



Representation of variable renewable energy sources in TIMER, an aggregated energy system simulation model



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ABSTRACT

The power system is expected to play an important role in climate change mitigation. Variable renewable energy (VRE) sources, such as wind and solar power, are currently showing rapid growth rates in power systems worldwide, and could also be important in future mitigation strategies. It is therefore important that the electricity sector and the integration of VRE are correctly represented in energy models. This paper presents an improved methodology for representing the electricity sector in the long-term energy simulation model TIMER using a heuristic approach to find cost optimal paths given system requirements and scenario assumptions. Regional residual load duration curves have been included to simulate curtailments, storage use, backup requirements and system load factor decline as the VRE share increases. The results show that for the USA and Western Europe at lower VRE penetration levels, backup costs form the major VRE cost markup. When solar power supplies more than 30% of the electricity demand, the costs of storage and energy curtailments become increasingly important. Storage and curtailments have less influence on wind power cost markups in these regions, as wind power supply is better correlated with electricity demand. Mitigation scenarios show an increasing VRE share in the electricity mix implying also increasing contribution of VRE for peak and mid load capacity. In the current scenarios, this can be achieved by at the same time installing less capital intensive gas fired power plants. Sensitivity analysis showed that greenhouse gas emissions from the electricity sector in the updated model are particularly sensitive to the availability of carbon capture and storage (CCS) and nuclear power and the costs of VRE.

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1. Introduction

Various projections show increasing demand for electricity in the coming decades, especially in developing regions (IEA, 2014a). The growing demand results from increases in population and income levels, as well as the trend towards a larger share of electricity in final consumption. Also, the electricity sector plays a key role in climate change. Electricity and heat generation together account for 25% of global anthropogenic greenhouse gas emissions and emissions from this sector have trebled since 1970 (IPCC, 2014). However, the sector offers options to contribute to climate change mitigation. Various electricity sources could play a role in decarbonising the energy system including nuclear power, biomass, carbon capture and storage (CCS) and variable renewable energy (VRE) sources.

The massive growth in the use of VRE sources, particularly wind and solar energy, has reduced emissions and the use of fossil fuels but is also

accompanied by several challenges. A key challenge is the difficulty of instantly balancing supply and demand, with currently limited storage capabilities. Unlike conventional generation, the output of solar and wind technologies depends on intermittent environmental conditions, which are not necessarily correlated with electricity demand. On an hour to hour basis this results in challenges concerning VRE over-supply, the varying technical capabilities of power plants to follow residual load fluctuations, and the cost implications of producing at load factors far below their maximum. A longer term challenge is to ensure that enough backup capacity is available to supply the annual residual peak demand. Such VRE integration constraints have been identified in various studies, including the work of Hirth (2013), Hirth et al. (2015), Holttinen et al. (2011), IEA (2014b), Sijm (2014) and Pietzcker et al. (2017-in this issue).

Because of the major role of the electricity sector in the global energy system, this sector and the challenges accompanied by the increasing share of variable renewable energy need to be appropriately represented in Integrated Assessment Models (IAMs). However, global IAMs, used for simulating future greenhouse gas emission projections and the potential for reducing these emissions, can only represent electricity system in an aggregated way because the focus is on long-term trends, large global regions and the associated large uncertainties.

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Recently representation of the electricity sector has been improved considerably in various IAMs. Sullivan et al. (2013) introduced reliability metrics to capture integration constraints related to VRE to the hybrid optimization IAM MESSAGE (Model for Energy Supply Strategy Alternatives and their General Environmental Impact). Ueckerdt et al. (2015) added residual load duration curves to the REMIND-D (Regional Model of Investments and Development) model to capture the effects of VRE. Finally, Pietzcker et al. (2014) derived VRE-share-dependent integration cost mark-ups to represent storage, grid and curtailment costs. These insights and the recent growth in the use of VRE source have prompted a need to update the electricity sector representation in the TIMER (IMage Energy Regional) model. This long-term global energy system simulation model is part of the IMAGE (Integrated Model to Assess the Global Environment) framework (Stehfest et al., 2014).

We have developed an improved heuristic methodology to contribute to representation of the electricity system in TIMER.

Our study has a two-fold purpose:

- To demonstrate the capabilities of the new load band based simulation model in representing the impact of increasing VRE penetration levels.
- To apply the model to explore the future electricity system developments in a scenario with and without climate policies and identify the key uncertainties.

2. Method

The TIMER model is used for simulating long-term trends in the global energy system. It describes the use of 12 primary energy carriers in 26 world regions, over the 1970–2100 period. As it is a simulation model, the results depend on a set of deterministic algorithms. The TIMER model consists of three modules: energy demand, supply and conversion. The energy demand module determines the final energy demand for 5 sectors (industry, transport, residential, services and other). Development of demand depends on economic, demographic, technological and behavioural trends. The supply module simulates the production by primary energy carriers and determines the prices for energy, based on so-called cost-supply curves. Future supply by each energy carrier in the module mainly results from the interplay between depletion and efficiency improvements. The conversion module describes how primary energy carriers can be converted into secondary energy carriers. The conversion module consists of two submodules: the hydrogen and power submodules. In TIMER, the power submodule is the most important part of the conversion module as a result of its high energy use and associated emission rate (Stehfest et al., 2014).

Hoogwijk et al. (2007) and Van Vuuren et al. (2014) describe the key characteristics of the electricity sector representation in TIMER. In TIMER, electricity can be generated by 28 technologies. These include the VRE sources solar photovoltaics (PV), concentrated solar power (CSP), and onshore and offshore wind power. CSP is semi-variable, as we assume all CSP capacity to be installed in combination with thermal storage. Other technology types are natural gas-, coal-, biomass- and oil-fired power plants. These power plants come in multiple variations: conventional, combined cycle, carbon capture and storage (CCS) and combined heat and power (CHP). The electricity sector in TIMER also describes the use of nuclear, other renewables (mainly geothermal power) and hydroelectric power. TIMER does not model interregional trade of electricity. Interregional trade of electricity is only included for model calibration. Grid costs result from a linear relation between installed power capacity and required transmission and distribution capital. The demand for electricity results from the various demand sectors. Based on the demand, power capacity is installed. TIMER explicitly simulates capacity stocks and lifetimes. A multinomial logit equation is applied to distribute market share based on the technology costs.

2.1. Previous electricity system representation

The previous version of the model already included simplified VRE integration constraints, the most notable of which are backup requirements and curtailments resulting from times of VRE oversupply. However, backup capacity was installed together with VRE, resulting in a limited VRE penetration. Electricity storage and the effects of declining residual load factors at higher VRE penetration levels were not considered. In light of the old model characteristics, recent developments in scientific literature and VRE growth, improvements to TIMER are required.

2.2. Improved electricity system representation

The improved representation of electricity demand, dispatch, capacity and investments in TIMER are described in the following subsections.

2.2.1. Demand

The annual regional demand for electricity is calculated using demand submodules that describe activity levels, energy efficiency and fuel substitution for the 5 end-use sectors in TIMER. This demand for electricity is translated into monthly load duration curves (LDCs). An LDC shows the distribution of load over a certain timespan in a downward form. The peak load is plotted to the left of the LDC and the lowest load is plotted to the right. The shape of the LDCs has been obtained from data in Ueckerdt et al. (2017-in this issue), in which LDCs are described for 8 world regions. The dataset provides the decreasing load as a fraction of the peak load in 5 h time step over the period of a year (see Fig. 1). Based on the level of development and geographical location of regions, these LDCs were assigned to the 26 TIMER regions. These normalized LDCs are translated into actual LDCs, so that the area under the LDC is equal to the electricity demand. The current LDCs do not vary over time, which is a limitation. Especially developing countries in warmer regions are expected to develop a higher correlation between electricity demand and solar energy supply as income levels increase, given the increasing demand for electric space cooling. The resolution of the LDC dataset was reduced to 13 time steps per month (156 time steps per year), to reduce simulation times. While decreasing the resolution, it was ensured that the peak load and the curtailments are still equal to the original dataset. As a result, there is a slight change of the shape of the LDC, compared to the original LDC dataset.

2.2.2. Dispatch

The demand for electricity is met by the installed capacity of power plants. The available capacity is used according to the merit order of the different types of plants; technologies with the lowest variable costs are dispatched first, followed by other technologies based on an ascending

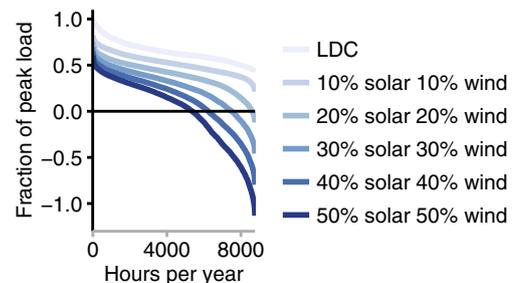


Fig. 1. Example of load duration curve and residual load duration curves at different shares of wind and solar power (Ueckerdt et al., in this issue).

order of variable costs. This results in a cost-optimal dispatch of technologies.

- VRE technologies are dispatched first, as they involve minimal variable costs. The dispatch pattern of VRE relative to the LDC is also described by Ueckerdt et al. The overlap with the load duration curve and the possibility for storage leads to the so-called residual load duration curves (RLDCs), showing the remaining load after supplying VRE. Ueckerdt et al. constructed these RLDCs for different gross shares of solar and wind power (VRE power supply including curtailments; Fig. 1). RLDCs provide valuable information on the electricity system. They show the residual peak load and therefore the aggregated VRE capacity credits. RLDCs also provide information on curtailment. Curtailments occur when the supply of VRE exceeds demand. Curtailments result in a decreasing load factor. RLDCs are available with and without optimized use of electricity storage. Storage use results in higher VRE capacity credits and lower curtailment levels. CSP dispatch is also determined using the solar RLDC data set. CSP is assumed to operate at higher load factors, and therefore CSP has higher capacity credits.
- The second technology group dispatched in TIMER is that of CHP. CHP technologies are assumed to be heat demand driven and are therefore regarded as must-run technologies. In TIMER, 50% of the heat demand is not related to space heating purposes, and hence independent from outside temperature. This heat is assumed to be demanded constantly over the whole year. The other 50% is distributed based on monthly heating degree days.
- The other renewable category (mainly consisting of geothermal power) is also assumed to be a must-run technology and is dispatched after CHP.

The remaining technologies are dispatched according to their variable costs. These technologies are not fully available throughout the year. For most technologies, it is assumed that there is a planned outage rate of 5% and a forced outage rate of 5%. Forced outage is equally spread throughout the year and influences the capacity credits of a technology. Planned outage is accumulated in low demand months. Fig. 2 shows the availability for supplying the residual load for a coal steam power plant with a planned outage rate of 5% and a hydroelectric power plant with a planned outage rate of 50% as a result of limited water discharge availability. Both plants have a forced outage rate of 5% and therefore capacity credits of 95%. The linear curves have been constructed so that the area under the curve equals the potential yearly electricity production of a technology. We make the optimistic assumption that hydroelectric power plants have the ability to release their annual accumulated discharge throughout the year. We do not take into account other dispatch constraints like minimum loads, limited ramping rates, network constraints, startup and shutdown costs and system service provisions. Papers like de Boer et al. (2014) show that these constraints can have a substantial influence on dispatch and curtailments, especially at increasing VRE shares. Therefore the assumptions on curtailments and dispatch in this paper can be regarded as optimistic.

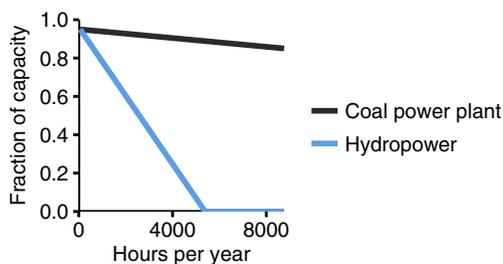


Fig. 2. Examples of the available capacity from hydroelectric and coal-fired power plants in the TIMER model.

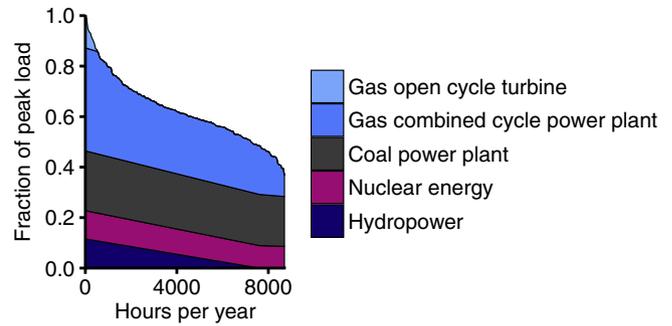


Fig. 3. Example of dispatch in the TIMER model.

Fig. 3 shows an example of the dispatch of technologies in TIMER. The technologies with the lowest variable costs are dispatched first (hydroelectric and nuclear power) and the technologies with the highest variable costs are dispatched last (gas fired power plants). Hydroelectric power plants are assumed to operate under the limited conditions described above. The capacity from coal and nuclear energy forms the base load. Combined cycle gas capacity forms the mid load and open cycle gas turbine capacity provides the peak load.

2.2.3. Capacity

TIMER is a deterministic simulation model with limited foresight that explicitly models the capacity stocks of the various technologies. The stock of each technology is a function of investment and retirement. Capacity is retired when reaching the end of its technical lifetime (varying from 25 to 80 years). Investments require some foresight: due to the inclusion of construction times, the capacity that is ordered does not directly become available for operation. The investments, or the *total ordered capacity* (Eq. (1)), are determined by the *total expected required capacity*. This in turn depends on the *expected peak demand* and the product of the *expected capacity* and the *capacity credits* per technology (Eq. (2)). The *expected peak demand* is the peak demand that is expected after the technology building time. The *expected peak demand* is determined by applying a forecast method that is based on the historical relationship between GDP and population, and electricity demand. The *expected capacity* equals the current operational capacity corrected for capacity currently under construction and going into operation and the expected retirement of capacity during the construction time. The *expected capacity* is corrected for *capacity credits*, and a small additional *reserve fraction* is added in Eq. (2) to ensure that enough capacity is installed to supply the *expected peak demand*.

$$\text{Total ordered capacity} = \text{total expected required capacity} - \text{total expected capacity} \quad (1)$$

$$\text{Total expected required capacity} = \sum_{tech=1}^{ntech} \text{expected capacity}_{tech} \times \frac{\text{expected peak demand} * \text{reserve fraction}}{\sum_{tech=1}^{ntech} \text{expected capacity}_{tech} * \text{capacity credits}_{tech}} \quad (2)$$

Capacity can also be decommissioned before the end of the technical life time. This so-called early retirement can occur if the operation of the capacity has become relatively expensive compared to the operation and construction of new capacity. The operational costs include fixed O&M, variable O&M, fuel and CCS costs. Capacity will not be retired early if the capacity has a backup role, characterized by a low load factor resulting in low operational costs.

2.2.4. Investment

The distribution of the different available technologies among the ordered capacity depends on technology costs. Investments into hydroelectric, other renewables and CHP form an exception: these

are exogenously determined, in the case of hydropower and other renewables, or heat demand driven, in case of CHP. In addition, CHP investments are determined by the demand for heat. For the other technologies, the total technology costs are captured in the levelised cost of electricity (LCOE). The LCOE is equal to all the costs (capital, O&M, construction and fuel and CO₂ storage costs) incurred during the life cycle of a technology, divided by the electricity produced (Eq. (3)). For annualizing costs, a discount rate of 10% is applied.

$$LCOE \left(\frac{\$}{kWh} \right) = \frac{cap + constr + O\&M + fuel + CO_2}{electricity\ generated} \quad (3)$$

in which:

- LCOE = levelised costs of electricity
- cap = annualized capital costs
- constr = annualized interest during construction
- O&M = annual operation and maintenance costs
- fuel = annual fuel costs
- CO₂ = annual carbon storage costs

2.2.4.1. *Basic costs.* Basic cost components include all costs included in the numerator of Eq. (3). The approach used to determine these costs differs per technology group.

Except for nuclear power, the capital costs and O&M costs of fossil fuel and biomass fired power plants are exogenously prescribed in TIMER as a function of time, based on the combination of various components (see Hendriks et al., 2004). For nuclear power, TIMER uses learning curves to describe the cost development over time. The data on capital costs, O&M costs and efficiency have been updated on the basis of state-of-the-art literature (Black and Veatch, 2012; IEA, 2014c; IRENA, 2015; Lazard, 2014). Regional distinction on capital costs and O&M costs is based on relative GDP level. The relationship was derived from IEA (2014c). Fuel costs are obtained from the TIMER supply module. In mitigation scenarios, the fuel price can include a carbon price. The costs of carbon storage depend on the utilization of carbon storage potential (Van Vuuren, 2007). For the construction costs, the electricity submodule assumes a linear cash flow during the period of construction. Construction times vary between 1 and 4 years. Regional availability is dependent on scenario input.

The capital costs of the VRE technologies are influenced by transmission costs and learning. Transmission cost increase as the distance between demand and VRE resource increase due to earlier deployment of local resource. The transmission costs are included in cost supply curves. These curves show the relation between the regional VRE potential utilized and the costs of this potential. For more information on

TIMER's VRE cost supply curves, see Hoogwijk (2004; PV and onshore wind power), Gernaat et al. (2014; offshore wind power) and Köberle et al. (2015, CSP). Experience (learning) lowers the capital costs of VRE. We apply the concept learning-by-doing: learning depends on the cumulative installed VRE capacity.

2.2.4.2. *Produced electricity.* An important variable used in determining the LCOE is the amount of electricity generated (Eq. (3)). Often, the LCOEs of technologies are compared at maximum full load hours. However, (R)LDCs show us that only a limited share of the installed capacity will actually generate electricity at full load. This effect is captured in a heuristic: 20 different load bands have been introduced to link the investment decision to dispatch. Fig. 4 shows an example of load bands. The left graph shows the situation without VRE (for illustration purposes, only 4 load bands are shown). Reserve factors have not been incorporated. The LDC has been split into 4 load bands of equal capacity. The load factor (LF) decreases from 1 (or full load) in the lower load band to 0.06 in the upper load band. For each of the load bands, TIMER calculates the LCOE of all the available technologies. For final investments, the LDC is corrected for potential hydropower dispatch. The dispatch of hydropower is easy to predict, as hydropower has low variable costs and a limited dispatch potential (Fig. 2). Incorporating hydropower has a flattening effect on the LDC and, therefore, less peak and mid load capacity is required in a electricity system with a large share of hydroelectric power.

The electricity submodule uses the RLDC to determine investments in a situation in which VRE is already installed (Fig. 4, right). As the dispatch of VRE is variable and does not exactly occur in load bands, an additional load band has been added (for illustration purposes, we only show 1 load band for all VRE sources, instead of 1 load band per VRE technology). The size of this load band equals the VRE capacity, and the load factor equals the VRE load factor. In this load band, all technologies (both VRE and non-VRE) compete based on their LCOEs at the VRE load factor. All the other load bands are equal in size; one fourth of the residual peak load. Again, the electricity submodule determines the LCOEs of all the technologies in all load bands.

2.2.4.3. *Additional costs.* Besides the basic cost components, additional cost components have been added to the LCOE:

- Backup costs (*back*)
- Curtailment losses (*curt*)
- Load factor reduction (*lfred*)
- Storage costs (*stor*)
- Transmission and distribution costs (*T&D*)

Costs related to backup and transmission and distribution (T&D) are applied to all technologies. The other markups are VRE-specific. All

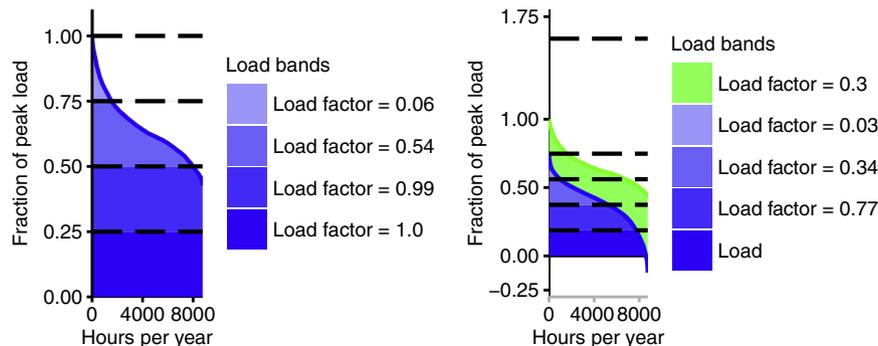


Fig. 4. Load factor per load band; without VRE (left) and with VRE (right).

these cost components have been included in the full LCOE used for investment as shown in Eq. (4).

$$\text{Full LCOE} \left(\frac{\$}{\text{kWh}} \right) = \frac{\text{cap} + \text{constr} + \text{O\&M} + \text{fuel} + \text{CO}_2 + \text{back} + \text{stor} + \text{T\&D}}{\text{electricity generated} - \text{ Curt} - \text{I Fred}} \quad (4)$$

Backup costs have been added to represent the additional costs required in order to meet the capacity and energy production requirements of a load band. Capacity backup is always required, as the capacity credits of all technologies are lower than 1. The capacity backup requirement for VRE is usually higher than that of conventional technologies, as the VRE capacity credits depend on the often imperfect correlation between VRE supply and peak load. Energy backup requirements depend on the difference between the required load band load factor and the potential load factor of the technology. The electricity submodule chooses the backup technology resulting in the lowest backup costs and adds these costs to the LCOE. The backup costs include all basic cost components. In a load band of 100 MW and 800 GWh, a solar PV technology with capacity credits of 0.2 and a potential load factor of 0.25 would require a backup technology which can provide $100 \text{ MW} \cdot (1 - 0.2) = 80 \text{ MW}$ of backup capacity and $100 \text{ MW} \cdot (1 - 0.25) \cdot 8760 \text{ h} = 657 \text{ GWh}$ of backup at the lowest costs. All technologies are available for determining backup costs, except for biomass technologies (limited potential), hydroelectric and the other renewables category (exogenous investments) and CHP technologies (heat-demand driven). VRE can be used to determine the backup costs if the marginal capacity credits are higher than 0. Usually, more backup capacity is required if VRE is used as backup.

Curtailment costs are only relevant for VRE technologies. Curtailments occur when the supply of VRE exceeds the demand. The degree to which curtailment occurs depends on VRE share, storage use and the regional correlation between electricity demand and VRE supply. Curtailment influences the LCOE by reducing the potential amount of electricity that could be generated. Curtailment levels are derived from the RLDC data set. The assumption that curtailments only occurs when VRE supply exceeds the demand is optimistic. Due to minimum loads and startup and shutdown costs of conventional power plants, curtailment is likely to occur at higher residual loads.

Load factor reduction results from the utilization of VRE sites with less favourable environmental conditions, such as lower wind speeds or less solar irradiation. This results in a lower potential load influencing the LCOE by reducing the potential electricity generation.

Storage use has been optimized in the RLDC data set. For more information on storage use, see Ueckerdt et al. (2017-in this issue). Storage costs are not applied for CSP, since the capital costs of CSP already include thermal storage costs.

Transmission and distribution costs are simulated by adding a fixed relationship between the amount of capacity and the required amount of transmission and distribution capital. The transmissions and distribution costs used for this paper are equal to 1.15 USD2005 per capacity credit adjusted kWe installed.

Spinning reserve requirements, start-up and shut-down costs of power plants, network congestion, ramp rate constraints and minimum loads are not considered in TIMER. The absence of these factors might result in a slight underestimation of curtailments and storage requirements.

2.2.4.4. *Multinomial logit.* The full LCOEs per load band are input for the investment decision. The inclusion of the different load factors for each load band means that less capital-intensive technologies are attractive to use for lower load factor load bands. These are likely to be gas-fired peaker plants. For load bands with higher load factors, the electricity submodule chooses technologies with lower operational costs. These are likely to be base load plants, such as coal-fired or nuclear power plants. Investments in hydropower and the other renewables category are exogenously determined. A system with more VRE sources will result in lower load factors and therefore in a higher demand for peak or mid load technologies. The full LCOEs of the various technologies are used in a multinomial logit equation to determine investment shares per load band. The electricity submodule divides the ordered capacity based on load bands size (Eq. (5)). The multinomial logit is a common model element in TIMER, used for distributing market share on the basis of costs, while maintaining some degree of heterogeneity (Van Vuuren, 2007).

$$\text{Investment}_{\text{tech}} = \text{ordered capacity} \cdot \sum_{\text{NLB}=1}^{\text{NLB}} \frac{\text{capacity}_{\text{LB}} \cdot e^{-\lambda \text{ Full LCOE}_{\text{tech}}}}{\sum_{\text{NLB}=1}^{\text{NLB}} \text{capacity}_{\text{LB}} \cdot \sum_{\text{ntech}=1}^{\text{ntech}} e^{-\lambda \text{ Full LCOE}_{\text{tech}}}} \quad (5)$$

in which:

- *tech* = technology
- *ntech* = total number of technologies
- *LB* = load band
- *NLB* = total number of load bands
- λ = logit parameter

2.3. Scenarios explored

This paper applies a set of scenarios also described in the ADVANCE comparison study (Luderer et al., 2017-in this issue). This study elaborates on the representation of the electricity sector in different IAMs. Table 1 shows a short description of the scenarios used. All the scenarios make use of renewable cost supply curves as constructed by Eurek et al. (in this issue; wind resource potential) and Pietzcker et al. (2014; solar resource potential). These cost supply curves contain regional potential for solar PV, concentrated solar power, and onshore and offshore wind power. To force endogenous learning, the capacity share of renewable energy in the regional electricity system is kept at least equal to 2015 shares. See the supplementary material for USA region technology assumptions in the *Baseline* and *Tax30* scenario.

3. Results

First, some key model dynamics are discussed, followed by default model outcomes for a scenario both with and without climate policy, and the sensitivity of the model is shown regarding important new model assumptions.

3.1. Dynamics of increasing VRE penetration levels

This subsection presents the increasing costs at increasing VRE penetration levels, followed by showing the effects of adding load bands to the investments decision in TIMER.

Table 1
Scenario description.

Scenario	Climate policy	Other
Baseline	None	
Tax30	USD 30 per tonne CO ₂ in 2020, annual increase 5%	
2 °C policy	1300 GtCO ₂ fossil fuel and industry carbon budget from 2000 to 2100	
RE 2 °C policy	1300 GtCO ₂ fossil fuel and industry carbon budget from 2000 to 2100	No CCS allowed and no new investments in nuclear power

3.1.1. Increasing costs at increasing VRE penetration levels

TIMER determines the additional costs of renewable penetration as markups as presented in Eq. (4). Fig. 5 shows these marginal markups as a function of the VRE penetration level in a situation in with and without storage use. The integration costs are determined at the marginal VRE load factor. To isolate integration costs, we fixed the capital costs of solar PV and onshore wind at 1300 USD per kW and the O&M costs at 40 USD per kW per year.

The marginal integration costs for solar PV in Western Europe and the United States (USA) are clearly increasing as a function of PV penetration (Fig. 5). The most important contribution at low penetration levels are back-up costs. For high penetration levels, storage costs (with storage) and curtailment (without storage) also become important. Without the use of storage, curtailments form the major share of the solar integration costs at penetration levels higher than 30% of the electricity demand. The graph also shows that the marginal backup and curtailment costs are lower in the USA than in the Western Europe. This is a result of the better correlation between solar supply and electricity peak demand in the USA as the higher electricity demand from of air conditioning coincides with the supply of solar PV during warm and sunny afternoons. Load reduction and additional transmission costs are also higher in Western Europe than in the USA. This, results from the higher quality renewable resource in the USA, resulting in higher load factors. Storage and curtailment costs only become relevant at higher shares of solar PV.

Fig. 5 also shows the markups for onshore wind power. The wind markups are much lower than the markups for solar power, especially at high penetration levels. This is partly a result of the higher wind load factor. More electricity production results in a lower LCOE and lower integration markups. There is also a better correlation between wind power generation and peak demand. Since wind power generation is more evenly distributed throughout the year, curtailments occur less often and only at higher penetration levels. Both factors result in a relatively low need for storage and therefore low storage costs. Removing storage hardly effects the integration costs. The markups for USA onshore wind power are very similar to those in Western Europe.

The curtailment data from the RLDC data set implemented in TIMER have been calibrated using the results of the detailed electricity system model REMix. REMix is a deterministic linear optimization model used for the assessment of investment and hourly dispatch in Europe over one year (Gils, 2015). Fig. 6 shows the curtailment and storage loss

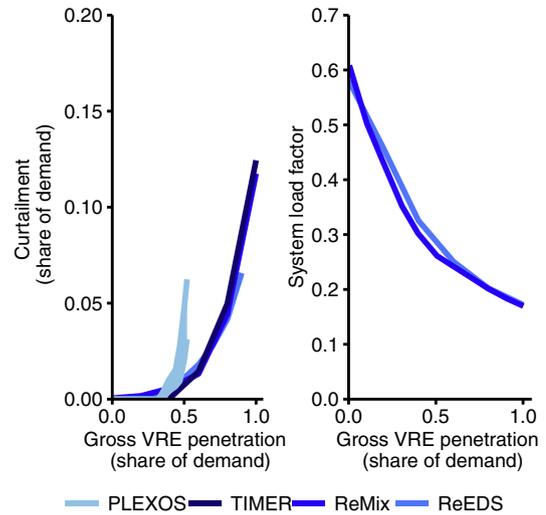


Fig. 6. Curtailment and storage losses (left) and average system load factor (right) at increasing gross VRE share (including curtailments) in the United States (ReEDS) and Europe (other models).

shares of demand in REMix and TIMER at increasing gross VRE shares in Europe (50% solar PV and 50% onshore wind power; gross share includes curtailments), showing that the implementation in TIMER indeed accurately represents the underlying REMix data. The curtailment in the Renewable Electricity Future Study, using the ReEDS model (Mai et al., 2012) is also included in Fig. 6. The scenario conditions differ from the TIMER and REMix data: the study focused on the USA where the individual renewable shares are different (relatively more wind power). Nevertheless, it seems safe to conclude that the ReEDS results show large similarities with the REMix and TIMER results. Fig. 6 also shows the curtailment data obtained by using the PLEXOS model in a study on the impact of generator flexibility on VRE integration (Palchak and Denholm, 2014). The upper bound represents the Western USA electricity system and includes more pessimistic assumptions on flexibility. For the lower bound, more optimistic assumptions are assumed. The curtailment rates obtained from this study are higher compared to those of the other studies.

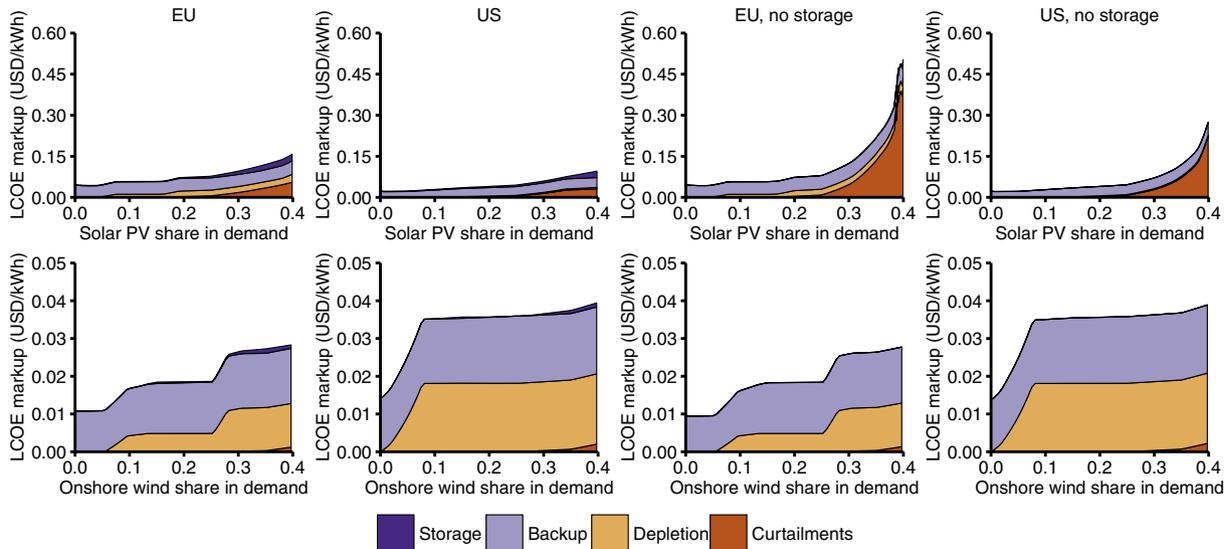


Fig. 5. Marginal TIMER integration costs for solar PV (upper panels) and wind power (lower panels) in Western Europe and the United States with (left panels) and without (right panels) storage use.

The right-hand side of Fig. 6 compares the average system load factor at increasing VRE penetration (of which 50% is solar PV and 50% onshore wind power) for the REMix and TIMER model. As the share of VRE increases, the average system load factor decreases, as less residual load is available, though backup is required due to low VRE capacity credits. Fig. 6 shows that the methodology applied in TIMER is able to capture electricity system dynamics also observed in more detailed electricity system models.

3.1.2. Effects of load bands

Fig. 7 compares the installed capacity in the *Tax30* scenario with and without the *load bands approach*, in order to look at the ability of this approach to capture the effect of load factor decline at higher VRE penetration levels. In a system without a load band approach, more base load technologies, such as coal and nuclear energy, are installed, which also leads to less additionally required capacity. In this situation, CSP actually becomes the most important VRE, since it has a high potential load factor and therefore a low LCOE and high capacity credits. When load bands are introduced, more mid load, peak load and VRE capacity enters the capacity mix. These technologies have relative advantages in load bands with a low load factor, due to their relatively low capital costs (VRE and peak capacity) or low potential load factors (VRE). Peak capacity has high operational costs and therefore it only operates during peak hours. Also an increase in VRE capacity can be observed. As VRE share increases, the load factor of the residual load decreases. In TIMER, this increases the relatively competitiveness of VRE compared to conventional technologies as VRE technologies operate at lower load factors.

Fig. 8 shows the global installed firm capacity (capacity multiplied with the capacity credits) and the global peak demand for electricity. VRE technologies have a lower contribution to peak demand compared to conventional technologies. The degree in which technologies

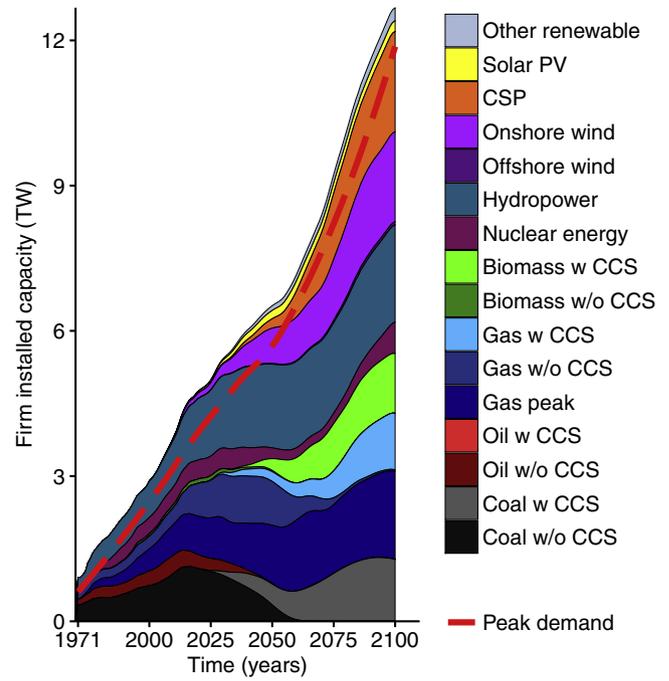


Fig. 8. Global installed firm capacity (stacked graph) and electric peak demand (line) under the *Tax30* scenario.

contribute to peak demand is very much dependant on the region and the share of VRE. Generally, CSP and offshore wind result in the highest peak load reduction. Onshore wind and solar PV have a lower contribution.

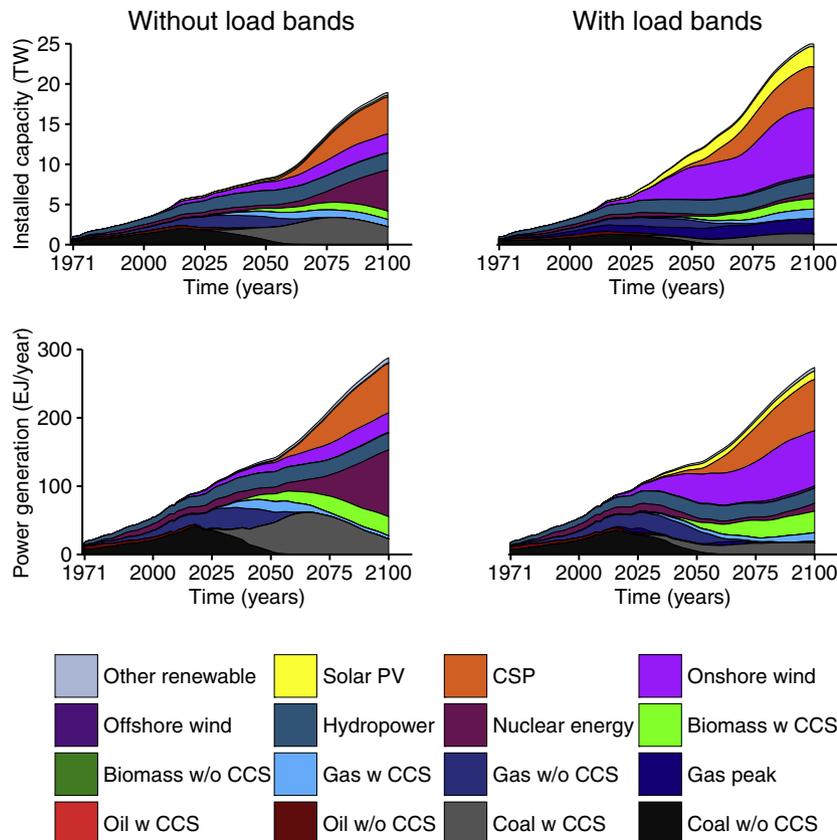


Fig. 7. Global installed capacity (upper) and electricity production (lower) without (left) and with (right) load bands under the *Tax30* scenario (for scenario definitions see Section 2.3.)

3.2. Scenario analysis

The three scenarios explored here (i.e. *Baseline*; *2 °C Policy*, and *RE 2 °C Policy*) look into possible development of the electricity sector with and without climate policy (under the *RE 2 °C Policy* scenario, the use of CCS is not allowed and nuclear power is phased out). Without climate policy, global electricity generation is expected to increase significantly (Fig. 9). Most electricity is produced by coal especially in the long-term, as a result of its increasingly competitive position compared to natural gas (natural gas prices increase substantially over time, whereas coal costs increase much less rapidly; fuel prices are endogenously determined in TIMER). A substantial share of the electricity is generated from VRE, natural gas and hydroelectric power. The natural gas capacity is relatively high compared to the electricity that is generated using gas, given the low load factors resulting from the role of natural gas in mid load and peak load.

Fig. 9 also shows the global electricity generation following the introducing of climate policy. The introduction of carbon policy induces a shift towards VRE, CCS and biomass technologies. VRE mainly consists of onshore wind power and CSP. These two technologies are attractive because of their low costs (especially onshore wind power) and high load factor and capacity value (especially CSP) even at higher VRE penetration. Due to the high carbon costs, fossil-fuel-fired power plants without CCS (coal and gas capacity) are rapidly depreciated under both scenarios. Nuclear power plays a minor role due to the high capital costs. Especially at high VRE penetration and therefore lower load factors, nuclear capacity proves to be too capital intensive. The *RE 2 °C Policy* scenario depends heavily on VRE technology that is backed up by electricity generated from natural gas.

The absence of the CCS technology in the *RE 2 °C Policy* scenario can also be observed when looking at total global emissions from the electricity sector (Fig. 10). Early mitigation under this scenario mainly results from the early retirement of power plants which are replaced

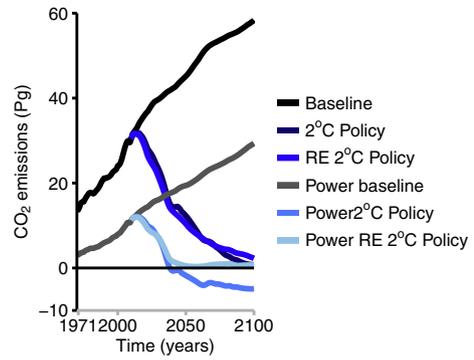


Fig. 10. CO₂ emissions in the total energy and industry sector and the electricity sector under the *Baseline*, *2 °C Policy* and *RE 2 °C Policy* scenarios.

by VRE capacity. From 2040 onwards, mitigation results mainly from other sectors, as electricity sector emissions have already approached their minimum level. In the *2 °C Policy* scenario, the electricity sector continuously plays a large role in mitigating carbon emissions, especially due to the negative emissions that results from biomass CCS at the end of the century.

Total global climate policy costs, measured as area under the marginal abatement curve, are about 30% higher in the *RE 2 °C Policy* scenario compared to the *2 °C Policy* scenario.

3.3. Sensitivity

This section shows some of the key sensitivities of the model. Four variations on the *Baseline* and *Tax30* scenarios are looked at. The variations include:

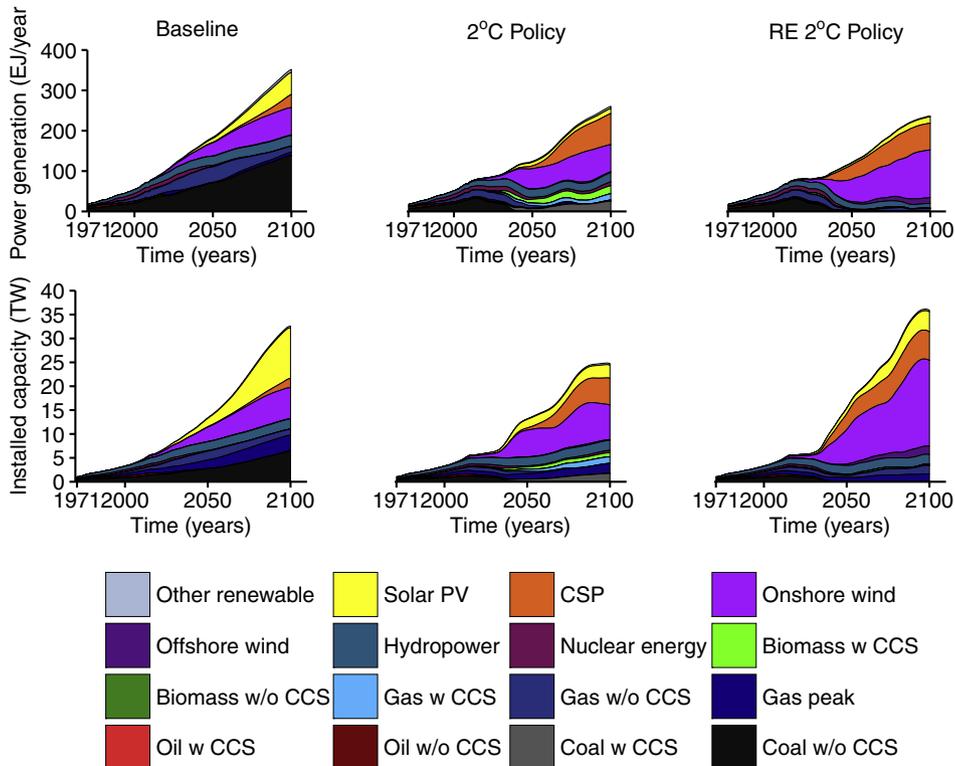


Fig. 9. Global electricity generation under the *Baseline* scenario (upper left), the *2 °C Policy* scenario (upper middle) and the *RE 2 °C Policy* scenario (upper right) and the global installed capacity under the *Baseline* scenario (lower left), the *2 °C Policy* scenario (lower middle) and the *RE 2 °C Policy* scenario (lower right).

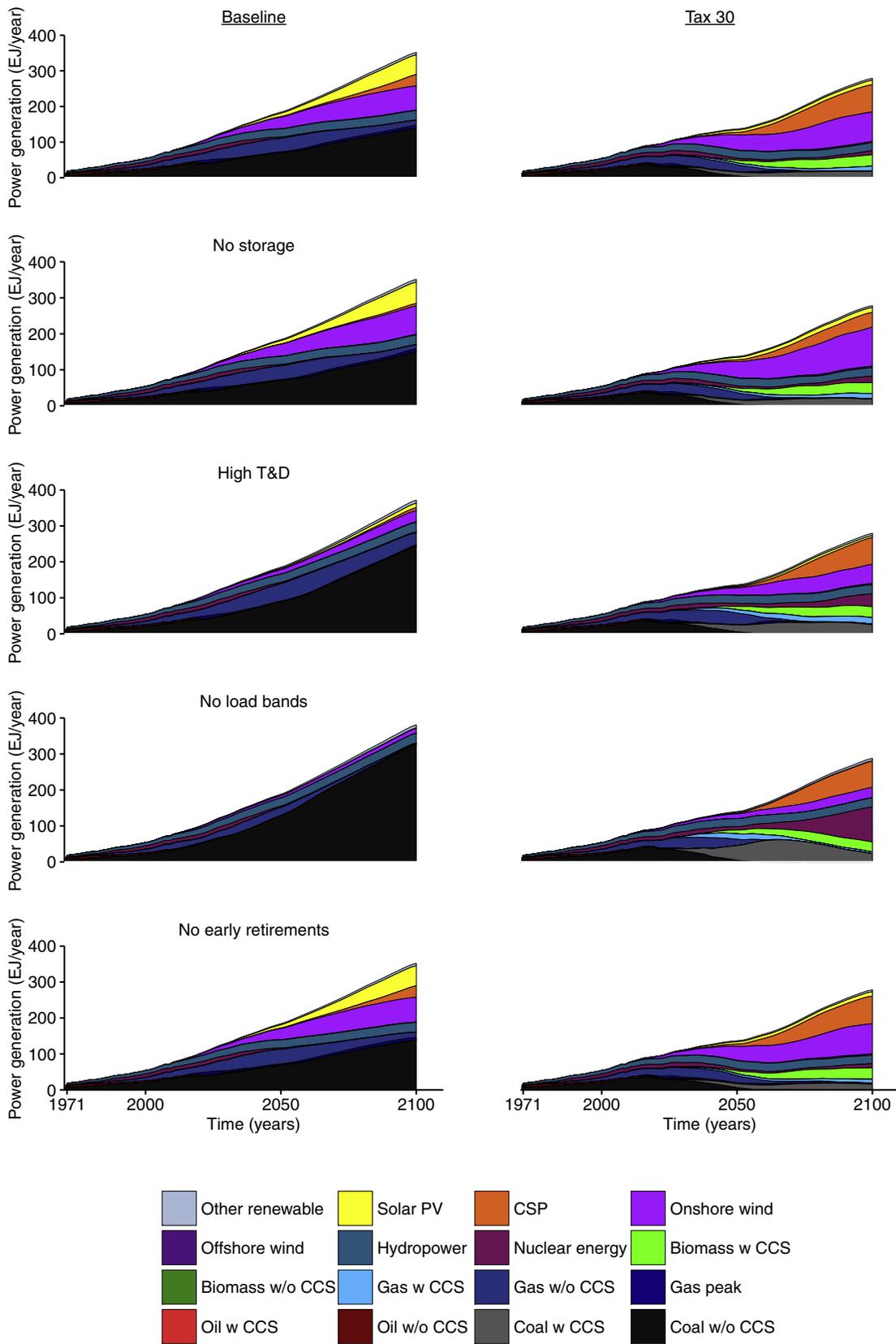


Fig. 11. Global electricity generation in multiple variations on the *Baseline* (left) and *Tax30* (right) scenarios.

1. No electricity storage
2. 50% higher transmissions and distribution costs for VRE
3. No load bands
4. No early retirement of capacity

Fig. 11 shows the global electricity generation in the sensitivity runs.

1. The use of thermal storage (CSP) or electricity storage (wind and solar PV) mainly influences the distribution among VRE technologies

in the *Tax30* scenario. Section 3.1 shows that the use of storage is more important for solar technologies than wind technologies. This is also reflected in the results; when no storage is allowed, relatively more wind power is installed. The results under the *Baseline* scenario are hardly influenced, as the renewable shares are lower in this scenario.

2. The increase in VRE transmission and distribution costs considerably lowers the VRE penetration under both the *Tax30* and the *Baseline* scenario. VRE become more expensive, and therefore alternatives gain more market share. The main alternative under the *Baseline* scenario is coal-fired capacity. Under the *Tax30* scenario, VRE is replaced by CCS and nuclear capacity.
3. The impact of the use of load band investments in mitigation scenario's is already discussed in Section 3.1.2. Under the *Baseline* scenario, hardly any capacity other than coal is installed when not using the load band approach. This is due to the low coal LCOE at maximum load factor as a result of the low fuel costs.
4. Not allowing the early retirement of power plants has a very small impact under the *Tax30* scenario. This is partly due to the gradual increase in carbon tax. Under the *Baseline* scenario, the influence of early retirement is negligible.

Fig. 12 summarizes the influence of these factors on the cumulative CO₂ emissions from the electricity sector. Variations on VRE costs, resource potential (both – 50%, + 100%) and CCS and nuclear energy availability have also been added. Under all scenarios, the *Tax30* carbon tax has been applied.

The largest impact resulted from the exclusion of CCS and nuclear technologies. Under this scenario, no negative emissions occur from the combined use of biomass and CCS. Also, VRE is unable to supply the total electricity demand due to its variability. This results in the use of fossil backup capacity, which results in emissions. Although the role of nuclear power seems limited under the *Tax30* scenario, the penetration would increase if only CCS use was restricted.

The sensitivity of the electricity sector emissions to the other variations is much lower. It is interesting to see that not only increasing the costs of VRE (either indirectly via T&D costs or directly via VRE technology costs) but also decreasing the cost of VRE can have an increasing effect on the electricity sector emissions. Before 2050, lower VRE costs result in a relative emission reduction resulting from the increasing share of VRE. However, this large VRE share also limits the potential for the negative emissions resulting from biomass CCS after 2050. Furthermore, not allowing early retirement of power plants has an emission increasing effect, as carbon-intensive technologies continue to

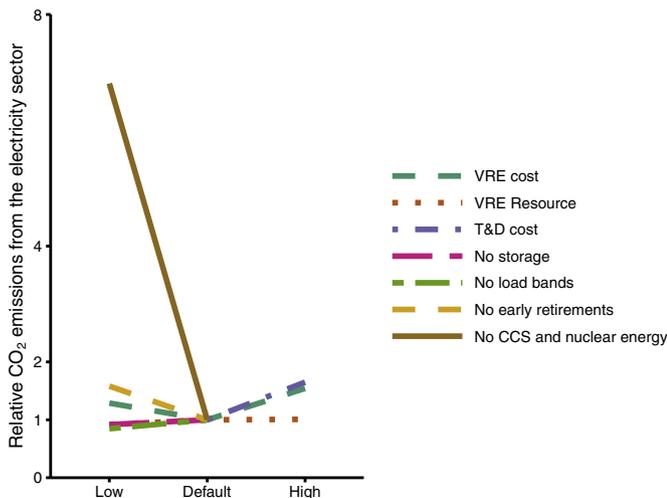


Fig. 12. Relative cumulative CO₂ emissions from the electricity sector under different variations on the *Tax30* scenario, from 2015 to 2100.

operate until the end of their lifetime, even at increasing carbon tax levels. The sensitivity of electricity sector CO₂ emissions to the use of load bands, electricity storage and resource size is relatively limited. The full potential of renewable energy is actually not achieved in most regions. Reducing or increasing the potential only changes the rate at which depletion costs increase.

4. Discussion and conclusions

4.1. Discussion

This paper presents a methodology for representing the electricity sector behaviour in the energy simulation model TIMER using a heuristic approach to find cost-optimal paths given system requirements and scenario assumptions. The model focusses on understanding long-term trends. Therefore, it does not represent the detail for doing in-depth electricity system analyses, but is designed to give an adequate representation of the electricity sector in a long term integrated assessment environment. This representation is tested by showing that key electricity system model dynamics behave similar compared to more detailed electricity models. This is consistent with Pietzcker et al. (2017-in this issue) who evaluated VRE integration in multiple integrated assessment models. However, while interpreting the results the following aspects need to be taken into consideration:

- The method applied uses a central planner perspective rather than considering individual investors. Investments are therefore based on one actor minimizing costs and not on the complex relationship between multiple actors trying to maximize profits. Therefore, the installed capacity in TIMER is always able to supply peak demand and no capacity market simulation is required. The heterogeneity that could result from multiple actors is obtained by applying a multinomial logit for investments.
- Investments into hydropower are exogenously determined. However, hydropower could play an important role in an energy system with a large share of renewables. Modern hydropower is known for having large ramping capabilities. Besides, pumped hydro storage can be used for (seasonal) electricity storage. The positive impact of hydropower on VRE integration in TIMER has been captured by forcing hydropower to dispatch in peak hours, therefore reducing the peak load.
- Interregional trade between the 26 world regions in TIMER is not simulated, and therefore scenarios in which renewable electricity is exported from resource-rich regions to resource-poor regions are not considered. However, the impact is expected to be limited by the fact that the TIMER regions are rather large and electricity exchange within a region is fully possible.
- Electricity system parameters, such as spinning reserve requirements, start-up and shut-down costs of power plants, ramp rate constraints and minimum loads, are not considered in TIMER. These are likely to result in larger VRE integration constraints. It should be noted that the increasing need for flexibility is indirectly addressed in TIMER by the fact that the less capital-intensive capacity applied in the mid and peak load is usually from gas-fired plants. This gas-fired capacity is known for having excellent flexibility coefficients. The impact of network congestion on VRE integration is included in the construction of the RLDC dataset.
- TIMER uses static (R)LDCs: the distribution of VRE supply and electricity demand is constant over the years. This assumption is most questionable for developing regions. The correlation between solar supply and demand in India is currently low, but is likely to increase due to the increasing use of air conditioning, as a result of economic development and increasing global temperatures.
- Besides, the RLDC data was available for a couple of regions, and has been allocated to other regions based on geographic location and

GDP. The quality of the method can be improved by developing a method that is able to produce RLDC data based on geographical location and regional TIMER demand sector characteristics.

- In addition, RLDC data for onshore wind and solar PV are available. These have been directly translated to offshore wind and CSP. This research could be improved by including dedicated offshore wind RLDC data, as the supply of offshore wind is likely to have different correlation with demand compared to onshore wind. The translation of solar PV with storage to CSP is probably more realistic.
- The RLDC data includes exogenously optimized use of storage at fixed storage costs. Because the application of storage is not determined by using TIMER parameterization, the use of storage could result in sub optimal outcomes. Also, storage cost developments are not considered.

4.2. Conclusions

IAMs explore long-term mitigation scenarios. At the aggregated level the model operates, it is difficult to represent all dynamics relevant for electric electricity sector behaviour. The paper describes a new load-band based simulation model for electricity supply. The paper looks into the ability of the model to represent the additional costs of VRE penetration and into future electricity system developments with and without climate policies, including key uncertainties.

Results show that key dynamics in the dispatch of and investment in electricity supply technologies can be represented using the proposed model. Earlier research has identified various integration constraints. The most important constraints have been added to TIMER in the form of a LCOE markup. Much of the size of this markup depends on the correlation between electricity demand and VRE supply. In the USA and in Western Europe, this correlation is often higher for wind technologies compared to solar technologies. The use of electricity storage or a mid-day high demand resulting from the use of air conditioning increases this correlation with solar PV. At lower penetration levels, backup costs generally form the largest part of the integration costs. Only at higher penetration level, when VRE supplies more than 30% of the electricity demand, the costs of storage and energy curtailments become increasingly important. This paper also shows that cost assumptions and the inclusion of (residual) demand fluctuations in capacity investment decisions considerably influences the electricity mix. Peak load and mid load require less capital-intensive technologies than base load. At higher VRE penetration, the need for mid and peak load technologies increases.

In a scenario without climate policy, coal is projected to be the major fuel used for generating electricity. This is due to the low total costs of coal capacity and operation in many regions. VRE and natural gas technologies play a smaller role. From 2050 onwards, the role of VRE increases due to reductions in VRE costs, while costs of natural gas increase. As a result of this increasing VRE share and the inclusion of load bands in the investment decision, gas technologies remain in the capacity mix to serve the increasing peak and mid load.

When introducing climate policy, carbon low technologies like VRE and CCS enter the capacity mix. Besides, fossil capacity is retired early and replaced by these technologies. At low carbon-tax levels, VRE technologies and fossil fuel with CCS are able to compete. At higher carbon tax levels, biomass combined with CCS enters the capacity mix, which results in negative emissions. Nuclear power is projected to play only a minor role due to its high capital costs. At higher load factors, nuclear power could be profitable. However, the increasing VRE share reduces the amount of full load hours available and the load band investment decision translates this into less investments into nuclear power.

If CCS and nuclear technologies are not to be available, a higher deployment of variable renewable technologies and additional effort from other sectors are required to achieve similar reduction levels. This leads to higher costs and less electricity sector emission reduction compared

to a scenario under which CCS and nuclear options are available. The capacity mix mainly consists of CSP and onshore wind. Gas capacity is installed for the remaining peak hours.

Main sensitivities of the model on greenhouse gas emissions from the electricity sector include the availability of carbon capture and storage (CCS) and nuclear power, and the costs of VRE. The mitigation also showed to be sensitive to VRE costs. Increasing or decreasing the regional VRE resource potential influenced the mitigation to a more limited extent.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <http://dx.doi.org/10.1016/j.eneco.2016.12.006>.

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