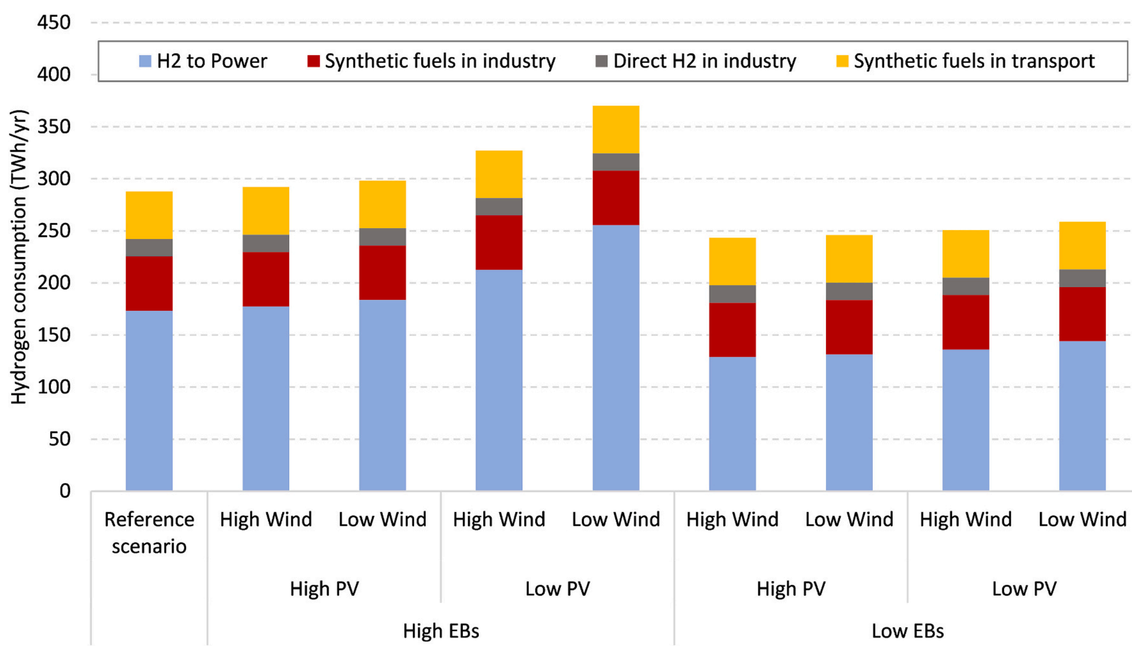

Fig. 13. Breakdown of hydrogen production by consumption item by 2050 in the different cost scenarios.

of wind installation potential. The reduction in the EB costs reduces the penetration of hydrogen in final energy consumption by increasing the share of VRES.

In Fig. 16, the annual costs of the energy systems by 2050 in the different cost scenarios have been depicted.

The annual costs associated with the configurations of the Italian energy system in different scenarios have been compared. Annual costs are defined as the sum of annualized capital expenditure and operating expenditure for the operation and maintenance of various plants and the fuel purchase.

The considered cost scenarios result in a variation of annual system costs ranging from +10% to −14% compared to the reference scenario. A significant portion of the annual costs are attributed to renewable energy sources and are therefore subject to the variations defined in the considered scenarios. Hydrogen and synthetic fuel value-chain, as well as heating equipment and infrastructure, are also major cost items, each accounting for approximately 20–25% of the total. These cost distributions in 100% renewable energy systems are, with due differences, consistent with existing literature [55,67].

With all other scenarios being equal, a decrease in PV costs has a greater impact on the total annual cost reduction than a decrease in wind costs. This depends on both the installed capacity of the optimal mix and how it is affected by the saturation of the installable wind potential.

The outcomes of the work show that a 100% renewable Italian energy system is technically and economically feasible. Power-to-X technologies are essential for balancing intermittent generation. Such

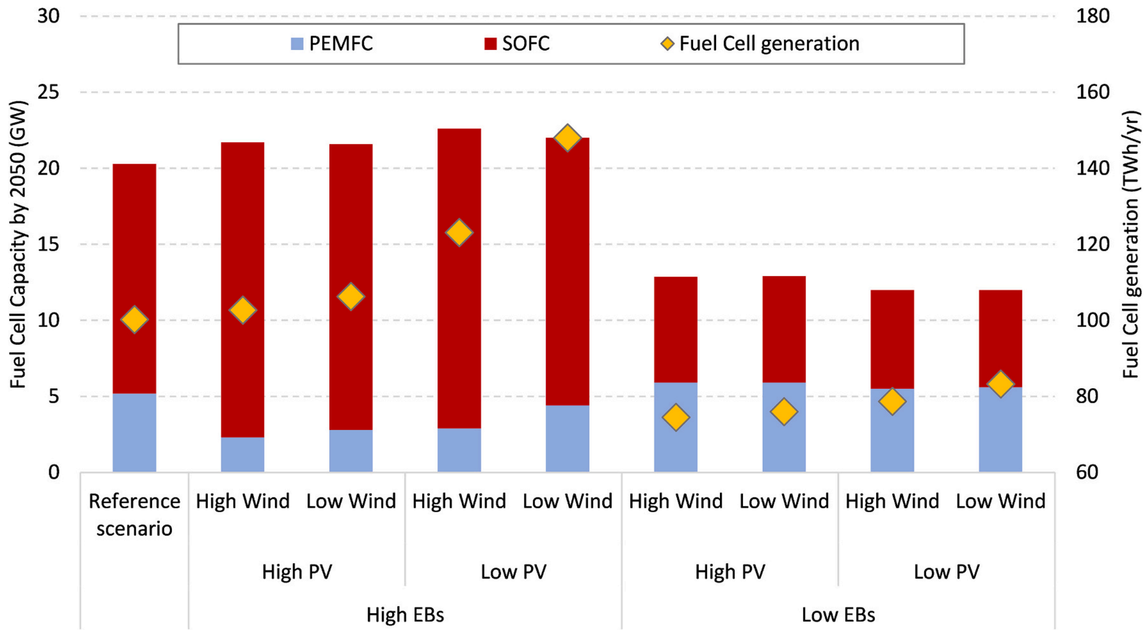

Fig. 14. Fuel cell capacity and electricity fuel cell generation by 2050 in the different cost scenarios.

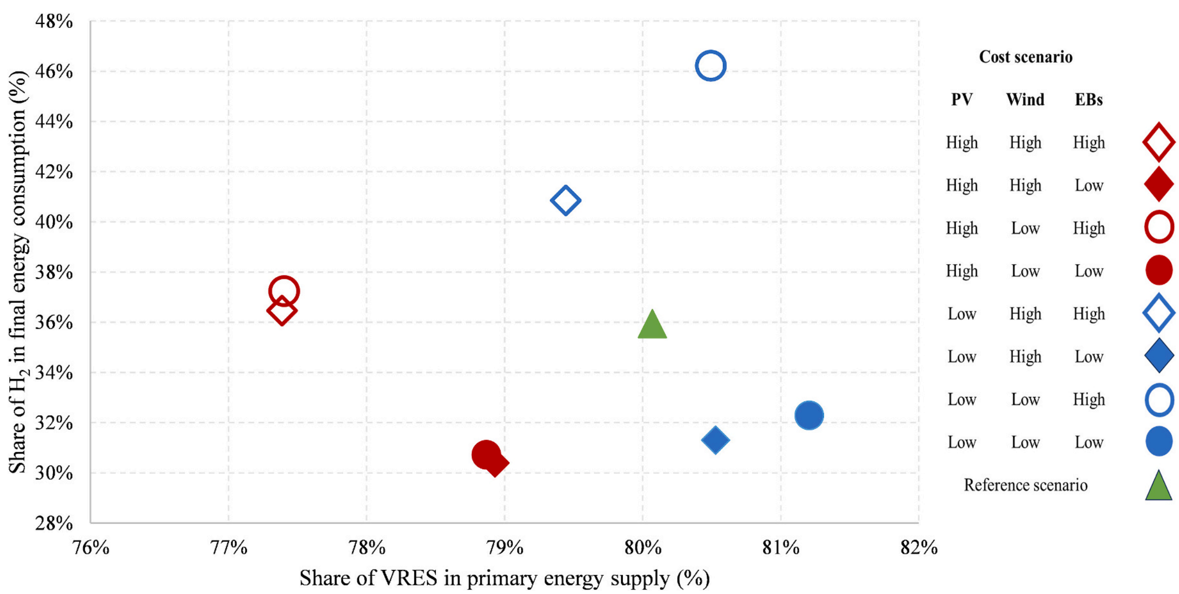

Fig. 15. Share of H_2 in final energy consumption versus share of VRES in primary energy supply.

systems allow to design an electricity generation with a VRES share of 93%.

Synergies between sectors allow for the integration of renewable generation and energy system decarbonisation, both by the electrification of energy end-uses and hydrogen deployment.

The optimal configuration by 2050 and the decarbonisation pathway are highly dependent on the renewable cost scenarios. Indeed, the H2RES model optimises the different steps by identifying the least-cost solution. In so doing, the capacity of the different technologies changes considerably depending on the cost scenario.

In the case of renewables, cost variation has an impact on the optimal mix, although this effect is severely limited by the maximum capacity potential. As a result, the renewable mix influences the use of storage systems, as is known from several other works in the literature [68]. The effect is not reciprocal; indeed, the variation in EB costs has negligible effect on the VRES mix, but slightly affects the role of biomass in dispatchable generation.

Indeed, the capacity and operation of technologies whose costs were not subject to sensitivity analysis are also strongly influenced by the costs of renewables and EBs.

This is particularly the case for hydrogen technologies, which, like any storage system, are strongly influenced by the wind-solar mix in the system, but also by the costs of the other main storage options, such as batteries. The results show how not only the installed capacity varies, but also the energy flows and the priorities for using one technology over the others.

Finally, these optimisation studies are highly conditioned by the goodness of the technologies' cost forecasts. Especially for long-term energy planning studies, it is crucial to integrate cost sensitivity analyses to identify how variations in cost forecasts may affect the best strategies for decarbonising energy systems.

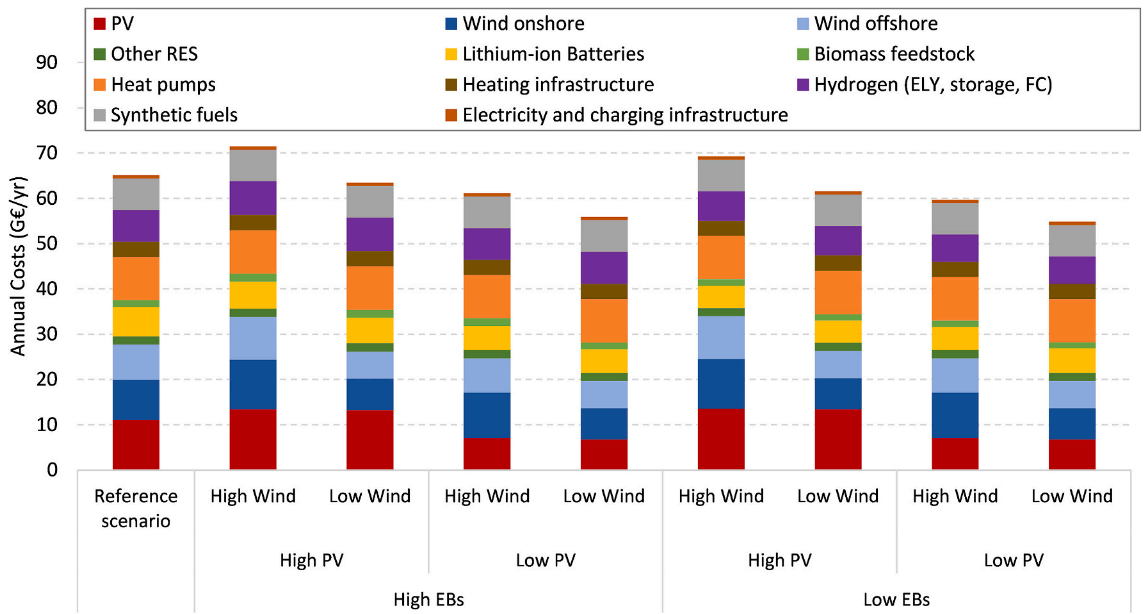

Fig. 16. Annual costs of energy system by 2050 in the different cost scenarios.

3.2. Limitations of the work and further developments

This paper analyses a techno-economic optimisation of Italy's decarbonisation pathway to 2050. However, as also demonstrated in this paper, such optimisation process is highly dependent on the technology cost forecasts. In the present work, cost analysis of photovoltaic, wind and lithium-ion batteries has been performed. However, this analysis can be extended to different technologies. In detail, some technologies related to the hydrogen value chain are currently in pre-commercial stage and their future price is difficult to estimate. A future development of this work can be the analysis of different technology cost forecasts beyond those taken into consideration.

Furthermore, the analysis in this paper has been carried out by assuming decarbonisation pathways for transport and industrial sectors. However, different strategies can be analysed, which affect the overall hydrogen and biomass demand, thus affecting the final energy system configuration. A future development of this paper can be the analysis of different strategies for the decarbonisation of hard-to-abate sectors.

Furthermore, the critical excess is high, with potential issues concerning network and plants' management. The analysis performed in this work does not integrate the issues due to excess and curtailment costs. These costs become an important factor in the identification of optimal capacities and the management of energy flows. Despite this, in almost all existing literature concerning energy planning, such costs are neglected. Therefore, this aspect represents a limitation of this paper, as well as a gap in the literature, and may be a future development of this paper.

4. Conclusions

The aim of the present work is to identify a cost-optimal pathway for the Italian energy system decarbonisation and assess how different decarbonisation strategies and renewable cost scenarios can affect the optimal solution.

The analysis has been conducted with the H2RES model, a single-objective optimisation algorithm based on linear programming. In order to analyse how the cost forecasts of the main technologies affect this analysis, different CAPEX scenarios have been developed for photovoltaics, wind power and lithium-ion batteries.

In detail, an optimistic and a pessimistic CAPEX scenario for each of these technologies has been considered on the basis of major international reports. Therefore, a reference scenario plus further eight cost scenarios, combining the different CAPEX scenarios, have been simulated and analysed.

The main findings can be summarised as follows:

- A 100% renewable Italian energy system can be achieved. Power-to-X technologies are essential for balancing intermittent generation. Such systems allow to design an electricity generation with a VRES share up to 93%.
- A minimum of 260 GW of PV is always necessary in each cost scenario. However, in the scenarios characterised by low PV CAPEX and high cost of electric batteries, around 350 GW of PV are required in the optimal configuration. The maximum potential capacity of both on-shore and off-shore Wind is saturated in almost all scenarios.
- The cost forecasts of lithium-ion batteries strongly affect their optimal capacity. For the same renewables cost scenarios, the battery capacity in the low-cost scenario is up to three times the installed capacity in the high-cost scenario.
- Biomass plays a marginal role in renewable generation and is only used to provide dispatchable generation. Especially in low EB cost scenarios, generation from biomass is very low, as fuel cells and lithium-ion batteries, along with hydroelectric power, provide sufficient dispatchable generation.
- The overall annual electricity demand of the energy system is about 500 TWh. In some scenarios, electricity generation is almost double the demand and the electricity excess is mostly converted into hydrogen, both for further synthesis into alternative fuels and use in hard-to-abate sectors, and for balancing purposes through conversion into electricity by fuel cells.
- Hydrogen plays a crucial role in power grid balancing and providing a significant portion of dispatchable electricity in all configurations. EB cost scenarios have a greater impact on overall hydrogen production, which varies between 240 TWh/yr and 370 TWh/yr.
- In high EB cost scenarios, hydrogen generation through fuel cells is the preferred method for storage and balancing, resulting in a decrease in EB capacity and utilisation. Conversely, enhancing storage services primarily involves a significant increase in EB capacity.
- The H2RES model optimises the different steps by identifying the least-cost solution. In so doing, the capacity of the different technologies changes considerably depending on the cost scenario. In

addition, the capacity and operation of other systems, like hydrogen technologies, whose costs have not been subject to sensitivity analysis, are also highly affected by the costs of renewables and electric batteries.

The findings reveal the technical and economic feasibility of a 100% renewable Italian energy system, with Power-to-X technologies playing a pivotal role in balancing intermittent generation. The optimal configurations, however, are shown to be highly dependent on the cost scenarios considered, emphasizing the need for rigorous sensitivity analyses in long-term energy planning studies. Therefore, it is crucial to integrate cost sensitivity analyses in energy planning studies in order to identify how variations in cost forecasts may affect the best strategies for decarbonising energy systems. Furthermore, the reliance on technology cost forecasts underscores the importance of continuous monitoring and updating of such forecasts for accurate long-term planning.

The final cost of technologies in a country also depended on the development of industries in that country and the value chain of the technologies. The speed of cost reduction also depended heavily on progress on the learning curve.

The development of strategies through a discussion between energy planners and policymakers and defining a clear energy policy can also guide the national industrial policy.

In addition, this kind of study can support the development of energy strategies and decarbonisation targets to identify priorities between sectors and technologies.

Therefore, this paper contributes valuable insights to the ongoing discourse on sustainable energy transitions, offering a roadmap for policymakers, researchers, and stakeholders in Italy and beyond as they navigate the complexities of achieving a carbon-neutral energy system.

Nomenclature

CAPEX	Capital Expenditure
CEEP	Critical Excess of Energy Production
CHP	Combined Heat and Power
DH	District Heating
DME	Dimethyl Ether
EBs	Electric Batteries
GHG	Greenhouse gases
FC	fuel-cell
H_2	Hydrogen
HPs	Heat Pumps
LP	linear program
NG	Natural Gas
PEMFC	Proton Exchange Membrane Fuel Cells
PtG	Power-to-Gas
PtH	Power-to-Heat
RES	Renewable energy sources
SLFs	Synthetic Liquid Fuels
SMR	Steam Methane Reforming
SOFC	Solid Oxide Fuel Cells
VRES	Variable RES

CRediT authorship contribution statement

Lorenzo Mario Pastore: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Daniele Groppi:** Software, Conceptualization. **Felipe Feijoo:** Methodology, Software. **Gianluigi Lo Basso:** Supervision. **Davide Astiaso Garcia:** Supervision. **Livio de Santoli:** Supervision.

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

No data was used for the research described in the article.

References

[1] Intergovernmental Panel on Climate Change. Climate Change 2022: Impacts, Adaptation, and Vulnerability. 2022. https://doi.org/10.1017/cbo9781107415379.

[2] Breyer C, Khalili S, Bogdanov D, Ram M, Oyewo AS, Aghahosseini A, et al. On the history and future of 100% renewable energy systems research. IEEE Access 2022;10:78176–218. https://doi.org/10.1109/ACCESS.2022.3193402.

[3] Hansen K, Breyer C, Lund H. Status and perspectives on 100% renewable energy systems. Energy 2019;175:471–80. https://doi.org/10.1016/j.energy.2019.03.092.

[4] Aghahosseini A, Solomon AA, Breyer C, Pregger T, Simon S, Strachan P, et al. Energy system transition pathways to meet the global electricity demand for ambitious climate targets and cost competitiveness. Appl Energy 2023:331. https://doi.org/10.1016/j.apenergy.2022.120401.

[5] Yuan M, Sorknæs P, Lund H, Liang Y. The bidding strategies of large-scale battery storage in 100% renewable smart energy systems. Appl Energy 2022;326:119960. https://doi.org/10.1016/j.apenergy.2022.119960.

[6] Ajanovic A, Hiesl A, Haas R. On the role of storage for electricity in smart energy systems. Energy 2020;200. https://doi.org/10.1016/j.energy.2020.117473.

[7] Peters JF, Weil M. Providing a common base for life cycle assessments of Li-Ion batteries. J Clean Prod 2018;171:704–13. https://doi.org/10.1016/j.jclepro.2017.10.016.

[8] Lund H, Østergaard PA, Connolly D, Mathiesen BV. Smart energy and smart energy systems. Energy 2017;137:556–65. https://doi.org/10.1016/j.energy.2017.05.123.

[9] Ramsebner J, Haas R, Ajanovic A, Wietschel M. The sector coupling concept: a critical review. Wiley Interdiscip Rev Energy Environ 2021;10. https://doi.org/10.1002/wene.396.

[10] Pavičević M, Mangipinto A, Nijs W, Lombardi F, Kavvadias K, Jiménez Navarro JP, et al. The potential of sector coupling in future European energy systems: soft linking between the Dispa-SET and JRC-EU-TIMES models. Appl Energy 2020;267:115100. https://doi.org/10.1016/j.apenergy.2020.115100.

[11] Aunedi M, Pantaleo AM, Kuriyan K, Strbac G, Shah N. Modelling of national and local interactions between heat and electricity networks in low-carbon energy systems. Appl Energy 2020;276:115522. https://doi.org/10.1016/j.apenergy.2020.115522.

[12] Ghaemi S, Li X, Mulder M. Economic feasibility of green hydrogen in providing flexibility to medium-voltage distribution grids in the presence of local-heat systems. Appl Energy 2023:331. https://doi.org/10.1016/j.apenergy.2022.120408.

[13] Kachirayil F, Weinand JM, Scheller F, McKenna R. Reviewing local and integrated energy system models: insights into flexibility and robustness challenges. Appl Energy 2022;324:119666. https://doi.org/10.1016/j.apenergy.2022.119666.

[14] Sorrenti I, Harild Rasmussen TB, You S, Wu Q. The role of power-to-X in hybrid renewable energy systems: a comprehensive review. Renew Sustain Energy Rev 2022;165:112380. https://doi.org/10.1016/j.rser.2022.112380.

[15] Jimenez-Navarro JP, Kavvadias K, Filippidou F, Pavičević M, Quoilin S. Coupling the heating and power sectors: the role of centralised combined heat and power plants and district heat in a European decarbonised power system. Appl Energy 2020;270:115134. https://doi.org/10.1016/j.apenergy.2020.115134.

[16] Qiu R, Zhang H, Wang G, Liang Y, Yan J. Green hydrogen-based energy storage service via power-to-gas technologies integrated with multi-energy microgrid. Appl Energy 2023;350:121716. https://doi.org/10.1016/j.apenergy.2023.121716.

[17] Yao Z, Wang Z, Ran L. Smart charging and discharging of electric vehicles based on multi-objective robust optimization in smart cities. Appl Energy 2023;343:121185. https://doi.org/10.1016/j.apenergy.2023.121185.

[18] Heinisch V, Göransson L, Erlandsson R, Hodel H, Johnsson F, Odenberger M. Smart electric vehicle charging strategies for sectoral coupling in a city energy system. Appl Energy 2021:288. https://doi.org/10.1016/j.apenergy.2021.116640.

[19] Wang B, Yu X, Xu H, Wu Q, Wang L, Huang R, et al. Scenario analysis, management, and optimization of a new Vehicle-to-Micro-Grid (V2μG) network based on off-grid renewable building energy systems. Appl Energy 2022;325:119873. https://doi.org/10.1016/j.apenergy.2022.119873.

[20] Zhang C, Greenblatt JB, Wei M, Eichman J, Saxena S, Muratori M, et al. Flexible grid-based electrolysis hydrogen production for fuel cell vehicles reduces costs and greenhouse gas emissions. Appl Energy 2020;278:115651. https://doi.org/10.1016/j.apenergy.2020.115651.

[21] Haugen MJ, Paoli L, Cullen J, Cebon D, Boies AM. A fork in the road: which energy pathway offers the greatest energy efficiency and CO2 reduction potential for low-carbon vehicles? Appl Energy 2021;283:116295. https://doi.org/10.1016/j.apenergy.2020.116295.

[22] Sgaramella A, Lo Basso G, de Santoli L. How the cylinder initial conditions affect the HCNG refuelling process - a thermodynamic analysis to determine the most effective filling parameters. Int J Hydrogen Energy 2023:1–17. https://doi.org/10.1016/j.ijhydene.2023.07.323.

[23] Oshiro K, Fujimori S. Role of hydrogen-based energy carriers as an alternative option to reduce residual emissions associated with mid-century decarbonization

goals. Appl Energy 2022;313:118803. https://doi.org/10.1016/j.apenergy.2022.118803.
[24] Dominković DF, Bačeković I, Ćosić B, Krajačić G, Pukšec T, Duić N, et al. Zero carbon energy system of South East Europe in 2050. Appl Energy 2016;184:1517–28. https://doi.org/10.1016/j.apenergy.2016.03.046.
[25] Ferrari S, Zagarella F, Caputo P, Bonomolo M. Assessment of tools for urban energy planning. Energy 2019;176:544–51. https://doi.org/10.1016/j.energy.2019.04.054.
[26] Lv F, Wu Q, Ren H, Zhou W, Li Q. On the design and analysis of long-term low-carbon roadmaps: a review and evaluation of available energy-economy-environment models. Renew Sustain Energy Rev 2024;189:113899. https://doi.org/10.1016/j.rser.2023.113899.
[27] Johannsen RM, Prina MG, Østergaard PA, Mathiesen BV, Sparber W. Municipal energy system modelling – a practical comparison of optimisation and simulation approaches. Energy 2023:269. https://doi.org/10.1016/j.energy.2023.126803.
[28] Kotzur L, Nolting L, Hoffmann M, Groß T, Smolenko A, Priesmann J, et al. A modeler's guide to handle complexity in energy systems optimization. Adv Appl Energy 2021;4:100063. https://doi.org/10.1016/j.adapen.2021.100063.
[29] Ommen T, Markussen WB, Elmegaard B. Comparison of linear, mixed integer and non-linear programming methods in energy system dispatch modelling. Energy 2014;74:109–18. https://doi.org/10.1016/j.energy.2014.04.023.
[30] Lund H, Arler F, Østergaard PA, Hvelplund F, Connolly D, Mathiesen BV, et al. Simulation versus optimisation: theoretical positions in energy system modelling. Energies 2017;10:1–17. https://doi.org/10.3390/en10070840.
[31] Després J, Hadjsaid N, Criqui P, Noirot I. Modelling the impacts of variable renewable sources on the power sector: reconsidering the typology of energy modelling tools. Energy 2015;80:486–95. https://doi.org/10.1016/j.energy.2014.12.005.
[32] Lund H, Thellufsen JZ, Østergaard PA, Sorknæs P, Skov IR, Mathiesen BV. EnergyPLAN – advanced analysis of smart energy systems. Smart Energy 2021;1:100007. https://doi.org/10.1016/j.segy.2021.100007.
[33] EnergyPLAN Advanced Energy Systems Analysis Computer Model Documentation Version 14. n.d.
[34] Prina MG, Lionetti M, Manzolini G, Sparber W, Moser D. Transition pathways optimization methodology through EnergyPLAN software for long-term energy planning. Appl Energy 2019;235:356–68. https://doi.org/10.1016/j.apenergy.2018.10.099.
[35] Feijoo F, Pfeifer A, Herc L, Groppi D, Duić N. A long-term capacity investment and operational energy planning model with power-to-X and flexibility technologies. Renew Sustain Energy Rev 2022:167. https://doi.org/10.1016/j.rser.2022.112781.
[36] Deane JP, Chiodi A, Gargiulo M, Ó Gallachóir BP. Soft-linking of a power systems model to an energy systems model. Energy 2012;42:303–12. https://doi.org/10.1016/j.energy.2012.03.052.
[37] Howells M, Rogner H, Strachan N, Heaps C, Huntington H, Kypreos S, et al. OSeMOSYS: The Open Source Energy Modeling System. An introduction to its ethos, structure and development. Energy Policy 2011;39:5850–70. https://doi.org/10.1016/j.enpol.2011.06.033.
[38] Welsch M, Deane P, Howells M, O Gallachóir B, Rogan F, Bazilian M, et al. Incorporating flexibility requirements into long-term energy system models - a case study on high levels of renewable electricity penetration in Ireland. Appl Energy 2014;135:600–15. https://doi.org/10.1016/j.apenergy.2014.08.072.
[39] Jenkins J, Sepulveda N. Enhanced Decision Support for a Changing Electricity Landscape: the GenX Configurable Electricity Resource Capacity Expansion Model. MIT Energy Initiat Work Pap. 2017. p. 1–67.
[40] Bogdanov D, Farfan J, Sadovskaia K, Aghahosseini A, Child M, Gulagi A, et al. Radical transformation pathway towards sustainable electricity via evolutionary steps. Nat Commun 2019;10:1–16. https://doi.org/10.1038/s41467-019-08855-1.
[41] Brown T, Schlachtberger D, Kies A, Schramm S, Greiner M. Synergies of sector coupling and transmission reinforcement in a cost-optimised, highly renewable European energy system. Energy 2018;160:720–39. https://doi.org/10.1016/j.energy.2018.06.222.
[42] Bellocchi S, Klöckner K, Manno M, Noussan M, Vellini M. On the role of electric vehicles towards low-carbon energy systems: Italy and Germany in comparison. Appl Energy 2019;255:113848. https://doi.org/10.1016/j.apenergy.2019.113848.
[43] Bellocchi S, Manno M, Noussan M, Prina MG, Vellini M. Electrification of transport and residential heating sectors in support of renewable penetration: scenarios for the Italian energy system. Energy 2020;196:117062. https://doi.org/10.1016/j.energy.2020.117062.
[44] Gaeta M, Businge CN, Gelmini A. Achieving net zero emissions in Italy by 2050: challenges and opportunities. Energies 2022:15. https://doi.org/10.3390/en15010046.
[45] Pastore LM, Lo Basso G, Cristiani L, de Santoli L. Rising targets to 55% GHG emissions reduction – the smart energy systems approach for improving the Italian energy strategy. Energy 2022;259:125049. https://doi.org/10.1016/j.energy.2022.125049.
[46] H2RES. Energy system modelling software. n.d. https://h2res.org/ (accessed May 17, 2023)
[47] Herc L, Pfeifer A, Feijoo F, Duić N. Energy system transitions pathways with the new H2RES model: a comparison with existing planning tool. E-Prime - Adv Electr Eng Electron. Energy 2021;1. https://doi.org/10.1016/j.prime.2021.100024.
[48] Groppi D, Feijoo F, Pfeifer A, Garcia DA, Duic N. Analyzing the impact of demand response and reserves in islands energy planning. Energy 2023;278:127716. https://doi.org/10.1016/j.energy.2023.127716.
[49] Pastore LM, Lo Basso G, de Santoli L. Towards a dramatic reduction in the European natural gas consumption: Italy as a case study. J Clean Prod 2022:133377. https://doi.org/10.1016/J.JCLEPRO.2022.133377.
[50] Sgaramella A, Pastore LM, Lo Basso G, de Santoli L. Optimal RES integration for matching the Italian hydrogen strategy requirements. Renew Energy 2023;219:119409. https://doi.org/10.1016/j.renene.2023.119409.
[51] European Union. Energy flow diagrams - energy Eurostat 2021. https://ec.europa.eu/eurostat/web/energy/energy-flow-diagrams.
[52] Statistical data and forecast - Terna spa 2021. https://www.terna.it/en/electric-system/statistical-data-forecast (accessed June 28, 2021).
[53] Ministero della Transizione Ecologica. Bilancio Energetico Nazionale 2021. https://dgsaie.mise.gov.it/bilancio-energetico-nazionale (accessed April 19, 2022).
[54] Ispra. Italian greenhouse gas inventory 1990-2019. National Inventory Report 2021. 2021.
[55] Hansen K, Mathiesen BV, Skov IR. Full energy system transition towards 100% renewable energy in Germany in 2050. Renew Sustain Energy Rev 2019;102:1–13. https://doi.org/10.1016/j.rser.2018.11.038.
[56] Korberg AD, Skov IR, Mathiesen BV. The role of biogas and biogas-derived fuels in a 100% renewable energy system in Denmark. Energy 2020;199:117426. https://doi.org/10.1016/j.energy.2020.117426.
[57] Ministero dello sviluppo economico. Strategia Nazionale Idrogeno Linee Guida Preliminari. 2020.
[58] Bellocchi S, Colbertaldo P, Manno M, Nastasi B. Assessing the effectiveness of hydrogen pathways: a techno-economic optimisation within an integrated energy system. Energy 2023;263:126017. https://doi.org/10.1016/j.energy.2022.126017.
[59] International Renewable Energy Agency. IRENA. Future of Solar Photovoltaic: Deployment, investment, technology, grid integration and socio-economic aspects (A Global Energy Transformation: paper). Abu Dhabi2019; 2019.
[60] International Renewable Energy Agency. IRENA. Future of wind: Deployment, investment, technology, grid integration and socio-economic aspects (A Global Energy Transformation paper). Abu Dhabi2019; 2019.
[61] Cole W, Frazier AW, Cole W, Frazier AW. Cost projections for utility-scale battery storage : 2020 update. Nat Renew Energy Lab; 2020.
[62] Paiano A, Lagioia G. Energy potential from residual biomass towards meeting the EU renewable energy and climate targets. The Italian Case Energy Policy 2016;91:161–73. https://doi.org/10.1016/j.enpol.2015.12.039.
[63] Lombardi F, Pickering B, Colombo E, Pfenninger S. Policy decision support for renewables deployment through spatially explicit practically optimal alternatives. Joule 2020;4:2185–207. https://doi.org/10.1016/j.joule.2020.08.002.
[64] Danish Energy Agency. Technology Data - Energy Plants for Electricity and District heating generation. http://www.ens.dk/teknologikatalog; 2016 (accessed January 31, 2022).
[65] Ram M, Child M, Aghahosseini A, Bogdanov D, Lohrmann A, Breyer C. A comparative analysis of electricity generation costs from renewable, fossil fuel and nuclear sources in G20 countries for the period 2015-2030. J Clean Prod 2018;199:687–704. https://doi.org/10.1016/j.jclepro.2018.07.159.
[66] Renewable Power Generation Costs | IRENA. Renewable Power Generation Costs in 2019. 2020.
[67] Child M, Breyer C. Vision and initial feasibility analysis of a recarbonised Finnish energy system for 2050. Renew Sustain Energy Rev 2016;66:517–36. https://doi.org/10.1016/j.rser.2016.07.001.
[68] Li C, Chen D, Li Y, Li F, Li R, Wu Q, et al. Exploring the interaction between renewables and energy storage for zero-carbon electricity systems. Energy 2022;261:125247. https://doi.org/10.1016/j.energy.2022.125247.