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Might future electricity generation suffice to meet the global demand?

D. Lerede [a,b,*], L. Savoldi [a]

[a] MAHTEP Group, Dipartimento Energia "Galileo Ferraris", Politecnico di Torino, Corso Duca Degli Abruzzi 24, 10129, Torino, Italy
[b] Eindhoven University of Technology, De Zaale, Eindhoven, 5612AZ, Netherlands

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ABSTRACT

Electricity supply is one of the critical issues in the energy field. Due to the high shares of greenhouse gases emissions, the electricity sector is experiencing a transition towards a progressively wider use of low-carbon technologies. At the same time, electrification of end-use sectors is identified as one of the most suitable mitigation strategies, although requiring larger electricity production. This paper relates the historical development trends for installed capacity of electricity production technologies to the theory of the S-curves, building a method to depict plausible developments in the electricity sector. Projections are performed considering the existence of an upper limit for industrial capacity development, and according to a path envisaging a revolutionary, an evolutionary and a maturity phase for technologies showing considerable growth trends. Oppositely, stagnation is taken into account for those not showing any remarkable progress. The computed curves are used to perform forecasts about electricity generation potentials until 2050, showing how the projected growth trend of electricity generation technologies would result in a production sufficient to meet the expected global demand, even excluding the contribution of fossil fuels in some cases. In perspective, the presented method can be applied to retrieve maximum capacity constraints for energy system models.

1. Introduction

The possible future developments of the energy system, needed to mitigate climate change effects, are widely studied using the energy scenario approach. Institutions, international organizations and governments worldwide strongly rely on energy scenario comparison based either on energy system simulation or on optimization-based models. That is the case of e.g., the World Energy Model [1], the main tool used by the International Energy Agency (IEA) to generate projections, or TIMES-Italy [2], adopted to support the Italian Energy Strategy [2]. Nonetheless, energy scenarios have been criticized mostly for their lack of realism, as they are not able to fully reproduce the actual behavior of the energy market and can be strongly biased by external assumptions out its developments [3]. Also, many studies focus on the development of energy strategies to achieve very high renewable energy shares (even up to 100%) [4,5], and such policies are also supported by national governments, like in the case of Germany [6].

Electricity generation represented 16% of the total energy supply (TES) worldwide in 2019 [7], while contributing for more than 40% of all energy-related greenhouse gases (GHG) emissions in 2020 [8]. The increasing electrification shares of end-use sectors to address climate change issues and fulfil decarbonization targets worldwide are driving a massive boost in electricity production [9], with a total generation more than doubled between 1990 and 2019 [7]. Nonetheless, electricity still represented less than 20% of world final energy consumption in 2021 [10], but its share, which was just 9.4% in 1973 [11], is expected to increase in the near future, also considering a shift towards non-fossil sources for end-use energy services [12]. In this framework, it is important to understand whether its anticipated increase is coupled to an adequate structure of the current electricity sector assessing, for instance, possible gaps in the future electricity generation.

The approach using "S-curves" to describe technology adoption is the most widely used in the literature, spreading in the more diverse disciplinary fields and validated against technology diffusion pathways in a variety of sectors, from domestic appliances to computers, cell phones and the internet [13] over the last century. In Ref. [14], innovation is compared to the spreading of epidemics, in which the limit to the speed of adoption is the lack of information about anything new. Concerning the electricity generation sector, the S-curve approach is adopted in Ref. [15] to fit growth models of wind onshore and solar photovoltaic (PV) technologies in different countries. The methodology is based on the Logistic model [16] and the Gompertz model [17], and the evolution of wind and solar production is modeled according to 4 phases

* Corresponding author. MAHTEP Group, Dipartimento Energia "Galileo Ferraris", Politecnico di Torino, Corso Duca Degli Abruzzi 24, 10129, Torino, Italy.
E-mail address: daniele.lerede@polito.it (D. Lerede).

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List of abbreviations

APS	Announced Pledges Scenario
BWR	Boiling water reactor
CCS	Carbon capture and storage
CSP	Concentrated solar power
GHG	Greenhouse gases
ESOM	Energy system optimization model
ETP	*Energy Technology Perspectives*
IAM	Integrated Assessment Model
IEA	International Energy Agency
IRENA	International Renewable Energy Agency
LWR	Light water reactor
NEMS	National Energy Modeling System
NZE	Net-Zero emissions
PV	Photovoltaic
PWR	Pressurized water reactor
SDS	Sustainable Development Scenario
STEPS	Stated Policies Scenario
TES	Total energy supply
TRES	Transforming Energy Scenario
WB2C	Well Below 2 °C
WEO	World Energy Outlook
YOY	Year-over-year

(pre-take-off, take-off, stalling and stability). The fitting parameters are established according to statistical variables representing drivers for the take-off and the maximum achievable growth in a certain region like, e.g., the share of nuclear power, being member of the European Union, the electricity demand growth rate, etc. Historical data are often used as basis to adopt S-curve forecasting approaches, like in the case of [18] to compute the evolution of electric vehicle uptake across countries in England: an exponential model depending on time and parameters based on speed and shape of the transition towards a full electric vehicle fleet is presented. The typical technological S-curve, sketched in Fig. 1, usually reports time on the x-axis and quantity on the y-axis. However, elapsed time is sometimes replaced as the relevant parameter by the amount of economic effort put into development [19] or the engineering effort (e.g. number of working hours, allocated budged, employed researchers, etc.) needed for the improvement of technological performances [20]. Whereas the use of time as independent variable is claimed to be erroneous in Ref. [21], it is often used in empirical models as data for establishing investment levels are difficult to be retrieved [20]. In general, three phases are identified in technological development: 1) embryonic, 2) growth and 3) maturity (and ageing) [19], supporting the validity of the three-phase sketched model in Fig. 1. Indeed, the embryonic phase cannot be skipped as time and experience are needed to develop and enhance technologies, and to deploy sufficient industrial capacity to support a growth phase [22]. In this work, the embryonic phase is associated to a “revolutionary” development phase characterized by fast (exponential) growth, the growth phase to an “evolutionary” phase of linear capacity deployment, while “maturity” to a phase of slow or null growth. The nomenclature “revolutionary”, “evolutionary” and “mature” adopted here is borrowed from the experience curve model adopted in the National Energy Modeling System (NEMS) by the U.S. Energy Information Administration [23].

The first aim of this work is to present a method based on the three

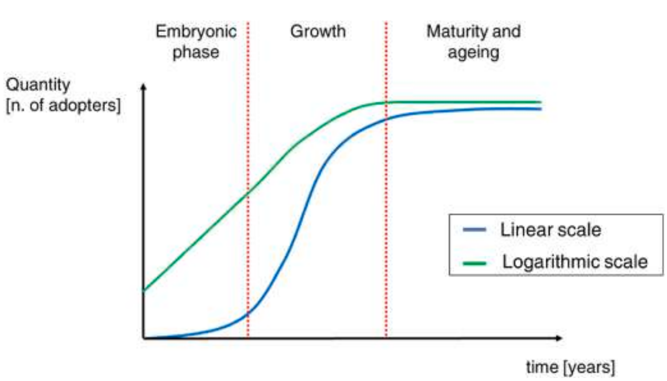

Fig. 1. Typical shape of the S-curve for technology adoption, represented both in linear and logarithmic scale on the y-axis.

phases of the S-curve in Fig. 1 and on the available historical data to forecast the deployment of electricity generation technologies until 2050. While a generic S-curve method for the whole electricity generation sector has already been applied in Ref. [24], the use of the historical data as a starting point has never been adopted so far. The method adopted here envisages three cases for the future development of the analyzed technologies: 1) extrapolation of historical data is performed in case maturity has been reached in the examined time frame; 2) a S-curve is depicted in case the technology has either shown the roll-over out of the embryonic phase or is still in its initial development stage and shows considerable growth; 3) in the last case, the technology shows not considerable growth despite being far from maturity, and a stagnation of the current capacity is taken into account.

Through the forecast of future developments of the electricity sector technology capacities based on current trends, this work will allow to identify possible gaps in future electricity generation until 2050 to be filled up by new technologies not yet visible on the radars of the electricity market (e.g. nuclear fusion) or to raise awareness on the inadequacy of either the current installation rates of particular technologies or policies related to their development. Indeed, the model presented here works considering that the evolution of the historical data driven by the policies already in place throughout the analyzed past time frame, will affect the further development of the examined technologies. The results of the projections will be compared to four IEA scenario results coming from the latest *World Energy Outlook* (WEO) *2021* [25], where the effect of different future policies in the power sector is accounted for, and namely.

- The Stated Policies Scenario (STEPS), exploring the development that the energy system might achieve without additional policy implementations than those already in places. It is the only IEAWEO 2021 scenario not designed to obtain a particular simulated outcome.
- The Announced Pledges Scenario (APS), taking into account all the climate commitments already made by governments around the world, assuming they will be met in full and on time.
- The Sustainable Development Scenario (SDS), depicting a pathway to achieve the well below 2 °C (WB2C) target (specifically 1.65 °C) by assuming that all the energy-related sustainable development goals will be satisfied and that all current net zero pledges met in full.
- The Net Zero Emissions by 2050 Scenario (NZE2050), representing an ambitious pathway to achieve net zero CO_2 emissions by 2050 and universal energy access by 2030, complying with the target of limiting temperature rise to 1.5 °C without a temperature overshoot.

Additionally, results from one of the scenarios produced by the International Renewable Energy Agency (IRENA), specifically the Transforming Energy Scenario (TRES), examined in the *Global Renewables Outlook, Energy Transformation 2050* [26], is considered here. It represents an ambitious, yet realistic, energy transition pathway largely based on renewable energy deployment and efficiency improvements satisfying the WB2C target.

The analysis in this work starts with the analysis of historical installed capacity trends for the electricity generation technologies listed above in **Section 2**. In **Section 3**, the model for the generation of capacity curves at the global level will be illustrated and applied to the different technological categories. In **Section 4**, the generated capacity curves will be translated in electricity generation projections and compared to projections for global electricity generation. **Section 5** presents the conclusions and future perspectives of this work.

2. Analysis of installed capacity trends and contribution to the generation mix for electricity production technologies

This section is dedicated to present the set of historical data used as base to build future installed capacity trends. The work is focused on the analysis of 10 categories of commercial-scale technologies with a relevant role (at different grades) in the global energy sector.

1) Fossil technologies, represented by coal, natural gas and oil power plants. As of today, fossil fuel-based power plants represent the largest electricity producers at global level [9] and are large emitters of pollutants, especially greenhouse gases, also due to the still limited application of carbon capture and storage (CCS) due to stalling technological and economic progresses [27]. For this reason, just unabated fossil fuel technologies are considered in this work.
2) Hydroelectric power plants. They can be based on impoundments, where a dam blocks the entire flow of a water stream, or diversions, where water is diverted from a waterway to glow through a turbine [28].
3) Nuclear fission power technologies. They generally use uranium as primary energy fuel in pressurized water reactors (PWRs) and boiling water reactors (BWRs), commonly referred to as light water reactors (LWR). Beside those widespread reactor concepts, also heavy water reactors are used and other more modern and secure nuclear fission reactor concepts are being developed and commercialized [28]. While being a carbon-free technological option, nuclear fission is at the center of energy disputes for the concerns about nuclear waste and catastrophic accidents (despite the very low rate of incidents) and strongly opposed by the public opinion [29].
4) Biomass technologies. Biomass-based direct-fired plants, co-fired plants and gasification plants have reached commercial use, while other concepts still require further development. Furthermore, whilst biomass fuels include a broad range of sources (e.g. wood, wood-derived fuels, black liquor, municipal solid waste and landfill gas), biomass power production is generally considered carbon-neutral [28].
5) Geothermal technologies. Commercial geothermal plants are based on dry steam, flash steam and binary-cycles [28].
6) Wind onshore technologies. Wind turbines can be utility-scale – in which multiple turbines are grouped to form a wind farm/plant – or used in distributed applications. Onshore wind power refers to turbines located on land [28].
7) Wind offshore technologies. While the electricity generation concept is the same as for onshore wind, technical limitations mainly due to the installation of turbines on the seabed and the long distances to be covered by electrical cables (resulting in higher installation costs) have hindered the diffusion of this technological category [30].
8) Solar photovoltaic technologies, which can be either distributed or utility-scale, as for wind onshore [28].
9) Concentrating solar power (CSP) technologies [28].
10) Marine energy technologies, referring to seawater-based energy, including tidal energy, wave energy, ocean current energy and energy generated from temperature and salinity gradients [31]. As oceans cover about two-thirds of the Earth's surface, marine energy is considered one of the most promising energy sources. However, most of marine energy-based technologies are still in their embryonic phase [32].

Among the listed technological classes, fossil and nuclear fission are the only ones considered as non-renewable energy sources. Renewable energy comes from natural sources or processes that are constantly replenished [33]. Despite "renewable" is usually associated with the concept of "clean" energy, it is undisputed that biomass and large hydroelectric dams create difficult tradeoffs when considering their impact on the wildlife and other climate change-related issues [33].

Fig. 2 collects the behavior of installed capacity of the ten categories of electricity generation plants illustrated above over the last four decades at global level. The detailed dataset used to generate Fig. 2 is reported in **Annex 1** (see Table A1.1) Note that, considering the validity of the S-curve model applied to electricity generation technologies, the different technological classes are clearly in different phases of their development throughout the analyzed time frame. In particular, looking at the trends for the categories fossil (including coal, oil and gas power plants), hydropower and nuclear in Fig. 2, they should be associated to maturity (saturation phase in Ref. [22]). Indeed, global capacity for those technologies is the highest among all sources and shows stable levels always well above 100 GW all over the last 40 years. The hypothesis is also supported by contribution shares to global electricity generation always below 10% for the three technology classes (up to more than 60% for fossil fuels between 1990 and 2019 [9]).

Considering trends in Fig. 2, nuclear fission experienced a growth of just 11% between 2000 and 2021, thus with an average yearly growth far lower than 1% and also some points showing a decrease in total installed capacity, especially between 2013 and 2014 and again between 2020 and 2021, in view of political issues envisaging, e.g., the phase-out from nuclear in Germany [40] and other countries, especially following the Fukushima accident in 2011. Fossil and hydroelectric capacity grew by 96% and 71% between 2000 and 2020, respectively, especially due to the contribution from developing countries.

On the other hand, a constantly growing trend is visible for biomass capacity, which has more than quadrupled in the last 20 years, with an average 7.5% yearly growth rate, corresponding to a doubling time slightly higher than 9 years. Also wind onshore and solar PV have been

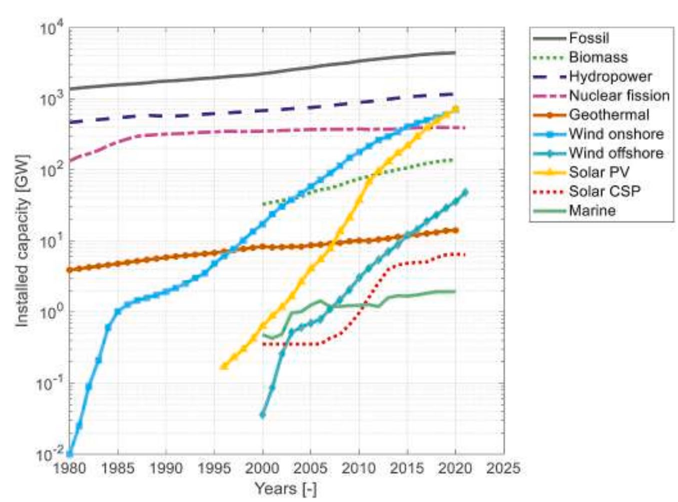

Fig. 2. Global trends for the installed electricity capacity 1980–2021 (according to the availability) for electricity generation technologies. Elaborated by the authors based on [34–39].

experiencing a clear growth trend, with far larger rates than the abovementioned biomass technological class: wind onshore capacity increased by more than 70 thousand times between 2020 and 1980, with an almost constant yearly growth rate around 20% until 2012. Solar PV capacity increased more than 4 thousand times between 1996 and 2020, as visible in Fig. 2, with a doubling time lower than 1.5 years until 2013. It has also to be observed that a clear decline of this growth rate has happened after that, with a yearly growth rate that is constantly decreasing and is now around 28%. Other renewable technologies like solar CSP and marine are clearly in their initial development stage; on the other hand, geothermal capacity shows a trend of slow and constant growth since the 1980s, with a doubling time over 20 years; wind offshore is the only technology showing the clear increasing trend typical of a revolutionary/exponential growth among them. The case of solar CSP is peculiar. Indeed, despite a capacity that was tripled between 2005 and 2010 (see Fig. 2), the rate of increase soon began to slow down after 2012 and is not showing evident signs of recovery, keeping total capacity still below 10 GW. On the other hand, geothermal and marine energy technologies have not been showing considerable progresses in the examined time scale.

Table 1 shows the percentage variation of the installed capacity, for the different technologies considered in Fig. 2, highlighting the astonishing growth levels experienced by wind and solar PV, especially in the first decade of their development. It is also clearly visible how technologies that can be considered as mature (fossil, hydropower and nuclear fission) present in most cases considerable positive variations, although far lower than those visible for, e.g., even biomass, geothermal and marine energy technologies. On the other hand, the case of solar CSP is singular as it is expected to be a groundbreaking technology but has not reached growth levels comparable to those of wind and solar PV in the last two decades.

3. Modeling future installed capacity trends for electricity generation technologies

In [24] it was observed that the historical development of the installed capacity for electricity generation technologies follows a recurring trend, characterized by three phases: an initial exponential growth, followed by a roll-over to linear growth, eventually reaching a steady market share.

In [22], these observations were used to formulate a mathematical growth model in three phases.

1) exponential growth with doubling of installed capacity every 2–4 years. In this phase, described by **Equation (1)**, the technology is taken from laboratory scale to a level of visibility in the global energy mix (identified as "materiality" state [24]), supposed to be reached at 0.1 ÷ 1% of the contribution to total energy supply;

$$P_t = P_{sat}\cdot\frac{\tau_{exp}}{\tau_{life}}\cdot\left[exp\left(\frac{t-t_{trans}}{\tau_{exp}}\right) - exp\left(\frac{t-t_{trans}-\tau_{life}}{\tau_{exp}}\right)\right] \text{ for } t < t_{trans} \qquad 1$$

where P_t is the capacity (in GW) at time t, P_{sat} is the asymptotic capacity level (in GW) in the saturated state, τ_{exp} is the characteristic time of exponential growth expressed in years, computed according to **Equation (2)**, τ_{life} is the characteristic lifetime of the electricity generation plants, expressed in years and computed again according to **Equation (2)**, t_{trans} is the time step at which the transition from the exponential to the linear phase occurs.

$$\frac{\tau_{exp}}{doubling\ time} = \frac{\tau_{life}}{technology\ lifetime} = (1 + 1\,/\,exp(1)) \qquad 2$$

2) linear growth, described by **Equation (3)**.

$$P_t = P_{sat}\cdot\frac{\tau_{exp}}{\tau_{life}}\cdot\left[1 + \frac{t-t_{trans}}{\tau_{exp}} - exp\left(\frac{t-t_{trans}-\tau_{life}}{\tau_{exp}}\right)\right] \text{ for } t_{trans} \le t \le t_{sat} \qquad 3$$

Note that, despite the definition of "linear" phase provided in Ref. [22], **Equation (3)** actually includes also non-linear terms.

3) saturation phase when the growth is stopped and the level of installed capacity remains fixed, as described by **Equation (4)**.

$$P_t = P_{sat} \text{ for } t > t_{sat} \qquad 4$$

The model is based on the fundamental that the rate of deployment, i.e. the number of plants installed each year, is equivalent to the industrial capacity, i.e. the capacity of the industry to produce plant components, to transport and install them, so that this includes workforce, logistics and the factories to produce plant components.

Fig. 3 provides a graphical representation of the model, highlighting how the duration of the linear growth phase equals the characteristic lifetime of the electricity generation technology ($t_{lin} = \tau_{life}$).

The model described above will be referred to as the 'fastest growth model' in this paper. The reason is that it describes deployment in a situation in which only the growth of the industrial capacity limits the rate of deployment of a specific technology, given a final target for its deployment (i.e. the saturation capacity) but independently from historical data. This paper is aimed at analyzing if the current rates of development, projected to the future decades according to the method described hereafter, are in line with the fastest growth towards a final level in agreement with the prescription of an ambitious energy scenario proposed by the IEA.

The approach described in this paper to generate S-curves for electricity generation technologies mainly requires the concept of doubling time to identify the development phase according to historical data.

The year-over-year (YOY) capacity growth rate (in %) is computed using **Equation (5)**, where P_t (in GW) represents installed capacity at time t.

Table 1
Installed capacity percentage variation through the four decades between 1980 and 2020.

Technology	Percentage variation [%]			
	1980–1990	1990–2000	2000–2010	2010–2020
Fossil	29.4	27.6	49.7	31.0
Biomass			128.2	85.1
Hydropower	22.5	19.9	30.3	31.4
Nuclear fission	139.2	10.0	7.2	4.6
Geothermal	50.6	42.2	21.5	39.2
Wind onshore	19200.0	792.1	930.0	294.9
Wind offshore			8366.7	1064.7
Solar PV			5789.2	1817.1
Solar CSP			173.7	571.5
Marine			159.5	55.8

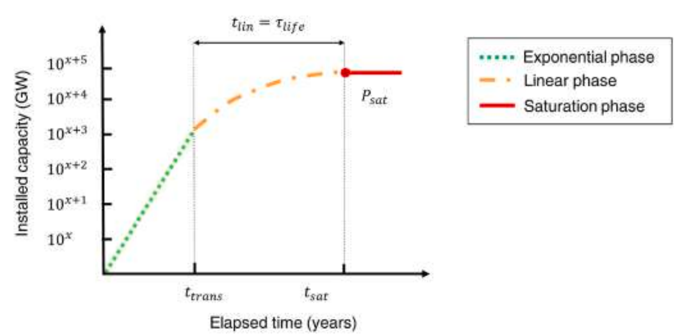

Fig. 3. Technology development model for the description of the fastest path towards saturation capacity for electricity generation technologies as from Ref. [22].

$$YOY\ capacity\ growth\ rate = \left(\frac{P_t}{P_{t-1}} - 1\right) \cdot 100 \qquad 5$$

The doubling time is the time needed for a quantity to double in size/value [41]. It is a concept widely applied in the more diverse fields for the calculation of population growth, inflation, volume of tumors and, more in general, for all things that tend to grow over time. The doubling time is simply calculated using the average capacity growth rate over a set of YOY capacity growth rates selected to identify the particular development phase of a certain technology.

The overall methodology for the definition of future capacity trends adopted in this work and based on Fig. 4 is articulated as described in the following bulleted list.

1) Case 1: for technologies that are already in their maturity phase in the time frame of Fig. 2, showing a slow growth in the last 40 years and installed capacity above 100 GW: their increasing trend over the last two decades suggests that the current industrial capacity is sufficient to support constantly growing capacity additions. However, policy commitments to phase out fossil fuels [42] or nuclear plants [43] cannot be recognized by this approach. The effect of policies on the electricity sector is only visible in the projections when they have been already put in place in the observed time scale, so to affect the historical data. Since historical data for the development in maturity phase are available here, that is modeled extrapolating the line of best fit of historical data to comply with the actual developments of the energy system (either according to an exponential trend as in **Equation (6)**, where the coefficients b and m are computed according to the Microsoft Excel function LOGEST [44], or to a linear trend as in **Equation (7)**, where the coefficients m and q are computed according to the Excel function LINEST [45]), corresponding to the trend with the maximum coefficient of determination R^2 [46]. Nonetheless, trends for fossil and nuclear installed capacities would be dictated by policy choices more than either actual technological development or capability of the industry to support technological advancement.

$$P_t = b \cdot a^t \qquad 6$$

$$P_t = m \cdot t + q \qquad 7$$

2) Case 2: for technologies showing exponential growth in Fig. 2 at the beginning of the available data set, with doubling times below 4 years for at least one decade and a roll-over between revolutionary and evolutionary phase, retracing the typical shape of a S-curve as from Fig. 3. In this case, an exponential regression is generated in the revolutionary phase, which is identified in the period presenting the best fit of historical data with an exponential curve [46], using **Equation (6)**. Then, the evolutionary phase of capacity growth according to a linear trend is modeled according to the linear interpolation between the YOY capacity growth rate at the end of the

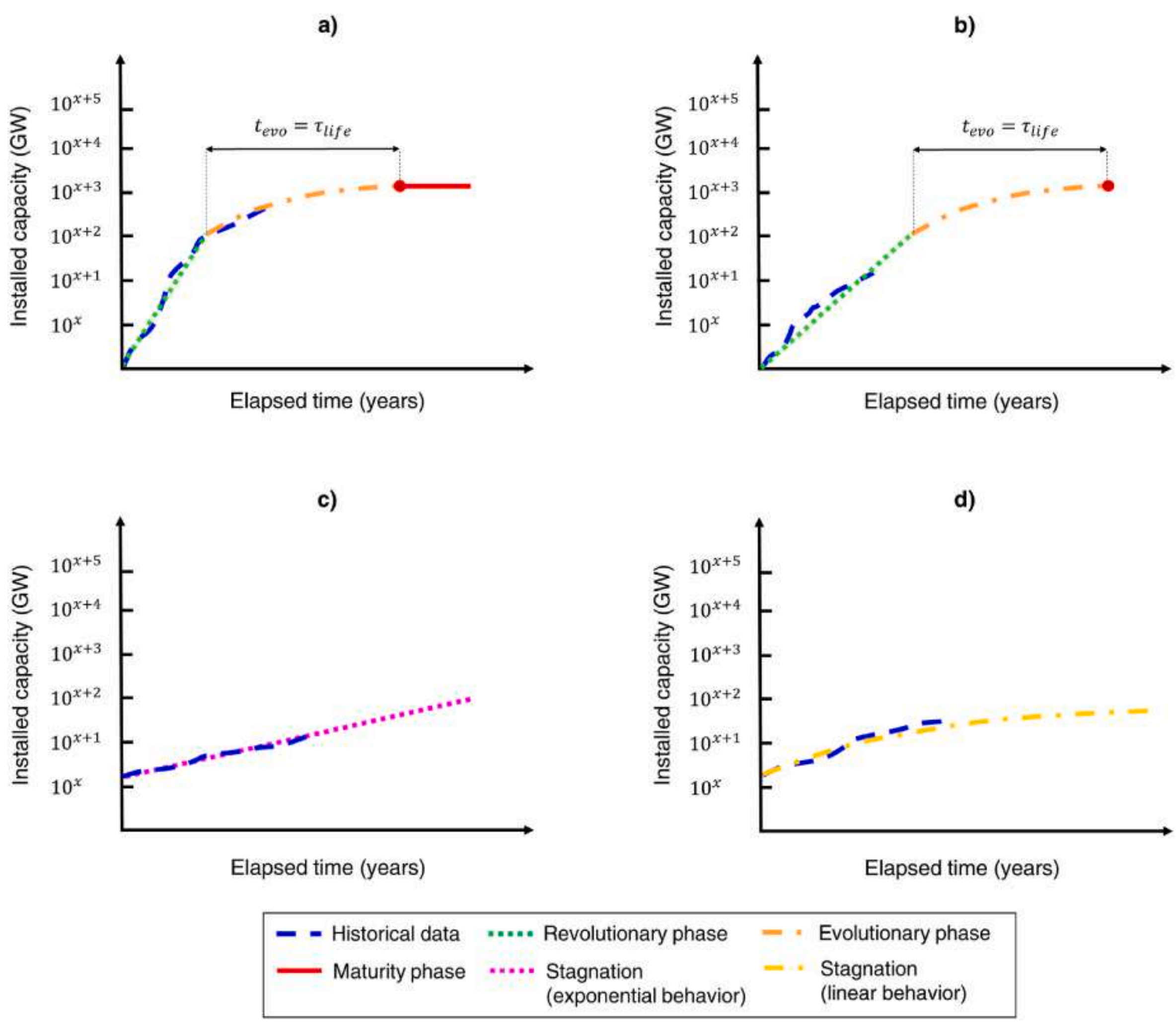

Fig. 4. Technology development model to forecast capacity curve trends for electricity generation technologies for a) case 2when a clear bend towards linearity is visible in historical data; b) case 3; c) case 4 when historical data retrace an exponential behavior and d) case 4 when historical data retrace a linear behavior.

revolutionary phase and 0, which is the growth rate associated to the end of the evolutionary phase (with a duration computed using **Equation (2)**). In the transition between the revolutionary and the evolutionary phase, the derivative of the installed capacity, i.e. the industrial capacity, is continuous, while the duration of the linear growth is limited by the maturity capacity level, as the duration of the evolutionary phase is limited by the assumption that it lasts for one characteristic lifetime of the technology. Case 2 responds to the representation in Fig. 4a.

3) Case 3: for technologies showing considerable growth in Fig. 2 at the beginning of the available data set, with doubling times below 4 years for at least one decade but no evident roll-over between revolutionary and evolutionary phase. In this case, an exponential regression is generated in the revolutionary phase using **Equation (6)**, as in case 2. The end of the revolutionary phase is computed backwards considering the assumption that the evolutionary phase would end in 2050 (that means maturity is reached at that point), as no data show evidence for that. Therefore, the projection in the evolutionary phase is already carried out as in case 2, corresponding again to the representation in Fig. 4b.
4) Case 4: for technologies showing slow growth over the analyzed time scale in Fig. 2. In this case, a clear revolutionary phase cannot be identified at any point of the considered time frame as doubling times well above 4 years are computed from the whole set of historical data, therefore stagnation is taken into account for the whole time scale analyzed here. The best fit of historical data (according to an exponential or a linear fashion as in Fig. 4c and d, respectively) is used to extrapolate future capacity trends, as the typical shape of a S-curve cannot be retraced.

The flowchart in Fig. 5 shows the required step to apply the method described above.

The characteristic parameters used to perform projections according to the abovementioned cases for the different technologies are listed in Table 2. The same parameters, besides the detailed values obtained for the installed capacity for each of the considered technologies are

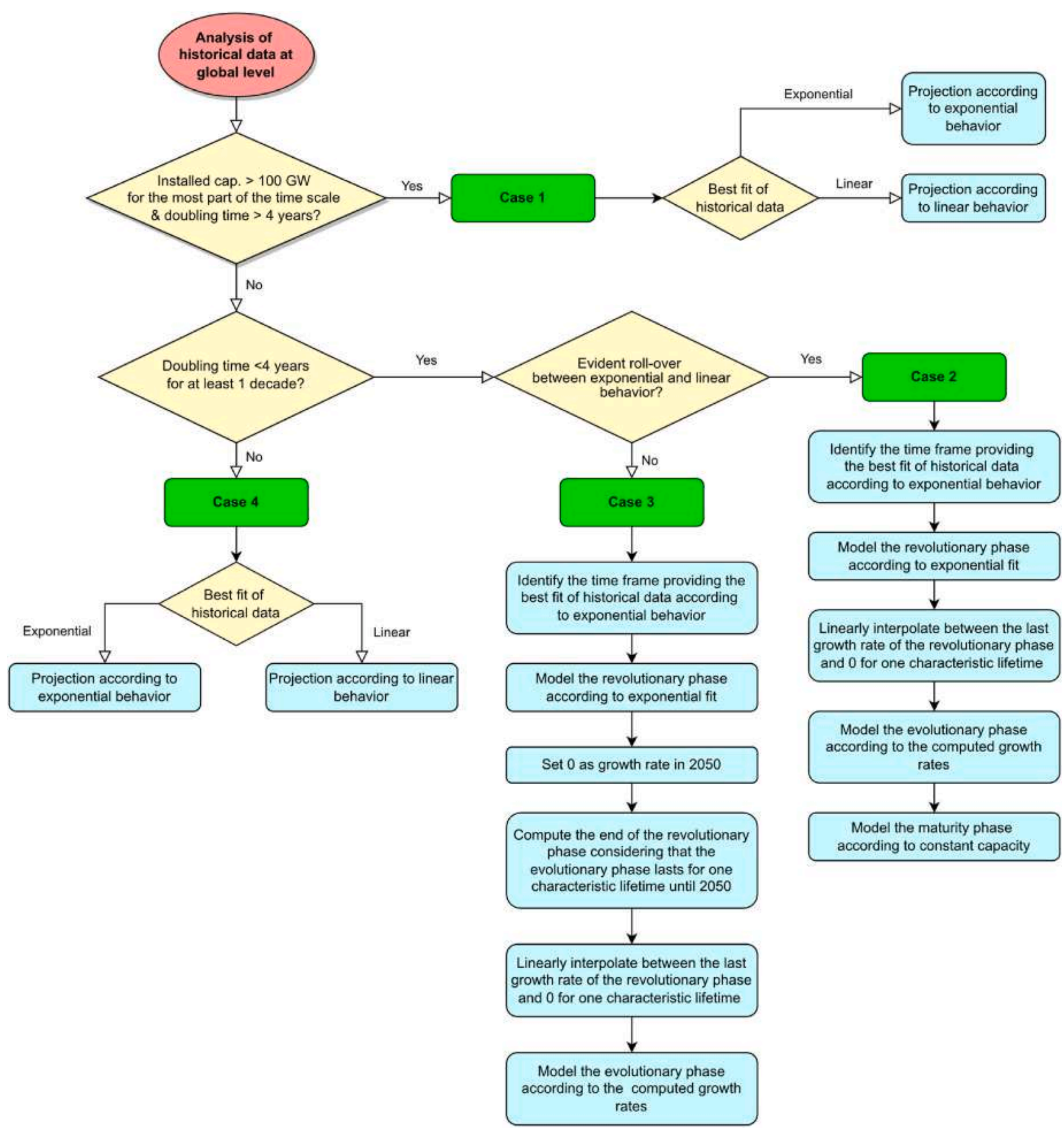

Fig. 5. Flowchart for the application of the method presented in this paper to compute installed capacity curves.

Table 2
Characteristic parameters for technology capacity projections.

Technology	Case	R^2 [%]	b [GW]	a [−]	m [GW/year]	q [GW]
Fossil	1 (Equation (6))	99.1	1256	1.031		
Hydropower	1 (Equation (6))	97.5	446.1	1.023		
Nuclear fission	1 (Equation (7))	94.6			2.481	316.3
Biomass	4 (Equation (6))	98.5	27.82	1.087		
Geothermal	4 (Equation (6))	98.9	4.072	1.030		
Wind onshore	2	99.9	0.657	1.248		
Wind offshore	3	99.6	0.996	1.302		
Solar PV	2	99.2	0.0840	1.492		
Solar CSP	2	84.1	0.1582	1.208		
Marine energy	4 (Equation (7))	87.4			0.07061	0.5397

reported in **Annex A1** (see Table A1.2).

The comparison against the installed capacities foreseen in the different scenarios by IEA and IRENA is performed to understand their compatibility with the trajectory computed here combining historical data with the S-curve approach (or stagnation, as in case 4). Therefore, when an agreement is found between the IEA/IRENA results and the ones computed here, it is not forced anyhow, but just maybe is the indication that also they use S-curves in some cases (even though without providing any information about their construction). On the contrary, in the case the results computed here strongly differ from (and underestimate) what is published in the others' scenario analysis, it means that policies should be enforced in the future to allow a capacity growth for some of the analyzed technology families.

Note also that to guarantee comparability of the results from the method presented in this paper and the fastest growth method, the technology lifetime (identifying the duration of the linear phase in the fastest growth model) will be taken the same as for projections depicted according to cases 2 and 3 described above, whereas the doubling time in the exponential phase in the fastest growth model in Ref. [22] is a direct consequence of the installed capacity target, and may be different from the one computed according to historical data.

3.1. Fossil, hydropower and nuclear fission capacity

Throughout the last 40 years, fossil, hydropower and nuclear installed capacities have shown a slowly increasing trend well above 100 GW. Therefore, those technologies can be considered as mature taking for granted that further dramatic capacity development is hard to be expected. Capacity curves are built according to case 1 stated in **Section 3**.

For fossil fuel technologies, the best fit is computed considering the whole set of historical data between 1980 ($t = 1$) to 2020 as reported in Fig. 2. The trend that best fits historical data corresponds to an exponential curve. The same applies to hydropower capacity, and the parameters used for the projections are listed in Table 2.

Concerning nuclear fission, the best fit curve corresponds to a linear trend considering historical data from 1988 ($t = 1$), as the historical data series between 1980 and 1987 presents a very different slope with respect to the rest of the curve in Fig. 2, possibly identifying the roll-over between the evolutionary and the maturity phase. The features of the computed curve are reported in Table 2.

Installed capacity projections until 2050 are reported in Fig. 6 following the red dash-dotted line. Fossil fuel capacity (see Fig. 6a) is anticipated to increase more than twice in 2050 with respect to 2000 levels, reaching 11 TW installed capacity. Hydropower capacity (see Fig. 6b) could reach almost 2.2 TW installed capacity in 2050, almost

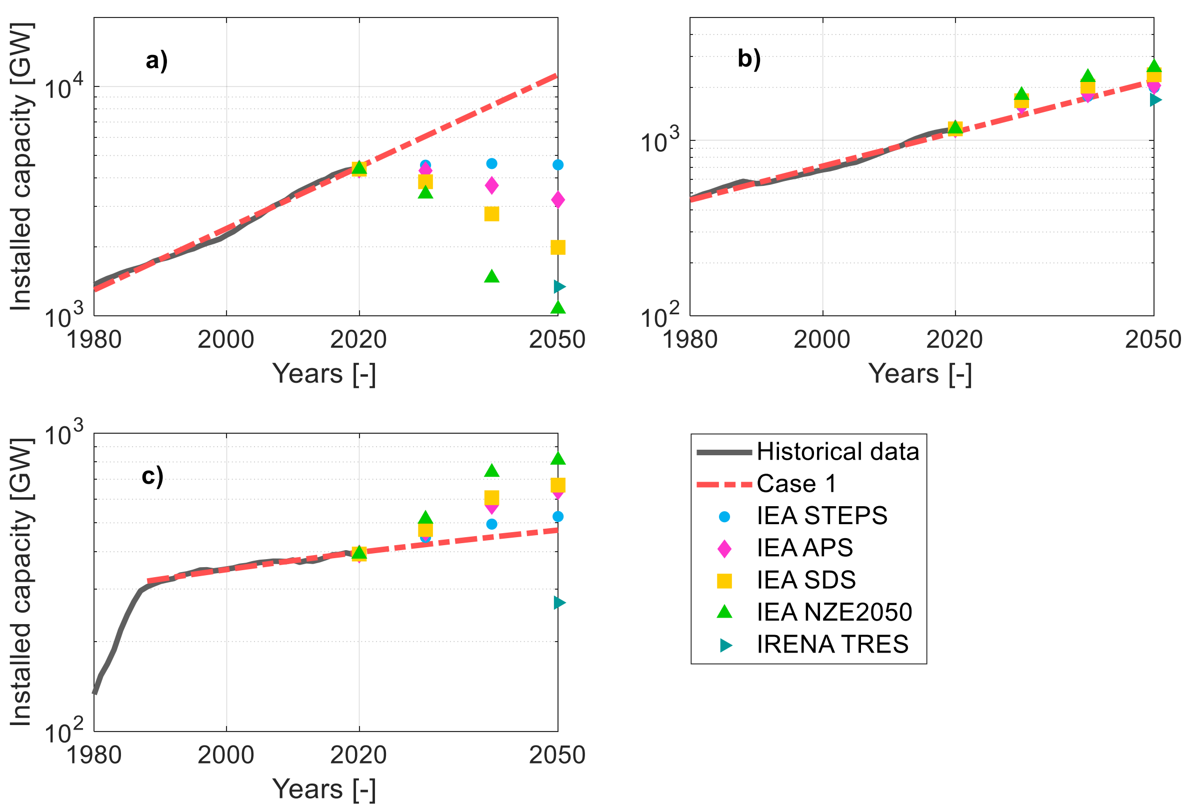

Fig. 6. Growth trend for a) fossil, b) hydropower and c) nuclear fission installed capacity as retrieved from regression and projection of historical data, computed according to case 1 and compared against IEA and IRENA scenarios.

doubling 2020 levels. Eventually, nuclear fission capacity (see Fig. 6c) shows the most modest growth, with a total 20% expected possible growth in 2050 with respect to 2000 levels in 2050, reaching slightly more than 470 GW installed capacity. Fig. 6 also reports projections made by IEA and IRENA compared to the values computed using case 1 for capacity development adopted in this work.

All the IEA and IRENA simulation scenario trajectories in Fig. 6a show pathways largely contrasting the historical development in the last 20 years and the consequent projection based on the average historical growth rate: the IEA STEPS scenario shows how current policies are already forecasting a brake in the development of further fossil capacity. The more environmental-friendly scenarios, and in particular the IEA NZE2050 and the TRES, forecast massive dismantling of fossil capacity with levels well below those attested at the beginning of this century and slightly higher than 1000 GW installed capacity (even getting to lower levels than in 1980 in the case of NZE2050). Note, however, that the reduction of installed capacity for fossil fuel plants must be strongly driven by policy constraints, since an unconstrained evolution based on the actual and historical industrial capability would lead to a much larger maximum installed capacity than what foreseen by IEA and IRENA. Therefore, the method presented here just provides a possible pathway for further development of fossil capacity in case no actions at all are taken to put in place mitigation strategies or due to other social, economic or geo-political issues.

Scenario results for hydropower capacity in Fig. 6b show great accordance with the projection made according to case 1, even though just two of them show values in 2050 above the projection formulated using **Equation (6)**: IEA SDS, requiring 8% higher capacity and IEA NZE2050, with a 20% higher target with respect to the projection final figure. As in the case of fossil fuels phase-out, a faster development of hydropower should be pushed by dedicated policies, since it overcomes the development rate foreseen by the current analysis, thus stronger efforts than those experienced in the last 40 years would be required.

Concerning nuclear fission capacity in Fig. 6c, all the analyzed scenarios but the TRES forecast higher levels of penetration contrasting the almost flat historical growth in the last 32 years, especially up to 2040. In particular, the IEA NZE2050 forecasts a capacity that is almost doubled with respect to the levels computed in the projections following case 1. Even the STEPS requires 11% higher capacity in 2050 with respect to the results of the projection made here, highlighting how worldwide policies are still pushing towards nuclear capacity deployment. The strongly renewable energy-focused TRES, instead, pushes towards nuclear phase out, just considering 270 GW installed capacity in 2050 (46% lower than 2020 levels). The projection based on case 1 described here lays between the IEA and the IRENA forecasts, highlighting how the development of nuclear fission strongly depends on policy-driven factors.

The results shown in Fig. 6 evidently show how the results of simulation models for fossil, hydropower and nuclear capacities are totally biased by policies constraints as they neglect the maximum capacity trends depicted in the curves obtained from case 1. Indeed, they simply prescribe future trends for the electricity sector in accordance with the targets of the analyzed scenarios, while the aim of this work is to assess future developments based on a large set of historical data to understand the direction taken with the investment decisions made in the last decades. On the other hand, the analysis in Ref. [47] concerning nuclear fission development, carried out adopting the Environmental Kuznets curve hypothesis [48], correlates economic status, environmental indicators and capacity development in a single approach providing an outlook about critical technologies concerning their role in the decarbonization process according to the income levels of specific countries. It shows, indeed, how the development of low-carbon technologies is mostly related to higher income levels, so that economic incentives facilitate the transition towards a decarbonized energy system.

3.2. Biomass capacity

For biomass, the historical dataset represented in Fig. 2 identifies non-negligible growth between 2000 and 2020, at a far higher rate than for fossil, hydropower and nuclear fission, but not even comparable to those experienced by wind and solar technologies. Indeed, an average 7.5% YOY growth rate is computed, corresponding to more than 9 years doubling time, very distant from the threshold of 4 years identifying a phase of exponential capacity development. Therefore, projections for biomass capacity are performed according to case 4 described in **Section 3** and the best fit curve corresponds to an exponential trajectory starting from 2000 ($t = 1$), with characteristic parameters as from Table 2.

In the projection reported in Fig. 7, obtained according to case 4 using the parameters mentioned above, biomass capacity would reach a maximum of 2 TW installed capacity by 2050. They show how such a linear development guarantee to achieve the targets set by all IEA and IRENA scenarios, all well below 1 TW. In this particular case, the TRES forecasts a 5 times growth with respect to current installation levels, representing the highest objective among the scenarios considered here. On the other hand, the S-curve computed for the fastest growth towards the IEA NZE2050 target (640 GW) considers a technology lifetime of 30 years [49] and requires a doubling time of 1 year in the exponential phase: it shows how current installed capacity levels are in line with the requirements needed to achieve ambitious targets by 2050. Indeed, keeping a constant growth rate in line with that experienced in the twenty years between 2000 and 2020 would allow it to comply with and even allow to surpass the target set by IEA NZE2050 scenario. Nonetheless, as biomass technologies have visibly never experienced a revolutionary phase, their evolution trend is clearly not attributable to a S-curve.

3.3. Geothermal capacity

Geothermal technologies, as visible in Fig. 2, present an almost null growth in the time scale 2000–2020 Indeed, the maximum growth for geothermal technologies happened between 2018 and 2019 (6% YOY), with even negative values found in few occurrences and an average 3.3% growth rate. That also corresponds to an average 21 years doubling time. Even just considering the maximum YOY growth rate mentioned above, the doubling time for geothermal technologies would be higher than 11 years, completely out of the range 2–4 years required to identify a revolutionary/exponential development phase. Therefore, capacity growth for geothermal technologies will be just modeled according to case 4 again, considering the whole dataset available for the period from 1980 ($t = 1$) and 2020 for fitting historical data. The best fit curve corresponds to exponential trajectory starting with $R^2 = 98.9\%$, considering $b = 4.072$ and $m = 1.030$ for the regression in **Equation (6)**.

The result is represented in Fig. 8, and the projection made according to case 4 reaches a maximum capacity level of 34 GW by 2050, increasing by less than 3 times with respect to 2020 installed capacity. On the other hand, all IEA and IRENA scenarios forecast more ambitious development targets: in particular, the STEPS computes 61 GW installed capacity in 2050, while the highest value is provided by IRENA TRES (200 GW). Such values require far higher efforts in geothermal capacity deployment as they are completely out of range with respect to the current trend. The S-curve for the fastest development towards IEA NZE2050 final target, computed considering a technology lifetime of 30 years [49] for the application of the fastest growth model would require far larger capacity with respect to the experienced trend. For instance, to reach 126 GW by 2050 in the fastest growth trajectory, 2020 capacity level would have corresponded to more than 46 GW, to be compared to the actual value of 14 GW. Therefore, the adoption of geothermal technologies is not on track with respect to the fastest possible track to reach IEA NZE2050 targets and is clearly not following a S-curve trend. That is highlighted by the fact that the fastest growth curve has a

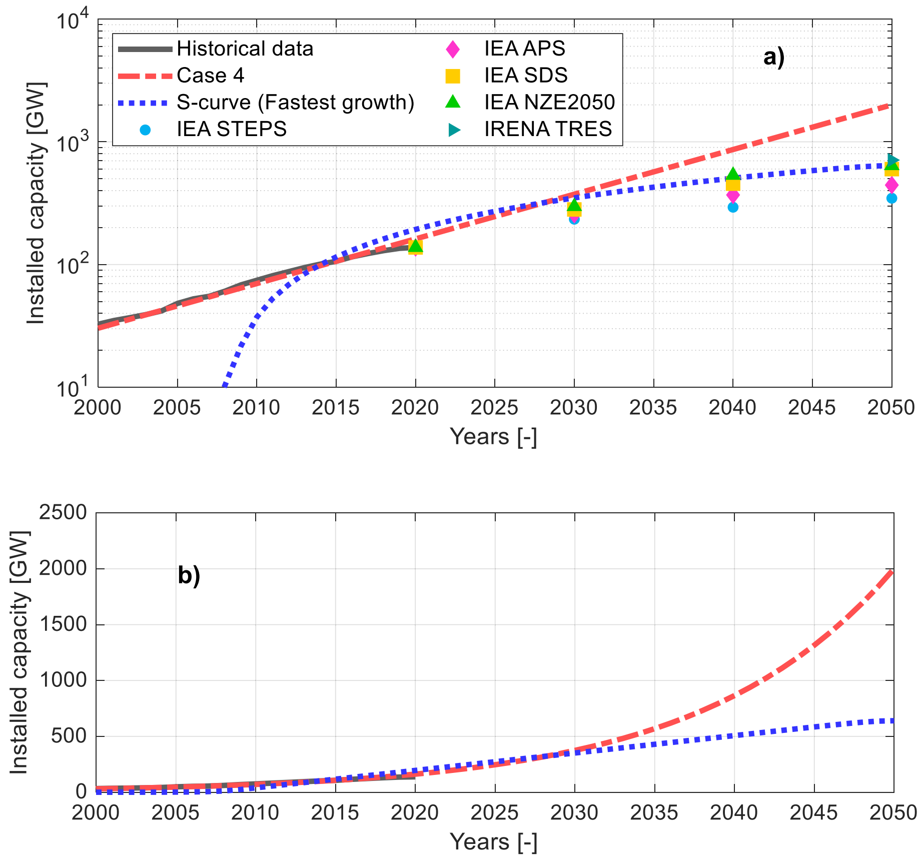

Fig. 7. Growth trend for biomass installed capacity as retrieved from historical data, computed according to capacity deployment case 4 and compared against the curve for the fastest growth towards the IEA NZE2050 target and IEA and IRENA scenarios, in a) logarithmic and b) linear scale.

completely different behavior with respect to the historical data series in the period 2000–2020, when it experiences an exponential growth phase and the roll-over to the linear phase. Moreover, the evolution prescribed by IEA, especially for the SDS and NZE2050 scenarios would require an abrupt and substantial change in the growth rate for geothermal technologies.

3.4. *Wind onshore capacity*

Wind onshore capacity is the first example for which historical data in Fig. 2 suggest a transition between the revolutionary and the evolutionary deployment phase. In particular, the curve shows rapid growth at different rates until the first decade of this century, with a clear bend towards linear development after 2010. Excluding the first six years from 1980 to 1986, presenting huge values for the YOY growth rate, with doubling times even lower than 1 years, the best fit curve for historical data is an exponential trajectory extended from 1986 ($t = 1$) to 2011 included, for a total duration of 26 years. In that period, the computed doubling time is 3 years. The coefficients for the exponential regression are listed in Table 2. Then, according to case 2 described in **Section 3**, an evolutionary phase is modeled in a linear fashion for a technology lifetime of 20 years [50]. Saturation capacity at the end of the evolutionary phase is attested at 5.9 TW. The trend depicted according to the described projection is represented in Fig. 9. That shows how, according to the observation above, the progresses in capacity additions for wind onshore technologies may soon experience a brake if the current trends are preserved, especially due to the poor growth rate observed growth rate experienced in the three years between 2017 and 2019 (10% in average, against values tending to 20% in the years immediately before them).

3.5. *Wind offshore capacity*

Wind offshore capacity showed a dramatic increase in the last twenty years as visible from the historical data in Fig. 2, growing by three orders of magnitude from 36 MW in 2000 to 48 GW in 2021 [9]. YOY growth rates for the period 2000–2006 present large variability (ranging from yearly growth rates higher than 100% between 2000 and 2003 and below 20% between 2004 and 2006), in line with what happens for wind onshore, too. A roll-over between revolutionary and evolutionary phase is not evident here, as it happened for wind onshore. Therefore, case 3 is used for the projection until 2050. As explained in **Section 3**, the passage between revolutionary and evolutionary phase is imposed to guarantee that the duration of the evolutionary phase equals the characteristic lifetime of the technology computed as in **Equation (2)** and that maturity is reached by 2050, to assess the possible contribution of the technology to the energy transition. Indeed, the best fit for historical data after 2007 retraces an exponential development with the characteristic parameters reported in Table 2 and a doubling time of 2.2 years. In order to guarantee that maturity is reached by 2050, the revolutionary phase has a duration of 16 years, so that the evolutionary phase starts in 2022. The maturity level would be then reached at 2.8 TW, considering a technology lifetime of 20 years as for wind onshore technologies, as visible in Fig. 10.

As [25,26] just report combined figures for wind onshore and offshore capacity, Fig. 11 compares the joined results of the S-curves computed according to the analysis above (summed up to give a single curve, defined as “Projection” in Fig. 11) against results from the method in Ref. [22] for the fastest pathway towards the IEA NZE2050 target and the IEA and IRENA scenarios. In particular, the fastest growth towards 8.2 TW by 2050 indicates how the actual growth of wind technologies outperformed for the most part from 2000 to 2017, indicating that the

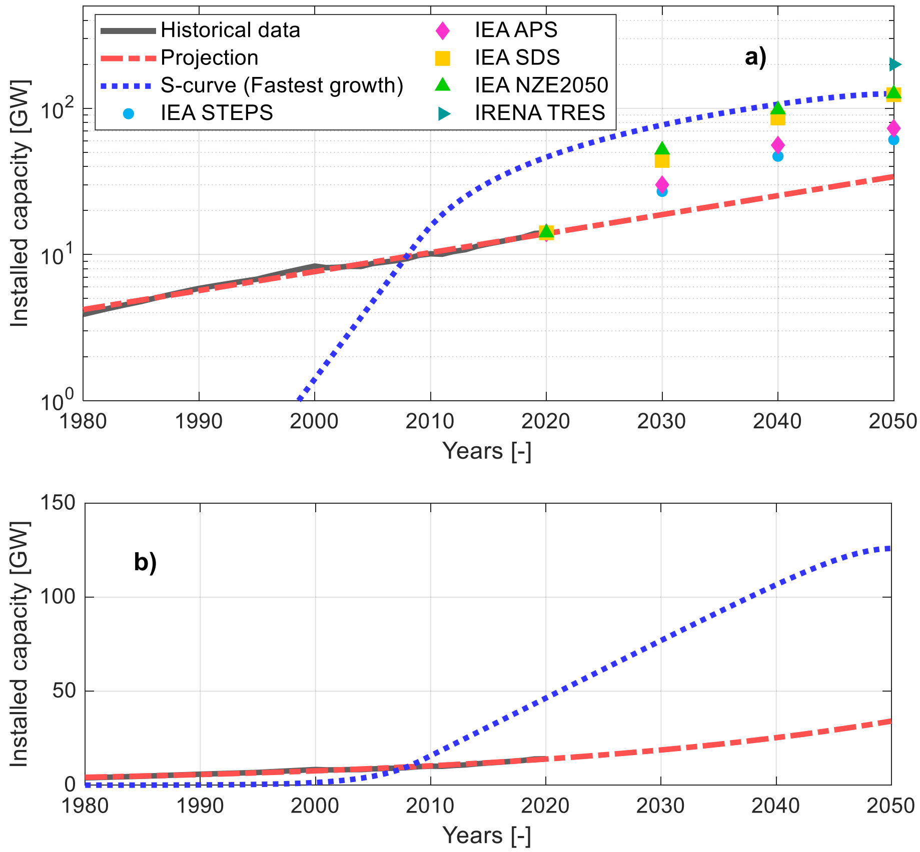

Fig. 8. Growth trend for geothermal installed capacity as retrieved from historical data, computed according to capacity deployment case 4 and compared against the curve for the fastest growth towards the IEA NZE2050 target and IEA and IRENA scenarios, in a) logarithmic and b) linear scale.

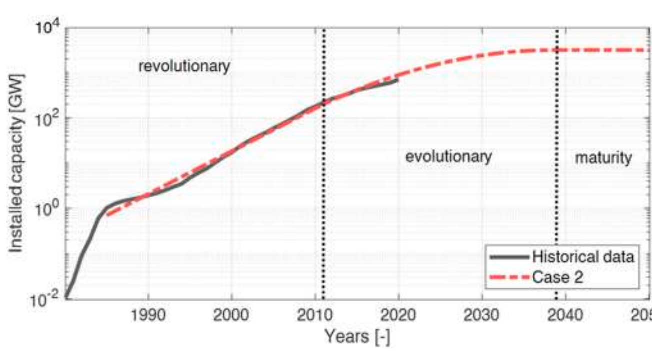

Fig. 9. Growth trend for wind onshore installed capacity as retrieved from historical data and computed according to capacity deployment case 2.

current industrial capacity for wind technologies may be able to target even more than the best-case scenario prescribed capacity. On the other hand, the abrupt slowdown in wind onshore installation after 2017 makes the projection curve not able to keep track of the fastest growth trend. Also considering the contribution of wind offshore, indeed, case 2 projections would be able to overcome the targets set by IEA SDS and IRENA TRES at most, while missing more than 2 TW installed capacity to comply with IEA NZE2050. Those results show how more efforts should be put in wind technologies capacity deployment, especially considering that the current trends show a tendency for wind onshore to approach maturity, also testified by stagnating investments in renewable energy technologies in the last five years [51].

3.6. *Solar PV capacity*

The historical data for installed solar PV show the fastest growth among the technologies in Fig. 2, with a capacity growth of more than 4000 times in the 24 years between 1996 and 2020. The revolutionary phase for solar PV technologies is identified between 1996 and 2013, according to the best fit of historical data with an exponential curve (see Table 2 for the characteristic parameters). In that period, YOY growth rates range from a minimum 30% to a maximum 83%, with an average 49% value. Those values lead to a 1.4 years-doubling time, thus even well below the threshold identifying the revolutionary phase (usually 2–4 years). Moreover, after 2013, data are available to identify a clear bend in the curve, justifying the roll-over to the evolutionary phase. Therefore, the projection is performed according to case 2, and the duration of the evolutionary phase is computed via **Equation (2)** considering a technology lifetime of 25 years [52]. Maturity would be reached in 2048 at 24 TW installed capacity, as visible in Fig. 12.

Applying the method for the fastest growth towards the IEA NZE2050 target (14.5 TW), the trend obtained in Fig. 12 shows how the actual development of solar PV capacity, despite clearly following a S-curve, has been far from the fastest growth development towards the prescribed value for the all period in which historical data are available. Indeed, the fastest growth would have required more than four times the actual installed capacity in 2020, while ending at a lower level than the one obtained projecting historical data according to case 2. That highlights how the actually experienced growth (thus investments to support the development of the solar PV industry), despite not representing the fastest possible trajectory, could lead to higher levels than the ones expected by the most ambitious scenarios, mainly due to the differences in the applied equations for Case 2 and for the model in Ref. [22], leading to different capacity developments.

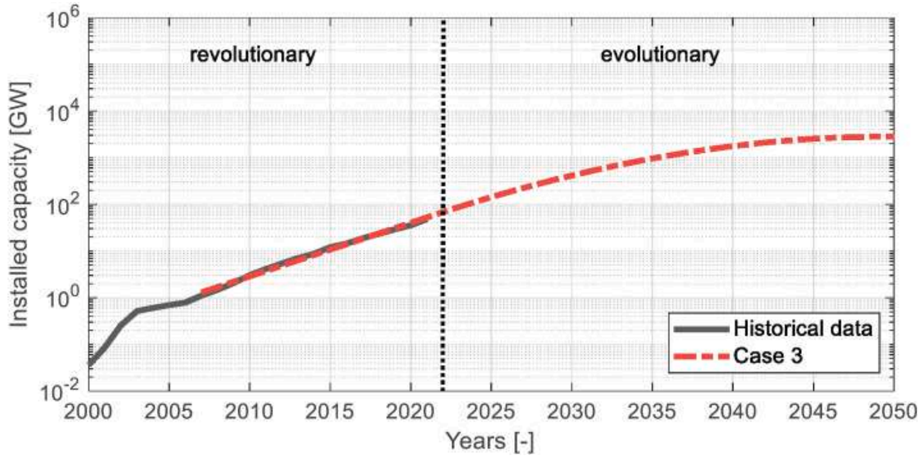

Fig. 10. Growth trend for wind offshore installed capacity as retrieved from historical data and computed according to capacity deployment case 4.

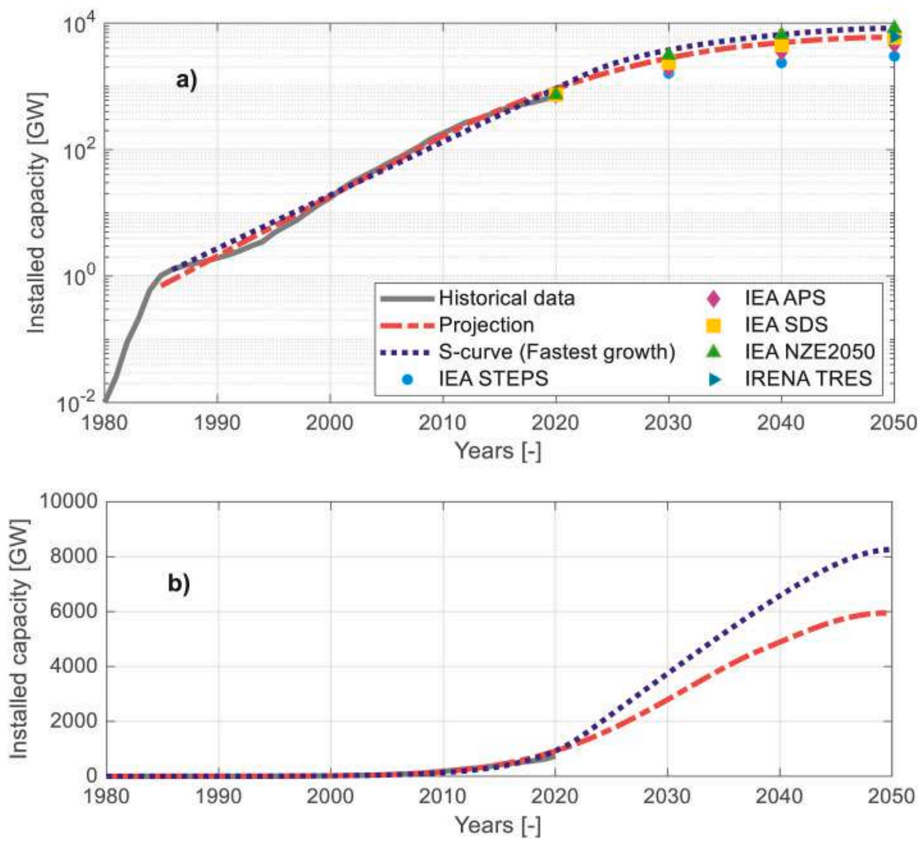

Fig. 11. Cumulative projected installed capacity for wind capacity (onshore + offshore), corresponding to the summation of the two fits, compared to the S-curve for the fastest growth towards the IEA NZE2050 target and IEA and IRENA projections, in a) logarithmic and b) linear scale.

3.7. Solar CSP capacity

The historical dataset for Solar CSP capacity in Fig. 2 highlights a non-constant increasing trend with almost no growth at all between 2000 and 2006, but an average 22% YOY average growth rate between 2000 and 2014, which is the period used to identify the revolutionary phase, assuming that maturity would be reached in 2050 and a technology lifetime of 25 years [49]. Indeed, doubling time is attested at 3.1 years between 2000 and 2014, and can justify the application of case 2, considering that the historical dataset is available until 2021 and shows a roll-over to an evolutionary phase with even much smaller YOY growth rate with respect to the previous years.

The best fit for historical data between 2000 and 2014 retraces an exponential development for which parameters are reported in Table 2. After the evolutionary phase, maturity would be reached at 38 GW installed capacity, as reported in Fig. 13. In this case, projections made according to case 2 are not able to comply with ambitious targets (none of them is satisfied in 2050), whereas the estimated CSP capacity in 2050 is more than 50 GW below the IEA STEPS expectation (92 GW). The comparison between historical data and the S-curve for the fastest growth towards IEA NZE2050 target (above 400 GW installed capacity) highlights how the development of solar CSP has not been sufficient so far and that strong efforts would be required to put it on track. Indeed, the 2020 installed capacity value is one order of magnitude lower than

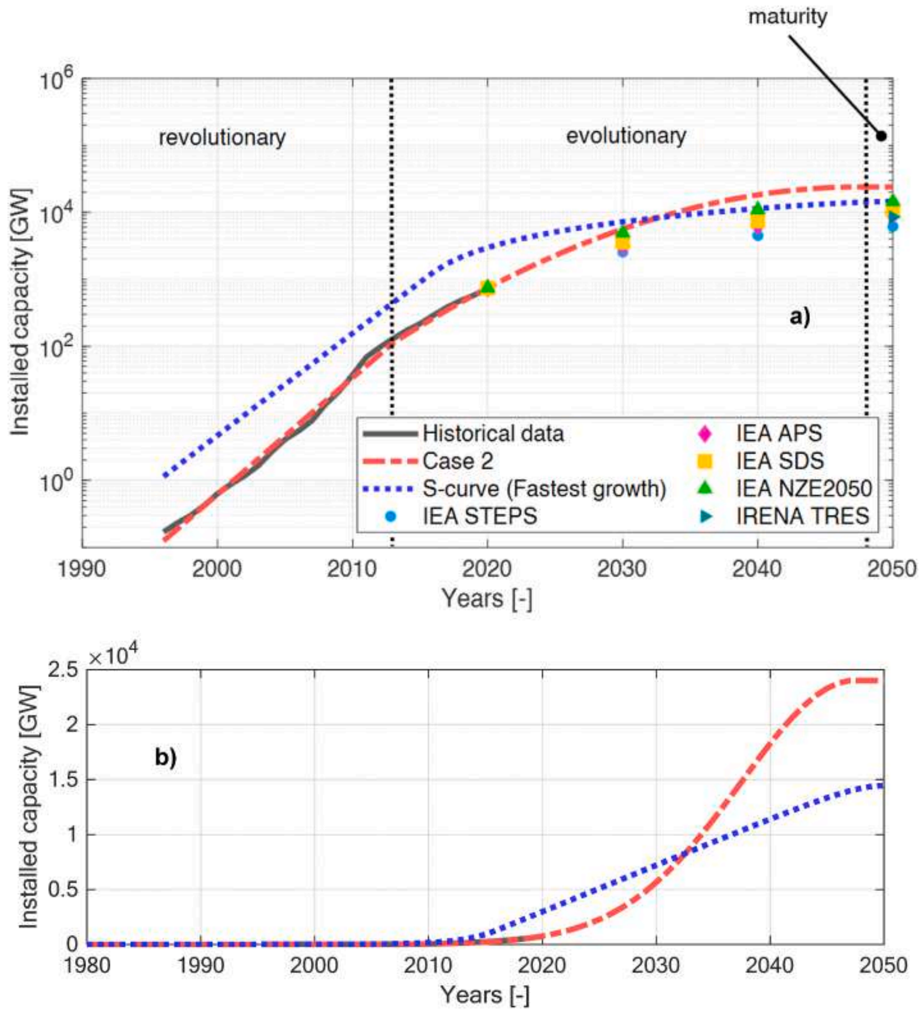

Fig. 12. Growth trend for solar PV installed capacity as retrieved from historical data, computed according to capacity deployment case 2 and compared against the curve for the fastest growth towards the IEA NZE2050 target and IEA and IRENA scenarios, in a) logarithmic and b) linear scale.

the value prescribed to reach the IEA NZE2050 objective, due to an exponential phase with a far lower doubling time than the one actually experienced in the historical data set. Therefore, despite following a trend that can be associated to a S-curve, the current development of CSP technologies would require strong efforts to play a major role in the energy transition, calling for further investments and industrial deployment.

3.8. *Marine energy capacity*

Marine energy technologies, as visible in Fig. 2, present the lowest installation levels after 2010 and an almost null growth in the time scale 2000–2020. While the maximum growth for marine energy technologies occurred between 2001 and 2002 with almost a capacity doubling, in the subsequent years this data point represented an outlier, as the average growth rate is slightly lower than 10%. Indeed, the doubling time in the time scale 2000–2020 is almost 8 years, thus out of the range 2–4 years required to identify a revolutionary phase, and sufficient to justify a stagnation, as in Fig. 4d. Therefore, projections for marine energy capacity are performed according to case 4 described in **Section 3**. The best fit curve corresponds to a linear trajectory starting from 2000 ($t = 1$) modeled according to the parameters in Table 2.

The projection in Fig. 14 obtained according to case 4 shows how, following the same linear trend experienced in the last two decades, marine energy capacity would reach 4 GW by 2050. That value would make marine energy capacity miss all the targets set by IEA and IRENA, even the IEA STEPS one, expecting 37 GW by 2050. The curve for the fastest growth towards 92 GW (IEA NZE2050 final value, that in this case is lower than the ambitious 480 GW set by IRENA) is computed using 30 years as technology lifetime [53], and indicates how strong efforts would be needed to put marine energy on track towards the required installation levels to comply with net-zero emissions objectives, with a rapid reversal of the current trend towards a larger and faster deployment. Differently from the other technologies previously examined, here the fastest growth trend would suggest that the current installation level is still sufficient to achieve ambitious targets, as the historical value and the fastest growth capacity in 2020 almost coincide. On the other hand, marine energy technologies have not followed any trajectory resembling a S-curve in the last twenty years, therefore it appears unlikely that an abrupt leap in investments to support industrial capacity growth would happen in a short time, leading to the prescribed IEA NZE2050 target. That is also suggested by an exponential phase showing a doubling time slightly higher than 2 years, against the 8 years of the actual development curve.

4. Application of the results of the three-phase capacity model to electricity generation projections

Summing up all the contributions of the different technologies to electricity generation [9], it can be observed from Fig. 15 that global electricity generation has grown by 2.3 times in the period 2000–2019, passing from 11.9 PWh in 2000 to 27.0 PWh in 2019. The YOY growth

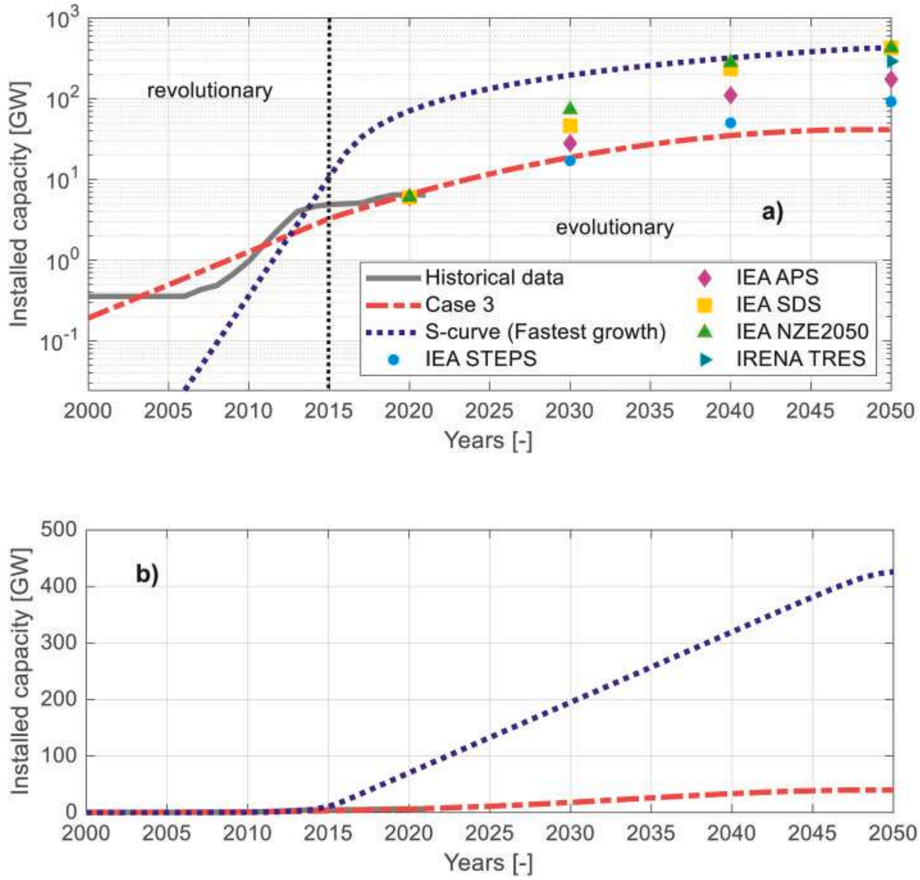

Fig. 13. Growth trend for CSP installed capacity as retrieved from historical data, computed according to capacity deployment case 4 and compared against the curve for the fastest growth towards the IEA NZE2050 target and IEA and IRENA scenarios, in a) logarithmic and b) linear scale.

rate has been almost constant for the whole abovementioned time scale, with just a negative value (0.4% between 2008 and 2009, corresponding to the period of the Great Recession [54]) and an average 2.9% growth rate. Since electrification of end-uses is deemed as a reliable strategy to reduce greenhouse gas emissions in hard-to-abate sectors [55] and in increase in economic growth is double-stranded to electricity consumption [56], considering a constant growth rate for the next years could be a plausible assumption. Indeed, the exponential regression of historical data provides a trend with $R^2 = 99.5\%$, and the extrapolation of that trend leads to 70.7 PWh by 2050. When comparing the obtained values from the extrapolation of the historical data trend to IEA expectations in Fig. 15, that is generally in line with the IEA NZE2050 targets for electricity production (the highest ones among all the reported scenarios). On the other hand, the IEA STEPS expects less than doubling of 2019 electricity generation levels in 2050, with just 46.7 PWh, due to a lower electrification of end-use sectors.

In order to compare the capacity levels projected until 2050 in **Section 3** to historical and future global electricity generation, the conversion in **Equation (8)** will be applied to convert the actual capacity in GW, obtained by weighting the installed capacity from historical data with the capacity factor *CF* of the different technologies, into electricity generation (expressed in PWh). Note that the capacity factor has to be accounted for in the passage between installed and actual capacity as it represents the percentage of time during the year in which a plant is available for electricity generation. The capacity factor is clearly dependent on the technology under exam. As both installed capacity and electricity generation trends are known, the capacity factors can be easily retrieved using **Equation (8)** for the different technological categories.

$$CF = \frac{Electricity\ production\ [PWh]}{Installed\ capacity\ [GW] \cdot 8760\ \left[\frac{h}{y}\right] \cdot 10^{-6}\left[\frac{P}{G}\right]} \tag{8}$$

Table 3 reports the set of capacity factors calculated coupling installed capacities and the actual electricity generation by technology in the time frame 2000–2019, highlighting how nuclear fission plants can achieve the highest average capacity factor (84%), while solar PV technologies present a very low capacity factor, attested at 12%.

Average capacity factors for the different technological classes are now used to transform the capacity curves computed so far and represented in Figs. 6–10, 12, 13 and **14** into electricity generation curves.

The projected contributions of the different technologies to electricity generation until 2050 are shown in Fig. 16. The analysis of the electricity production potential provided by each technology highlights how the projections to 2050 would make fossil (47.9 TWh) and solar PV (25.3 TWh) the largest contributors. For fossil fuels, that corresponds to an increase of almost 3 times with respect to current levels. On the other hand, electricity production from solar PV would be 37 times higher than today, while hydropower and nuclear fission experience the lowest growth, with just 96% and 26% more than current production, respectively. The potential contribution from wind technologies, considering the sum of onshore and offshore, is slightly higher than 16 TWh, thus well below solar PV power, but reaching levels comparable to the current electricity generation from fossil fuels (around 18 TWh [9]).

Fig. 17 compares trajectories for total electricity generation in three cases.

1) Total electricity production computed from the regression of historical data as in Fig. 15 (“Regression” curve in Fig. 17);

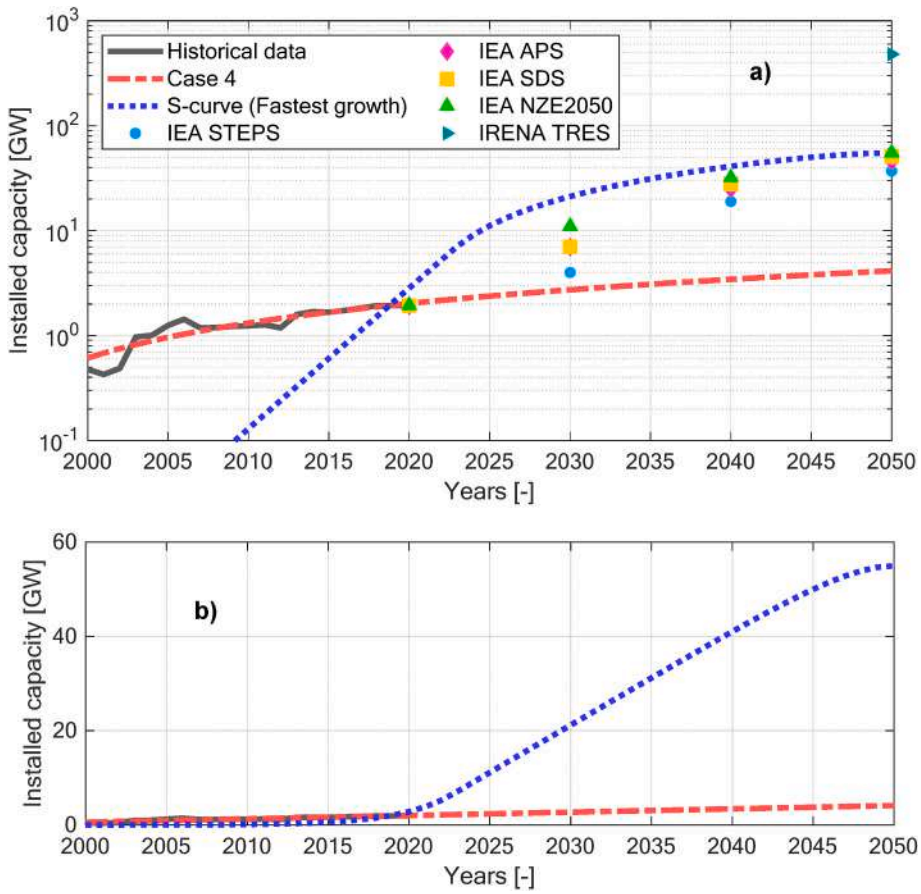

Fig. 14. Growth trend for marine energy installed capacity as retrieved from historical data, computed according to capacity deployment case 4 and compared against the curve for the fastest growth towards the IEA NZE2050 target and IEA and IRENA scenarios, in a) logarithmic and b) linear scale.

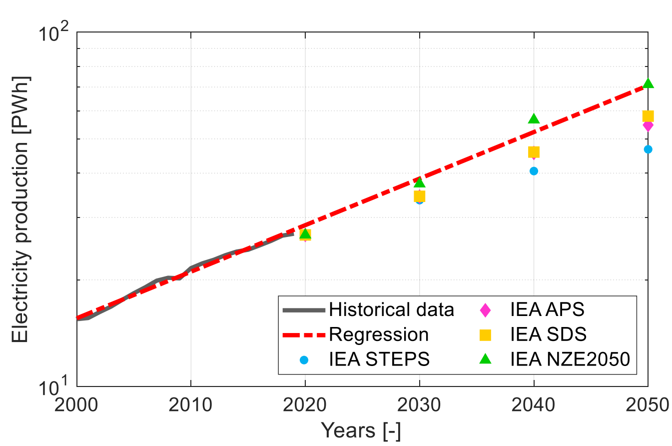

Fig. 15. Statistic trend for global electricity generation in the time frame 2000–2019, projected electricity generation using an exponential regression of available data extrapolating until 2050 and expectations of IEA scenarios, in a) logarithmic and b) linear scale.

2) Total electricity production coming from the projections shown in Fig. 16 ("Potential" curve in Fig. 17);
3) Total electricity production coming from the projections shown in Fig. 16, but accounting for the fossil fuel contribution considering the interpolation of data provided by IEA for the NZE2050 scenario, rather than the projection in Section 3 ("Fossil IEA NZE2050" curve in Fig. 17).

Also, expectations for total electricity production in the IEA scenarios considered in this work are reported in Fig. 17.

Starting from the left part of the graph, it is visible how projections computed using average historical capacity factors in Equation (8) to the projections computed in Section 3are in line with the regression of available historical data.

The "Regression" curve highlights how slightly more than 70 PWh might be sufficient to cover electricity demand in 2050. Therefore, the first evident result is that the IEA STEPS (46.7 PWh) and APS (54.7 PWh) expectations may be satisfied considering the contribution of renewable technologies alone (if they develop at the extrapolated rate) in 2050, as data from Fig. 16 sum up to a total of 57.3 PWh. However, that option would present non-negligible dispatchment issues, yet they do not represent the focus of this work.

Fig. 17, and in particular the "Fossil IEA NZE2050" curve, suggests that a considerably reduced contribution from fossil fuel generation by 2050 would be possible in all the reported scenario trajectories but IEA NZE2050. Indeed, almost 6 PWh would be missing when considering a progressive phase-out of fossil fuels contribution. Therefore, that gap should be covered envisaging a broad range of possibilities, among which.

1) Develop alternative technologies (e.g., fossil fuel plants equipped with CCS or nuclear fusion);
2) Adopt alternative strategies to electrification, to decarbonize end-use sectors in order to lighten the load on the power sector and reduce demand for electricity;
3) Increase efforts to develop those technologies that are not on track to reach the targets set in IEA NZE2050: using the projections computed in this work, those are identified in wind (see Fig. 11), solar CSP (see

Table 3
Collection of the yearly capacity factors for the different technological categories considered in this work, calculated using historical data for installed capacity and electricity generation through Equation (8). The arithmetic average value for the time series 2000–2019 is also reported.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
Fossil	0.50	0.49	0.49	0.50	0.50	0.51	0.50	0.51	0.50	0.48	0.49	0.49	0.49	0.48	0.48	0.47	0.45	0.45	0.45	0.45	0.48
Biomass	0.57	0.55	0.56	0.55	0.56	0.54	0.53	0.55	0.54	0.52	0.56	0.54	0.54	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
Hydropower	0.45	0.44	0.44	0.43	0.45	0.46	0.46	0.45	0.45	0.45	0.46	0.45	0.46	0.45	0.44	0.43	0.44	0.43	0.44	0.43	0.45
Nuclear fission	0.84	0.85	0.85	0.84	0.86	0.86	0.86	0.84	0.84	0.83	0.84	0.80	0.75	0.76	0.77	0.77	0.76	0.77	0.78	0.81	0.81
Geothermal	0.72	0.73	0.73	0.74	0.78	0.77	0.77	0.78	0.79	0.78	0.77	0.79	0.77	0.76	0.78	0.78	0.77	0.77	0.77	0.75	0.76
Wind onshore	0.21	0.18	0.20	0.19	0.20	0.20	0.21	0.21	0.22	0.21	0.22	0.22	0.22	0.24	0.23	0.23	0.23	0.25	0.26	0.26	0.22
Wind offshore	0.00	0.27	0.18	0.31	0.38	0.43	0.41	0.37	0.39	0.27	0.29	0.33	0.31	0.34	0.33	0.35	0.33	0.34	0.33	0.34	0.31
Solar PV	0.14	0.15	0.14	0.13	0.11	0.10	0.11	0.11	0.10	0.11	0.10	0.11	0.12	0.12	0.12	0.13	0.13	0.13	0.13	0.13	0.12
Solar CSP	0.17	0.18	0.18	0.18	0.19	0.19	0.18	0.18	0.21	0.16	0.19	0.20	0.21	0.17	0.21	0.23	0.24	0.24	0.22	0.24	0.20
Marine	0.13	0.14	0.12	0.06	0.06	0.05	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.07	0.07	0.07	0.07	0.06	0.06	0.06	0.07

Fig. 13) and marine energy (see Fig. 14). Also nuclear fission (see Fig. 6c) falls in this category, but that is especially subject to political and social acceptance issues;

4) Keep fossil fuels in the electricity production mix and develop alternative solutions (e.g., use of CCS in the industrial sector, afforestation, etc.) to comply with the net-zero emission target for the whole energy system. Indeed, the capacity target for fossil technologies set by IEA NZE2050 (see Fig. 6a) would allow 4.6 TWh (computed again using **Equation (8)**) of electricity produced using unabated fossil technologies;

5. Conclusion and perspectives

This work presents a model to forecast capacity curves for electricity generation technologies on a long time scale up to 2050, based on the collection of historical data at the global level. Trends for fossil, hydropower, nuclear fission, biomass, geothermal, wind, solar and marine energy technologies are computed using a method based on the regression of historical data and their projection adopting the concept of S-curves to describe the process of technological innovation. The method developed in this work generally describes technology deployment in three phases: a revolutionary phase of exponential development, an evolutionary phase where linear growth occurs and a final maturity stage in which either slow or null growth is accounted for according to data availability. Additionally, stagnation is envisaged for some technologies, following the same path of the last two decades (or more, according to data availability). The results of the projections performed according to that method are compared to the fastest growth model described in Ref. [22], considering as desirable target that set by IEA for their Net-Zero Emissions by 2050 scenario for those technologies still out of the maturity phase.

The computed trends towards 2050 show how strong commitments to reduce the dependence on fossil fuel technologies for electricity generation require a decisive steering of the current trends to achieve ambitious environmental targets, as they have been experiencing a non-negligible growth in the last decades, whilst even the least ambitious scenarios envisage (at least) a stop in their deployment and use. Also nuclear fission (reaching $\sim$ 470 GW by 2050), solar CSP (with just 40 GW by 2050, despite large progresses in percentage terms achieved in the last two decades) and marine energy (stagnating up to a 4 GW capacity by 2050) development are dramatically not on track with the targets set by the IEA NZE2050, but due to the high expectations for their development. A faster growth of solar CSP and marine energy technologies would require a rational buildup of industrial capacity, requiring in turn a change of pace with respect to the current situation. On the other hand, the situation for nuclear power drags large uncertainty, as all IEA scenarios fix targets above the curve computed considering linear development in the maturity phase, even considering more than doubling of the current capacity, while IRENA forecasts a progressive phase out of nuclear technologies. In the case of wind power, reaching the IEA NZE 2050 target would be challenging if especially considering that wind onshore is approaching maturity. Therefore, larger investments would be needed to sustain further development of wind onshore capacity in the evolutionary phase.

The projected installed capacities curves are transformed into electricity generation potentials using the average capacity factors observed in the time period 2000–2019 and compared to electricity production projection over a time scale up to 2050. The electricity generation potential results in a deployment of electricity production technologies that appears sufficient to meet the expected power sector requirements until 2050, compared against both an extrapolation of the regression of the historical data – leading to slightly less than 80 PWh required by 2050 – and against IEA projections in four scenarios, ranging from the least ambitious Stated Policies Scenario to a Net-Zero Emissions by 2050 scenario. The computed curves for the potential contribution to electricity generation by 2050 highlight how an electricity generation sector

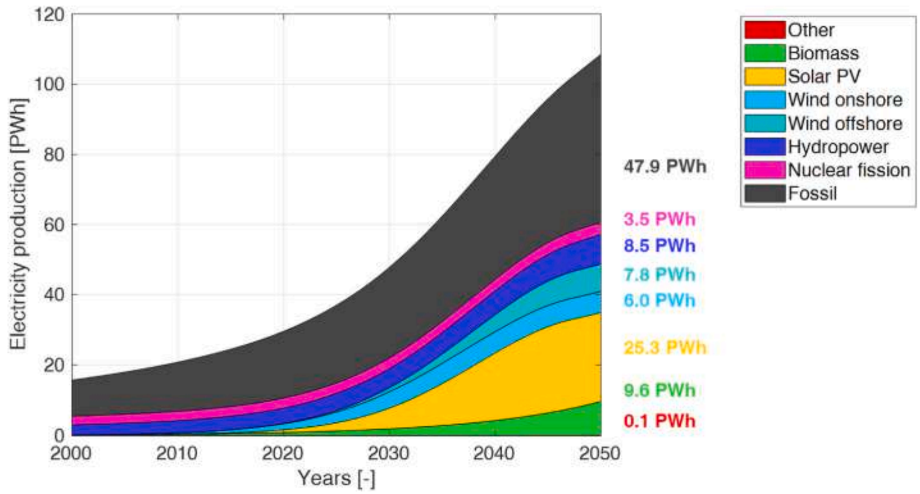

Fig. 16. Electricity generation potential for the technologies analyzed in this work. The computed production level in 2050 is reported next to the graph.

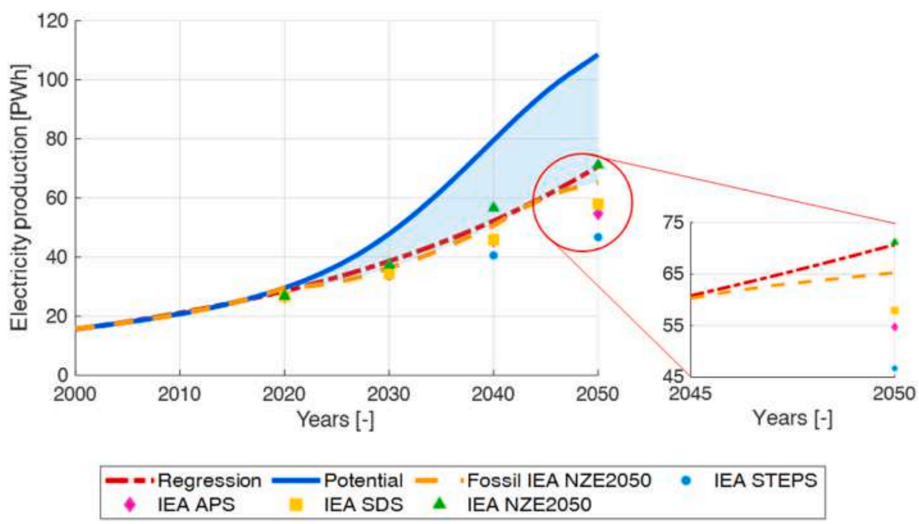

Fig. 17. Projected total electricity production curves in the time scale 2000–2050. The regression and extrapolation of historical data for total electricity production is compared to the potential contribution computed in this work, either considering those computed for all the technologies (Potential) or the same but considering the IEA NZE2050 trend for fossil fuel plants (Fossil IEA NZE2050). The trends are also compared to expectations for electricity production in IEA scenarios.

not envisaging fossil fuels is not feasible only when considering the expectations of IEA NZE2050 for electricity production, as almost 6 PWh would be missing in 2050. That situation makes room for a bunch of alternatives, ranging from efforts to develop either innovative carbon-free technologies or strategies to reduce the burden on the power generation sector, or to increase investments in industrial capacity for larger deployments of currently existing low-carbon technologies or, eventually, to consider some level of use of fossil fuels. Note that, if new technologies are targeted, they should be already well developed (out of the revolutionary phase) in 2050, especially in case of a complete phase-out of fossil fuels.

Concerning limitations of the presented approach, the model is not able to capture desired policy-driven trajectories if they are not already visible in the analyzed set of historical data. Indeed, the current trend for nuclear fission at the global level clearly indicates a weak but constant growth, as some countries (like Germany) are considering phase-out albeit with great indecisiveness, while others (like the USA, China and South Korea) are pushing towards larger deployment of their reactor fleets. On the other hand, claims to reduce the reliance on fossil fuels almost worldwide [57,58] are in place, but fossil technologies for electricity production still present dramatic growth with no sign of decline. Moreover, limits for the exploitation of some of the analyzed technologies in terms of availability of resources (e.g. solar/wind potential, biomass or fossil fuels) either due to natural or geo-political reasons are not recognizable by the S-curve model presented in this work.

Therefore, a model based on S-curves and historical data, like the one presented in this work, may be qualitatively indicative concerning technology penetration especially for those technologies still in an intermediate (evolutionary) phase of their development when the analysis is carried out. On the other hand, it has not the capability either to catch possibly disruptive events that would stimulate the development of a technology for which few historical data are available (e.g. Solar CSP) or to identify factors that would stop the growth of mature technologies (e. g. fossil fuel plants).

The method presented in this paper is bounded to the availability of historical data and is not able to provide trends for technologies that are still not visible on the radars of energy production like, e.g., fossil fuel plants equipped with CCS or nuclear fusion reactors. Note, however, that the fastest growth model presented in Ref. [22] is adapt to projections based on a larger number of assumptions and may completely neglect historical data, but also requires a target value for the capacity, introducing a non-negligible bias to the analysis.

In perspective, the set of capacity curves retrieved for the different technologies, both in the case of the projections following the historical trends and those for the fastest growth towards ambitious environmental-friendly scenarios, will be applied to work as constraints in energy system optimization models. Indeed, ESOMs usually lack to ensure accordance with historical data and may compute scenario results not in line with the actual development trend of certain technologies. Then, taking advantage of open source ESOM frameworks with an easier formulation (e.g. TEMOA [59]) and a higher possibility to access and perform modifications to the code, already demonstrated in Ref. [60], an attempt will be made to integrate the calculation of capacity curves endogenously in the modeling paradigm, in order to replicate the method described in this work to different regional scales. This would provide a more realistic evolution of the power system depicted in energy scenarios, especially in strong decarbonization scenarios which, without appropriate constraints on the development of carbon-free electricity sources may lead to unreasonable results.

Credit author statement

Daniele Lerede: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Laura Savoldi**: Conceptualization, Validation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

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

All data required to reproduce the presented methodology are reported in the paper in tabular form.

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Annex 1.

Table A1.1
Historical data for the installed electricity capacity 1980–2021 (according to the availability) for electricity generation technologies at the global level. The underlined values represent the dataset considered to compute the characteristic parameters adopted to perform the projections.

	Technologies									
Years	Fossil [34]	Biomass [34]	Hydropower [34]	Nuclear fission [35]	Geothermal [34]	Wind onshore [36]	Wind offshore [36,37,39]	Solar PV [38]	Solar CSP [38]	Marine [34]
1980	1363.58		461.90	133.04	3.89	0.01				
1981	1410.88		476.99	153.83	4.06	0.03				
1982	1453.08		493.40	168.32	4.24	0.09				
1983	1488.48		505.88	187.76	4.41	0.21				
1984	1531.11		521.60	218.45	4.59	0.60				
1985	1566.01		538.25	245.78	4.76	1.02				
1986	1596.85		552.28	272.07	4.98	1.27				
1987	1626.51		569.00	295.81	5.20	1.45				
1988	1667.63		582.93	305.21	5.42	1.58				
1989	1727.24		573.16	311.94	5.64	1.73				
1990	1764.21		565.99	318.25	5.85	1.93				
1991	1792.37		569.54	321.92	6.04	2.17				
1992	1832.96		578.09	325.26	6.22	2.51				
1993	1877.41		590.54	333.91	6.40	2.99				
1994	1926.04		604.30	336.90	6.59	3.49				
1995	1962.27		615.88	341.39	6.77	4.78				
1996	2021.00		625.63	347.28	7.08	6.10		0.17		
1997	2072.88		640.07	347.88	7.39	7.60		0.23		
1998	2114.52		649.76	344.90	7.70	10.20		0.30		
1999	2164.84		666.28	347.35	8.01	13.60		0.42		
2000	2250.71	32.62	678.54	349.98	8.32	17.22	0.04	0.63	0.35	0.48
2001	2327.64	34.97	688.26	352.72	8.12	23.77	0.09	0.88	0.35	0.43
2002	2436.50	36.88	702.95	357.48	8.17	30.57	0.26	1.17	0.35	0.49
2003	2549.05	39.05	722.59	359.83	8.30	38.01	0.52	1.65	0.35	0.97
2004	2642.57	41.88	737.60	364.67	8.28	46.41	0.61	2.65	0.35	1.01
2005	2740.65	48.20	749.62	368.13	8.67	58.52	0.70	4.08	0.35	1.25
2006	2884.52	52.48	773.20	369.58	8.87	72.20	0.79	5.44	0.36	1.43
2007	3002.05	55.09	798.57	371.71	9.07	90.49	1.11	7.77	0.43	1.18
2008	3097.01	60.69	825.50	371.56	9.37	113.71	1.48	13.60	0.48	1.19
2009	3205.75	68.27	855.09	370.70	9.87	147.93	2.06	21.19	0.66	1.22
2010	3370.08	74.44	884.21	375.28	10.11	177.34	3.05	37.30	0.97	1.24
2011	3498.69	81.12	909.44	368.92	10.04	215.93	4.12	68.23	1.60	1.27
2012	3612.78	87.49	937.13	373.25	10.49	262.56	5.42	96.04	2.57	1.19
2013	3729.52	94.38	982.24	371.78	10.78	294.61	7.05	129.66	3.94	1.59
2014	3853.00	100.76	1019.79	376.26	11.37	340.58	8.77	171.72	4.60	1.69
2015	3948.71	106.22	1051.29	382.81	11.83	403.82	12.11	217.50	4.85	1.67
2016	4113.13	115.56	1082.46	390.49	12.23	452.06	14.38	291.26	4.97	1.74
2017	4211.72	122.93	1105.82	391.72	12.68	495.42	18.81	384.33	5.07	1.83

(continued on next page)

Table A1.1 (*continued*)

Years	Fossil [34]	Biomass [34]	Hydropower [34]	Nuclear fission [35]	Geothermal [34]	Wind onshore [36]	Wind offshore [36,37,39]	Solar PV [38]	Solar CSP [38]	Marine [34]
2018	4304.73	129.80	1124.83	396.62	13.14	540.61	23.14	481.04	5.81	1.93
2019	4356.48	135.58	1140.07	392.10	13.92	593.11	29.14	580.67	6.37	1.93
2020	4414.61	137.80	1161.63	392.61	14.07	700.41	35.50	714.99	6.51	1.93
2021							48.18		6.39	

Table A1.2
Installed projections for the installed capacity of electricity generation technologies according to the methodology presented in the paper. The green cells represent projections obtained according to an exponential fashion; the blue cells represent projections obtained according to a linear fashion; the red cells represent the maturity phase with constant capacity level. Also note that the parameter "Characteristic lifetime" corresponds to the duration of the evolutionary phase in cases 2 and 3.

	Case 1			Case 2			Case 3		Case 4	
	Fossil	**Hydropower**	**Nuclear fission**	**Wind onshore**	**Solar PV**	**Solar CSP**	**Wind offshore**	**Biomass**	**Geothermal**	**Marine energy**
***R*^2 [%]**	99.1	97.5	94.6	99.9	99.2	84.1	99.6	98.5	98.9	87.4
***b* [GW]**	1256	446.1		0.657	0.084	0.1582	0.996	27.82	4.072	
***a* [-]**	1.031	10.23		1.248	1.492	1.208	1.302	1.087	1.03	
***m* [GW/year]**			2.481							0.07061
***q* [GW]**			316.3							0.5397
Characteristic lifetime [years]				27	34	34	27			
1980	1296	456.2							4.195	
1981	1337	466.4							4.323	
1982	1378	477.0							4.454	
1983	1422	487.7							4.590	
1984	1466	498.7							4.729	
1985	1512	510.0		0.6985					4.873	
1986	1560	521.5		0.8684					5.021	
1987	1609	533.3		1.080					5.173	
1988	1659	545.3	318.8	1.342					5.330	
1989	1711	557.6	321.3	1.668					5.492	
1990	1765	570.2	323.8	2.074					5.659	
1991	1820	583.0	326.2	2.579					5.831	
1992	1877	596.2	328.7	3.206					6.008	
1993	1936	609.6	331.2	3.985					6.191	
1994	1997	623.4	333.7	4.954					6.379	
1995	2060	637.5	336.2	6.159					6.573	
1996	2124	651.8	338.6	7.657	0.1254				6.773	
1997	2191	666.6	341.1	9.518	0.1870				6.978	
1998	2260	681.6	343.6	11.83	0.2789				7.191	
1999	2331	697.0	346.1	14.71	0.4161				7.409	
2000	2404	712.7	348.6	18.29	0.6207	0.1911		30.26	7.634	0.6103
2001	2479	728.8	351.1	22.74	0.9259	0.2309		32.90	7.866	0.6810
2002	2557	745.2	353.5	28.26	1.381	0.2790		35.78	8.105	0.7516
2003	2637	762.0	356.0	35.14	2.060	0.3370		38.91	8.351	0.8222
2004	2720	779.2	358.5	43.68	3.073	0.4071		42.31	8.605	0.8928
2005	2805	796.8	361.0	54.30	4.585	0.4919		46.01	8.867	0.9634
2006	2893	814.8	363.5	67.51	6.839	0.5942		50.03	9.136	1.034
2007	2984	833.2	365.9	83.93	10.20	0.7179	1.297	54.41	9.414	1.105
2008	3078	852.0	368.4	104.33	15.22	0.8673	1.689	59.17	9.700	1.175
2009	3174	871.2	370.9	129.71	22.70	1.048	2.199	64.34	9.994	1.246
2010	3274	890.8	373.4	161.25	33.86	1.266	2.863	69.97	10.30	1.316
2011	3377	910.9	375.9	200.46	50.52	1.529	3.728	76.09	10.61	1.387
2012	3482	931.5	378.3	242.5	75.35	1.847	4.853	82.74	10.93	1.458
2013	3592	952.5	380.8	291.5	112.4	2.232	6.319	89.98	11.27	1.528
2014	3704	974.0	383.3	348.1	150.6	2.696	8.227	97.85	11.61	1.599

2015	3821	996.0	385.8	413.1	200.3	3.133	10.71	106.4	11.96	1.670
2016	3940	1018	388.3	486.9	264.4	3.625	13.95	115.7	12.32	1.740
2017	4064	1041	390.7	570.1	346.4	4.177	18.16	125.8	12.70	1.811
2018	4192	1065	393.2	663.1	450.4	4.794	23.64	136.8	13.08	1.881
2019	4323	1089	395.7	766.2	581.0	5.479	30.78	148.8	13.48	1.952
2020	4459	1114	398.2	879.3	743.6	6.235	40.07	161.8	13.89	2.023
2021	4599	1139	400.7	1002	944.4	7.067	52.18	176.0	14.31	2.093
2022	4743	1164	403.2	1135	1190	7.975	67.93	191.3	14.75	2.164
2023	4892	1191	405.6	1276	1487	8.963	87.71	208.1	15.20	2.234
2024	5045	1217	408.1	1424	1844	10.03	112.3	226.3	15.66	2.305
2025	5204	1245	410.6	1579	2269	11.18	142.6	246.1	16.13	2.376
2026	5367	1273	413.1	1739	2768	12.40	179.5	267.6	16.62	2.446
2027	5535	1302	415.6	1901	3349	13.70	224.0	291.0	17.13	2.517
2028	5709	1331	418.0	2064	4019	15.07	277.2	316.4	17.65	2.588
2029	5888	1361	420.5	2224	4783	16.50	340.0	344.1	18.19	2.658
2030	6073	1392	423.0	2380	5644	18.00	413.3	374.2	18.74	2.729
2031	6263	1423	425.5	2527	6603	19.54	498.0	406.9	19.31	2.799
2032	6460	1455	428.0	2665	7659	21.12	594.7	442.5	19.89	2.870
2033	6662	1488	430.4	2789	8808	22.73	703.7	481.2	20.50	2.941
2034	6871	1522	432.9	2898	10040	24.36	825.1	523.3	21.12	3.011
2035	7087	1556	435.4	2988	11350	25.98	958.6	569.0	21.76	3.082
2036	7309	1591	437.9	3057	12710	27.59	1103	618.8	22.43	3.152
2037	7539	1627	440.4	3105	14110	29.16	1258	672.9	23.11	3.223
2038	7775	1664	442.8	3129	15520	30.69	1421	731.7	23.81	3.294
2039	8019	1701	445.3	3129	16910	32.15	1589	795.7	24.53	3.364
2040	8271	1740	447.8	3129	18270	33.53	1761	865.3	25.28	3.435
2041	8530	1779	450.3	3129	19550	34.81	1932	941.0	26.05	3.505
2042	8798	1819	452.8	3129	20720	35.97	2098	1023	26.84	3.576
2043	9074	1860	455.2	3129	21760	37.00	2257	1113	27.65	3.647
2044	9359	1902	457.7	3129	22630	37.88	2403	1210	28.49	3.717
2045	9652	1945	460.2	3129	23300	38.60	2532	1316	29.36	3.788
2046	9955	1989	462.7	3129	23770	39.15	2642	1431	30.25	3.859
2047	10267	2034	465.2	3129	24000	39.52	2727	1556	31.17	3.929
2048	10590	2080	467.7	3129	24000	39.71	2786	1692	32.12	4.000
2049	10922	2127	470.1	3129	24000	39.71	2816	1840	33.09	4.070
2050	11264	2175	472.6	3129	24000	39.71	2816	2001	34.10	4.141

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