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Capturing physical, technical and economic constraints on electricity generation: a description of the IMACLIM-R electricity module

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IMACLIM-R is a twelve region, recursive hybrid general equilibrium model that in- cludes a technology-rich,bottom-up electricity module. The long-term investment decision is represented by a modified multinomial logit structure in which 20 explicit technologies compete based on the most current electricity generation costs. The cost competition takes place under imperfect foresight and with various possible regimes of beliefs about future climate policy. Key characteristics of electricity supply are presented: Capital obsolescence, fuel efficiency, load factor, carbon capture and storage, renewable integra- tion challenges. Both investment and dispatch decisions are made on an annual basis, beginning in 2015, to provide meaningful insights into future electricity systems, their contribution to climate change mitigation, and their linkages with the rest of the economy.

Working paper

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I. INTRODUCTION

Climate change mitigation goals require profound changes in socioeconomic production systems. This is especially true for the energy system (electricity and heat generation), which is responsible for 15.5 Gt CO2 emissions in 2021, or 43% of energy-related CO2 emissions (IEA, 2021). Emissions from the power generation sector come from the com- bustion of fossil resources, namely coal, oil, and gas, in existing power plants. It is now widely recognized that achieving ambitious decarbonization targets requires a rapid phase-out of fossil fuel combustion. However, given the inertia of capital in this sector (power plants are expected to operate for decades), today's option for power generation is determined by the capacity built in the past. Therefore, an accurate representation of power generation capacity expansion decisions is key to capturing current and future power system developments needed to address climate change. The presentation of the main characteristics of electricity systems ultimately requires consideration of two types of decisions made under techno-economic constraints:

the long-term choice of optimal capacity to match future electricity demand (invet- ment)

the short-term choice of capacity utilization to supply current load (dispatch)

The investment and dispatch decisions are addressed in separate sub-modules of the elec- tricity module (or electricity nexus) of IMACLIM-R. Note that in our framework, the electricity sector refers to the sector in the macroeco nomic core of IMACLIM-R, while the electricity module or nexus refers to its dynamic, bottom-up counterpart.

Below, one will learn more about the modeling framework for investment and dispatch decisions. We begin with a characterization of the technical and economic conditions of electricity generation: section 2 describes the technical and cost assumptions underlying the choice of electricity generation capacity, while section 3 presents the inclusion of demand-side and renewable energy generation constraints. The next sections detail the investment (section 4) and dispatch (section 5) decision frameworks. Section 6 details the link between the electricity nexus and the rest of the economy, while section 7 presents the main results of the nexus.

A bottom-up description of electricity generation conditions

II. Explicit electricity generation technologies described in terms of capital generation

Cost assumptions and technical change in the electricity sector. In the current version of IMACLIM-R, 20 technologies are available for investment in electricity genera- tion. Each of the 20 technologies is characterized by a set of techno-economic parameters that can be used to calculate the levelized cost of electricity (LCOE). These parameters include: Investment costs, energy efficiency, fixed and variable operation and maintenance costs, an availability factor for dispatchable technologies (in % of full load hours), a capacity factor for non-dispatchable technologies (in % of full load hours), lifetimes, and adiscount rate that includes both the opportunity cost of capital and a unique risk factor for each technology (Briera and Lefèvre, in prep.).
The techno-economic parameters for each technology are calibrated using sectoral technology models or information from the literature (IEA, 2020b, IRENA, 2020) For immature technologies, costs decrease over time through a global learning process modeled by learning curves (Neij, 2008). Learning curves link production costs to cumulative production through a learning coefficient. In the case of the electricity sector, the cost of electricity production is expected to decrease with cumulative installed capacity for a given technology. In the base year of the model (2014), all regions in the IMACLIM-R model start with different cost assumptions. In addition, minimum costs are defined in each region: these are the lowest costs that can be achieved through a learning process. As a result, the learning process is global (each region benefits from the capacity additions of the others), but the initial and asymptotic costs remain differentiated. This decision is justified by two findings:
1) wind turbines and PV modules are traded as commodities.
2) capital costs varies by location due to national or regional circumstances, such as labor costs. With $CINV_{k,j}(t)$ the current investment cost for technology *j* in region *k* at time *t*, $CINV\_ref_{k,j}$, the reference investment cost (at calibration year), $A\_CINV\_ref_{k,j}$ the floor cost, LR_j the learning rate, $Cum\ Inv\ ref_{k,j}$ the cumulative investment of technology *j* in region *k* in the calibration year, $Cum\ Inv_{k,j}(t)$ the cumulative investment at time *t*:

$$CINV_{k,j}(t) = max(A\_CINV\_ref_{k,j}, CINV\_ref_{k,j} * (1 - LR_j)^{log(\frac{Cum\_Inv_{k,j}(t)}{Cum\_Inv\_ref_{k,j}})}) \quad (1)$$

As the cost of renewable energy has declined recently, the CAPEX and OPEX curves for wind and solar (including CSP) are driven to adjust to recently observed levels in the region. This means that the decline in renewable energy costs between 2014 and 2019 is monitored and not driven by the learning curve.

Carbon Capture and Storage. The electricity nexus of IMACLIM-R includes both fossil fuel carbon capture and storage (CCS) and bioenergy with CCS (BECCS) technolo- gies. In the current version of the model, CCS for power generation technologies does not enter the R&D phase until a threshold for the current regional carbon price is reached to prevent early CCS deployment despite low or negative profitability. The market share of each CCS technology is limited by an S-shaped technology development function. In the case of BECCS, an additional biomass supply curve limits the deployment of this technology (Hoogwijk et al., 2009). In the current structure of IMACLIM-R, BECCS are the only source of negative emissions. Therefore, the pace of BECCS deployment is critical in very low-carbon/net-zero mitigation pathways. Fossil fuel technologies cannot be retrofitted with CCS, so new power plants must be built to capture and store carbon. Retrofits and early decomissionning will be added in future versions of the model.

Capital inertia. In the electricity sector, the capital stock is path-dependent, as each investment at time t adds to the capacity built in previous periods. The variable Cap vintagek,j (t) tracks annual capacity additions for technology j in region k. Thus, the depreciated capital at time t is the sum of the generations of capital that reach the end of their lives from time t − lifetime to t − 1 (Cap depk,j (t) in Equation 3). Adding the new investments to the depreciated capital stock at time t gives the functioning capital at time t before the new capacity addition from the investments.

$$Cap\_vintage_{k,j}(t) = Inv_{k,j}(t) \quad (2)$$

$$Cap\_dep_{k,j}(t) = \sum_{i=t-lifetime_k}^{t-1} Cap\_vintage_{k,j}(i) \tag{3}$$

$$Cap_{k,j}(t) = Cap\_dep_{k,j}(t) + Inv_{k,j}(t) \tag{4}$$

At each time step of the model, the average characteristics of installed production ca- pacity are the weighted average of the technical characteristics of the different generations of power plants still in operation. The inertia of power plant capacity is represented by the tracking of capital across generations along with their technical characteristics.
Each year, the production units that reach the end of their life are decommissioned. If we add the annual capacity additions i.e. investments, we get a net installed capacity.
The new generation of capital capacity and its technical characteristics are determined by the investment decisions described in the following sections.

III. A challenge to incorporate demand-side and renewable energy supply constraints in a compact electricity module

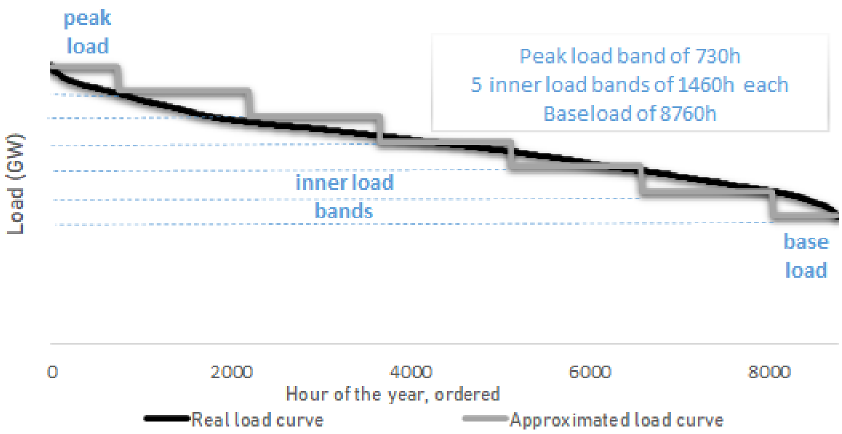
Final energy demand in IMACLIM-R. In IMACLIM-R, final energy demand re- sults from three (meta) sectors: productive sectors, transport sectors, and the residential sector. For the transport and the residential sectors, which benefit from detailed bottom- up representations, the use of electricity depends on explicit technology choices, e.g. the purchase of electric cars instead of internal combustion engine cars. In the case of pro- ductive sectors (agriculture, industry, construction, composite goods), electricity demand is determined by input-output coefficients.

The load duration curve. It is common to combine the daily load curves over the 365 days of the year into a single curve, the load duration curve. It summarizes information about the size and degree of utilization of the capacity needed to meet demand throughout the year. The load duration curve is obtained by plotting hourly load values over the year against the duration for which that load was requested. The highest recorded load over the 8760 hours of the year is called the peak load. The minimum power supplied over the year is the base load. Thus, the balance between electricity demand and supply can be resolved annually using the load duration curve. It allows not relying on an external high-resolution energy model, but it also has its pitfalls, especially in terms of information losses in intraday processes such as short-term storage. These limitations are overcome by integrating additional bottom-up data into the nexus (see subsection "The Residual Load Duration Curve and the challenges to VRE integration").

The shape of the load duration curve is specific to each region, as it is directly related to the temporal variability of electricity demand. This variability depends in particular on the seasonal climate variations in the region. For numerical simplicity, the regional load duration curves were approximated by segmented linear functions:

- the possible annual loads (measured in hours) are divided into seven intervals with the following boundaries: [0, 730, 2190, 3650, 5110, 6570, 8030, 8760];
- the maximum load lasts 730 hours (peak load);
- the minimum load lasts 8760 hours (base load);

Figure 1:
Load duration curve approximation in IMACLIM-R's electricity module



- the load level for the other periods of time is calculated by dividing the interval between baseload and peak load into six equal segments *i.e.* 760 hours of baseload, 760 hours of peak load, and five segments in between of 1460 hours each.

This results in the shape of the load duration curve in Figure 1: a peak load band, 5 inner load bands, and a base load band. With this simplified scheme, the load duration curve of each region can be fully characterized by two values: peak load and baseload. The annual electricity produced is given by the area under the curve in Figure 11.

To calibrate and reconfigure the load duration curve for each time period, we assume that the ratio of peak load to baseload, (written bp ratiok) remains constant and equal to a value supplied by the POLES model.2 The load duration curve approximation associated

with a quantity Q_elec_k of electricity produced in the region k, is obtained by solving the equation system, formed by the ratio constancy equation and the constraint equation on the quantity of energy produced, as described in equations 5 and 6 where basek and peakk are the loads required during the base or peak periods respectively.

$$\frac{base_k(t)}{peak_k(t)} = bp\_ratio_k \tag{5}$$

$$\begin{aligned} Q\_elec_k(t) &= 730 * peak_k(t) + 8760 * base_k(t) \\ &+ (8030 + 6570 + 5110 + 3650 + 2190) * \frac{peak_k(t) - base_k(t)}{6} \end{aligned} \tag{6}$$

The shape of the load duration curve provides information about the optimal amount of electricity generation capacity needed to meet peak demand and when that capacity should be used during the year. To go further, we need to consider the impact of renew- ables on the load curve. Residual load duration curves (RLDCs) describe the physical and temporal constraints on electricity demand and supply, including the challenges of integrating variable renewables into power systems.

1
In this figure, the "real load duration curve" corresponds to a hypothetical example to illustrate how load duration curves are approximated. The reader should keep in mind that there is no such "real load duration curve" in IMACLIM-R, only an annual electricity demand from which an approximated load curve is derived

2
In principle, this ratio could vary in an exogenous or endogenous manner to integrate, for example, its modification under the effect of policies of demand side management. These policies are not implemented in the current version of the model.

The residual load duration curve and the challenges to VRE integration. Variable renewable energy sources (VRE) such as photovoltaics or wind are inherently non- dispatchable. Therefore, their deployment affects the operation of power systems (Hirth et al., 2015). Renewable generation increases the need for flexibility in the power system, including dispatchable power to meet peak demand. Indeed, the capacity credit of VRE (the ability to contribute to meeting peak demand in a power system) is low and decreases as the share of VRE in the mix increases.

In order for the technologies to compete on an equal footing (dispatchable vs. vari- able), we must first adjust the LCOE of VRE to account for its low capacity credit, i.e., the contribution of variable renewables to meeting peak demand. In other words, the "hidden costs" associated with VRE generation are not included in VRE's LCOE. There- fore, we add to VRE's LCOE what is called "integration costs" to calculate VRE's system LCOE, which covers the full economic cost of solar and wind generation. Integration costs measure the costs imposed on the power system to maintain the marginal value of renew- able electricity. This includes investments in storage facilities, grid costs, backup costs, etc. Typically, integration costs are divided into three categories, each related to the basic characteristics of renewable energy: uncertainty, locational constraints, and variability.

- Balancing costs (uncertainty). They gather actions taken to face VRE output un- predictability, for instance, the cost of intraday trading. Balancing costs tend to zero in absence of forecasting errors on VRE output.
- Grid-related costs (locational specificity). Grid-related costs measure the reduction in market value due to the specific generation location of power plants.
- Profile costs (variability). Profile costs reflect the marginal value of electricity at different moments in time. As the demand varies through time, profile costs measure the cost of matching this demand with VRE storage devices or conventional backup power.

However, estimating value ranges for profile costs and other integration costs is not straightforward. With 20% renewables in the electricity mix, reported values for integra- tion costs range from €0/MWh to €49.2/MWh (Heptonstall & Gross, 2021), reflecting a high degree of uncertainty in integration cost estimates. Indeed, the extent of the loss in the market value of renewable electricity depends on the (in)flexibility of the rest of the electricity system. The more flexible the system, the lower the integration costs. Con- sequently, estimates of integration costs depend on the underlying energy model and its techno-economic assumptions. The alternative to estimating integration costs would have been to rely on a much more detailed, soft-linked energy system op- timization model that includes explicit flexibility solutions for VRE deployment. In this way, we would have lost all the benefits of an embedded power module. Therefore, we chose a synthetic way to account for integration costs through an integration cost markup for PV and wind. The PV (or wind) markup, expressed in $ per MWh of PV (or wind), is linear with respect to the fraction of wind and PV gross generation and sums to the PV (or wind) electricity generation cost. The parameters α,β, γ and δ are calibrated to reflect typical values of integration costs (in $ per MWh of VRE generation).

$$Markup_k^{pv}(t) = \alpha * Gross\_pv\_share_k(t) + \beta * Gross\_wind\_share_k(t) \tag{7}$$

$$Markup_k^{wind}(t) = \gamma * Gross\_pv_share_k(t) + \delta * Gross\_wind\_share_k(t) \tag{8}$$

$$Integration\_costs_k(t) = Markup_k^{pv}(t) * \frac{Gross\_pv\_share_k(t)}{Gross\_pv\_share_k(t) + Gross\_wind\_share_k(t)} + Markup_k^{wind}(t) * \frac{Gross\_wind\_share_k(t)}{Gross\_pv\_share_k(t) + Gross\_wind\_share_k(t)} \tag{9}$$

We still lack robust data to calibrate the integration cost markup parameter and rely on the few existing studies. These parameters will be updated as comprehensive, peer- reviewed studies on integration costs are published. The sensitivity analysis in the figure [forthcoming: sensibility analysis on the markup parameters] shows that the integration cost markup parameter is of great importance for VRE deployment.

The VRE markup is the counterpart of the cost of variable renewables in the rest of the power system. This is captured by a distortion of the residual load duration curve as the share of renewables in the mix increases: the higher the share of renewables, the steeper the residual load duration curve (Ueckerdt et al., 2015). Thus, following the ADVANCE "Variable Renewable Energy integration module project (Ueckerdt et al., 2017), the residual peak load becomes a function of VRE gross generation:

$$peak\_res_k(t) = f(Gross\_wind\_share_k(t), Gross\_pv\_share_k(t)) \tag{10}$$

with the f a third-order polynom (see Annex for the polynomial coefficients).

This way, base res and peak res are now determined by Equations 10 and 11: Equa- tion 5 no longer holds. However, Equations 10 and 11 do not prevent negative residual baseload. Thus, Equation 11 includes the possibility to adapt if solving the system of equations 10 and 11 yields negative residual baseload. If for nb steps = 6 (starting case), the residual baseload is negative, the 8760h load band is removed, and the system of equations 10 and 11 is solved again with one less load band, as shown on Figure 2. It implies that the conventionnal capacity does not provide a minimum power throughout the year. This way, the residual load curve is always positive and conserves its proper- ties. A version of the residual load duration curve design with a miminum load band (Ueckerdt et al., 2015) (continuous supply from dispatchable plants throughout the year) is currently under developement.

$$Q\_elec\_res_k(t) = peak\_res_k(t) * 730 + base\_res_k(t) * lower\_load\_bands_k + \frac{peak\_res_k(t) - base\_res_k(t)}{nb\_steps_k} * (\sum inner\_load\_bands_k) \tag{11}$$

The residual peak load and the net share (without curtailment) of non-VRE generation in total demand depend on the gross VRE generation. Additionally, the ADVANCE project module was also used to calibrate 1) VRE curtailment and storage losses 2) storage capacity and output as a function of the share of solar PV and wind energy in the mix, the same way the residual peak load does (see equation 10).

$$curt_k(t) = g(Gross\_wind\_share_k(t), Gross\_pv\_share_k(t)) \tag{12}$$

$$stor\_cap_k(t) = h(Gross\_wind\_share_k(t), Gross\_pv\_share_k(t)) \tag{13}$$

$$stor\_output_k(t) = m(Gross\_wind\_share_k(t), Gross\_pv\_share_k(t)) \tag{14}$$

In the end, this residual load duration curve design allows representing VRE integra- tion challenges in a compact electricity module such as IMACLIM-R's by relying on the highly resolved Dispatch and Investment Model for Electricity Storage (DIMES) outputs. Basically, it allows the electricity sector of IMACLIM-R to include the impact of variable renewable energy on the electricity system in a simple, yet robust manner. It captures key mechanisms behind the variable renewable energy penetration challenge and yields consistent projections (see section 7).

Storage. For now, only short-term storage is represented in the electricity nexus: stor- age capacity, outputs and losses are extracted from the DIMES output (see equation 13 and 14) and DIMES only optimizes short-term storage. Thus, seasonal (long-term) storage is not included yet in the electricity nexus. An explicit representation of storage capacity needs and ouputs is currently under developement.

Grid and Transmissions and Distribution Losses. Investments in grid infrastruc- tures are not modeled in the electricity module of IMACLIM-R. The extra needs related to VRE deployment are included in the VRE markup. Transmissions and Distribution (T&D) losses are included in the form of an intra electricity sector input-output coefficient, expressing T&D losses as a share of total electricity output.

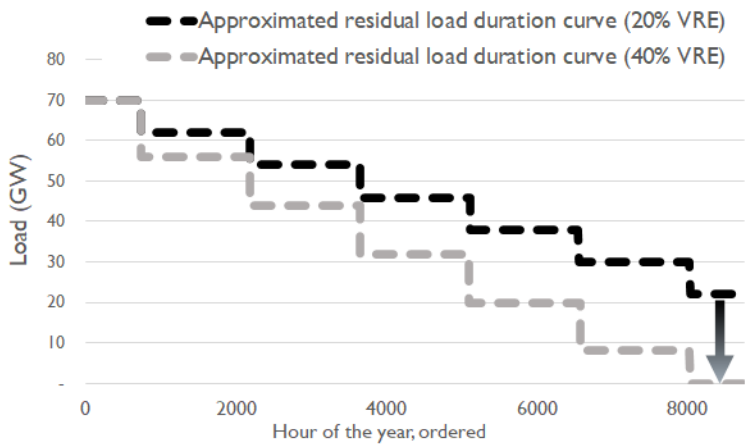


Figure 2:
Illustrative RLDC approximation for 20% and 40% net VRE share

IV - Optimal planning of investments under imperfect foresight

With the compact representation of power generation technologies and the (residual) load duration curve presented above, we have the necessary technical details to model investment decisions in the power sector on an annual basis. The optimal capacity to meet expected demand over an intermediate time horizon (t+10 by default) is then compared to existing capacity to derive the annual investment plan. The final investment decision is decomposed into five sequential steps:

1. Formulating expectations about future demand and future fuel prices;
2. Choosing wind turbine and solar PV electricity production capacity;
3. Choosing hydroelectric production capacity;
4. Projecting the optimal conventional (non-renewable) production capacity to meet domestic demand;
5. Deciding on the annual investment necessary to move the existing production ca- pacity towards the optimal capacity that has just been calculated.

The optimal planning procedure relies on a modified multinonial logit structure (Clarke & Edmonds, 1993), which is an alternative to forward-looking cost optimization in simula- tion and recursive dynamic Integrated Assessment Models (Joint Global Change Research Institute, 2022). The modified multinomial logit structure acknowledges for the fact that determining factors in the investment decision are not modeled, such as individual pref- erences (e.g for nuclear power) and local variations in electricity generation conditions. The separate treatment of VRE and hydropower is justified by the special characteristics of these energy sources. A more detailed explanation of these peculiarities is provided below.

Projected demand, fuel prices and carbon tax. The optimal installed capacity and level of annual investments are determined using backward-looking expectations of electricity demand growth and future fossil fuels prices over the coming ten years.
The projected electricity demand for the period $t+10$ in region k, written $Q\_elec_k^{anticip}(t)$ (in MWh), is computed assuming an arithmetic growth of future demand, with Q_elec_k the final electricity demand of period $t-1$:

$$Q\_elec_k^{anticip}(t) = Q\_elec_k(t) + (Q\_elec_k(t) - Q\_elec_k(t-1)) * 10 \tag{15}$$

Expected electricity demand addressed to conventional (non-renewable) power plants is associated with an anticipated residual load duration curve which is determined using the results from the resolution of the equation system 10-11.
Current fossil fuel prices are taken as anticipated future prices. Thus, we assume that, given the uncertainty of short-term fluctuations in fossil fuel prices, electricity producers consider current prices to be the best available information Regarding the carbon tax on fossil fuels, the IMACLIM-R rationale allows for different beliefs regarding climate policies. By default, the trajectory of the carbon tax is not known. The current carbon tax is projected over the lifetime of the power generation project to calculate its LCOE. Therefore, the current carbon tax is the main climate policy tool. However, it is possible to allow for :

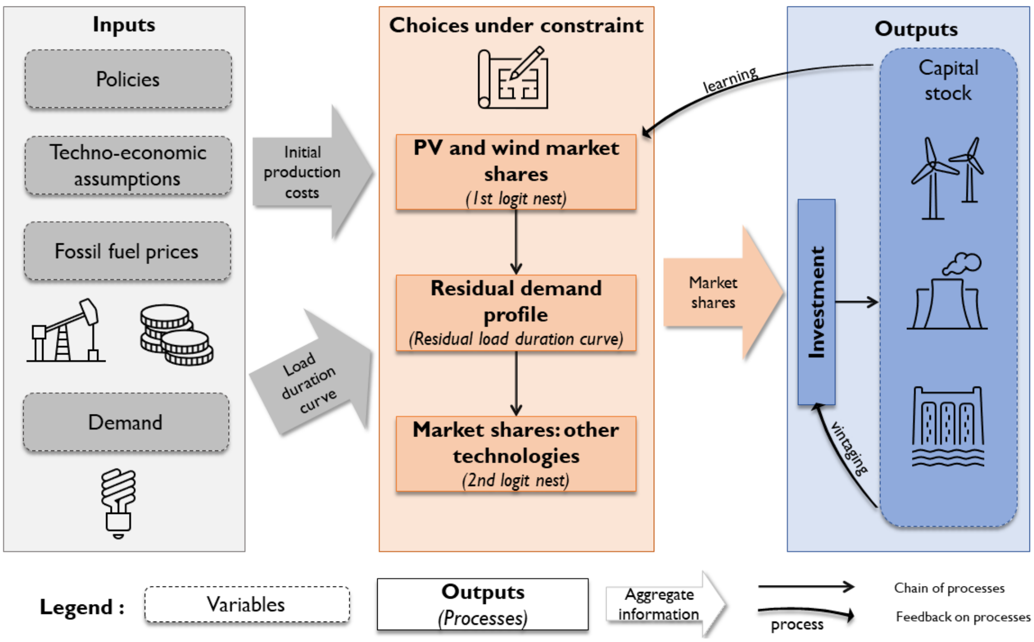
- alternative regimes of expectations, e.g. perfect foresight on the carbon tax trajec- tory
- divergent beliefs among actors about the future carbon tax, depending on the level of confidence in climate policy. These divergent beliefs could even be endogenized in future model developments.

Determining investments in non-hydroelectric renewable production capacity. The investment decision in IMACLIM-R for both renewable and non-renewable technolo- gies is based on a modified multinomial logit (or modified logit). It also accounts for the fact that the cheapest option does not displace more expensive technologies in the electricity market when there is uncertainty, incomplete information, energy security con- cerns, etc. The modified multinomial logit choice function takes as input a vector of LCOE (referred to as the choice indicator in the logit framework) and returns a vector of market shares for the corresponding alternatives. The random term is assumed to follow a Weibull distribution such that the market share Sk,i for technology i in region k is given by equation 16: With γ the logit exponent, $LCOE_i$ the LCOE, $\alpha_{k,i}$ the share weight of technology i, and *N* the number of technological options. We also assume that the central planner in the electricity market selects the market share for a medium-term horizon (ten years) based on the current costs of the technologies.

$$S_{k,i}(t) = \frac{\alpha_{k,} * LCOE^{\gamma}_{k,i}(t)}{\sum_{j=1}^{N} \alpha_{k,j} * LCOE^{\gamma}_{k,j}(t)} \tag{16}$$

In the electricity sector of IMACLIM-R, a first logit nest determines the share of vari- able renewables (wind and solar PV) and the aggregate share of non-variable renewables in total electricity generation. The market share for each non-variable renewable energy is determined by a second logit nest. The choice indicator for the aggre- gated dispatchable plants' share is the lowest LCOE on baseload[3]. The weight shares $\alpha_{k,i}$ are calibrated to reproduce 2018 observed market shares for the four VRE technologies (wind onshore, wind offshore, central PV and rooftop PV) and progress thereafter towards equal weight- ing. Thus, we assume that all non-LCOE factors driving VRE deployment (financial support like feed-in tariffs, national preferences etc.) are declining, electri- city generation technologies ending by competing solely based on their economic costs.
The sum of the VRE market shares yields the share of net VRE generation in the total expected electricity de- mand in region k. The remaining ("residual") demand must be met with dispatchable power plants, including hydropower, CSP and conventional thermal power plant.
As shown in Figure 3, the first logit nest determines the global share of variable renewables from which the residual electricity demand for dispatchable capacity is derived. Once the residual load duration curve is approxi- mated, dispatchable technologies compete for each load band in the second logit nest.

Figure 3:
Summary of the investment procedure in the electricity sector



3
Technologies with limited potential due to resource endowment constraints (hydro, CSP) or social acceptance (nuclear) were excluded from the non-variable renewables choice indicator.

Investment in hydroelectricity Hydropower is treated in a special way because in- vestment in this technology is contrained by the regional physical potential. In this mod- ule, we make no distinction between run-of-river and conventional (dammed) hydropower plants. Therefore, investments in hydropower plants in this module are exoge- nous and comes from the POLES model (Keramidas, K. et al., 2018).

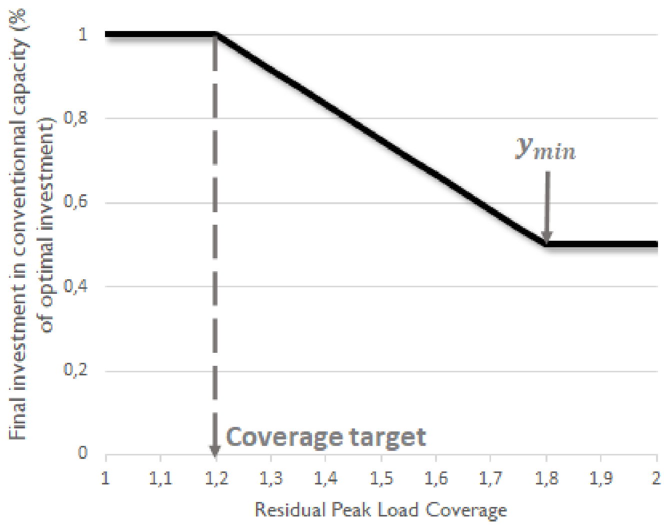
Conventional installed production capacity Once the optimal share of VRE gener- ation is know, the residual load duration curve is derived following the procedure described in the "Residual load duration curve" section.
Planning the conventional installed production capacity at minimal cost for the period t+10 means determining, for each discrete segment of annual utilization, the cheapest production mix. Assessing the competitiveness of a technology to satisfy a fixed annual utilization period is done by calculating the discounted total production cost of a *kW* over this utilization period. The corresponding variable, written $LCOE_H$, is computed for each load band of width *H*. In other words, the module computes for each conventional technology the levelized cost of producing 1 *kW* of power for *H* hours over the plant's lifetime, *H* corresponding to one of the seven load bands width. When H equals full load hour (8760h), then this metric corresponds to the standard LCOE.
LCOEH includes:

- the (annualized) capital cost or construction cost
- the fixed total discounted operation and maintenance costs per kWh installed
- the variable total discounted operation and maintenance costs per kWh produced
- the total discounted fuel costs, calculated using the final price scenarios of the anticipated fossil energies.
- the availability factor, which incorporates planned outages and maintenance
- the cost of capital which serves as a proxy for the discount factor

Thus, the market share for each load band is derived by a second modified multino- mial logit nest where only dispatchable power plants compete. Hydropower generation is removed from the lower bands of the residual load curve because hydropower investments are autonomous and hydropower is dispatched first (i.e in the lower load bands) due to its very low variable cost. The module can determine the required installed capacity of conventional power technologies available for investment to meet the expected electricity demand of t+10 by summing the desired capacity for each load band.

Final investment: minimizing the distance between the optimal production capacity and the installed capacity
The procedure described in the previous sub- section allows us to define at each period t the optimal anticipated produc- tion capacity for the period t + 10. Between t and t + 10 an investment plan determines the yearly capacity additions needed to reach the optimal t + 10 capacity.
In the present version of the model, it is not possible to either remove certain produc- tion capacity before the end of their lifetime or modify the technologies embodied in the installed plants, i.e. there is no early decommissioning or retrofitting. We thus treat the inertia of the equipment and technologies as if they are utilized for their full lifetime.
Moreover, investments in the electricity sector are constrained by the availability of capital, like any other sector of IMA- CLIM-R. The composition of the actual investment made is obtained by solving the program that minimizes the distance between optimal investment and available capital. Renewable investment needs are prioritized over conven- tionnal capacity additions if the available capital cannot satisfy both. To avoid oversizing capacity, an additional constraint is added to the investment decision in the form of max- imum residual peak load coverage. The residual peak load cove- rage serves as a measure of the grid reliability.
If the existing dispatchable capacity covers the residual peak load beyond a cover- age target, the final investment is re- duced with regard to the investment determined by matching the residual load duration curve with the optimal market shares from the mod- ified multinomial logit nest. This prevents the electricity module from overinvesting in conven- tional capacity even if the current capacity is sufficient to meet the residual de- mand. Such a situation would occur in the case of a sudden fuel switch, for example when coal-fired generation temporarily becomes cheaper than gas-fired generation, resulting in investment in both coal and gas capacity to meet baseload. Note that the final investment is always a non-negative fraction of the optimal investment, *i.e* $y_{min} > 0$. Variable renewables and CCS are excluded from the investment constraint.

Figure 4:
Constraint on investment - residual peak load coverage



These investments create a new generation of capital that marginally changes the composition of installed power capacity for the next static equilibrium. The figure 3 summarizes the investment process of the power sector of IMACLIM-R, from the ideal power mix at time t + 10 to the annual capacity additions. Based on this newly installed generation capacity and the depreciated capital, the current electricity demand can be met.

V. Dispatch decision in a compact electricity module

Once the characteristics of the installed operating capacity for the current period of the model are known, the equilibrium between electricity demand and supply can be found. Since the model solves the equilibrium in the electricity market annually, the dispatch decision also relies on (residual) load duration curves. Renewable electricity generation at time t is subtracted from total demand because it is not dispatchable. The use of non-renewable power generation capacity to meet residual demand is done according to the merit order of technologies. In practice, this means that for each load band (starting with the lower band), the technology with the lowest variable production cost is used until:

- the power called for exceeds the available production capacity for this technology and the next cheapest installed production capacity is exploited to obtain the additional power or,
- the available production capacity of this technology exceed the power demanded for this load duration and the remaining available production capacity will be used to answer demand associated with the load duration that is immediately inferior.

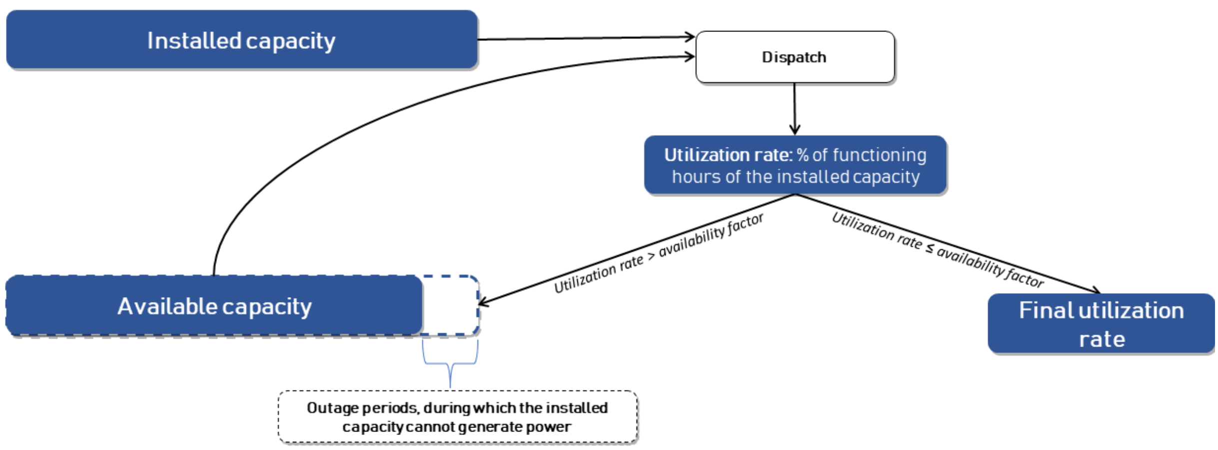


Figure 5:
Installed and available capacity during dispatch

This production cost minimization program allows associating an average annual uti- lization period (in hours) in each region k and for each technology. For conventional technologies, the utilization rate (the average functio- ning time of the installed capacity over the 8760 hours of the year) cannot exceed the availability factor. When this occurs for some technologies (e.g. coal units would operate 100% of the time according to the dispatch procedure, while their availability factor is 85%), we introduce an available ca- pacity variable to account for outages and maintenance, and perform the dispatch again as shown on Figure 5.

VI - Linkage between the electricity sector and the macroeco- nomic core of IMACLIM-R

The link between the electricity module and the macroeconomic core of IMACLIM-R runs mainly through electricity demand, electricity prices, and fossil fuel prices. Electricity demand and fossil fuel prices are inputs to the electricity nexus: this was discussed in Section 4. The price of electricity is the most important output of the electricity nexus, as it is determined both by the share of fossil fuels in electricity generation (via the input-output coefficients IC), by the investment required to provide electricity and the available power generation capacity. The bottom-up information from the nexus (input- output coefficients, installed capacity per technology) are the building blocks for the electricity sector supply curve in the IMACLIM-R macroeconomic equilibrium. The input-output coefficients IC encapsulate the merit order and dispatch decision from the dynamic module as described above. The final supply curve is used only in the static equilibrium. The shape of the supply curve determines the market clearing conditions and hence the final electricity price. The electricity sector supply curve (more precisely, the inverse supply curve) can be interpreted as the sum of marginal production costs *(Cm)* plus a sector-specific profit markup (ϖ), like any sector of IMACLIM-R Unless otherwise stated, the electricity sector is assumed to be perfectly competitive. Thus, the markup covers only the costs of investment and capital depreciation. The markup is set prior to market clearing. It is calibrated so that, at current intermediary and final prices, the sum of average electricity generation costs (including investment costs) and the profit markup equals the regional market price of electricity. Thus, the marginal cost of electricity generation in region k is given by:

$$Cm_k = \sum_j pIC_{j,k} * IC_{j,k} + (\Omega_k * w_k) * l_k * (1 + tax_k^w) \qquad (17)$$

and the electricity price is given by :

$$p_k = \sum_j pIC_{j,k} * IC_{j,k} + (\Omega_k * w_k) * l_k * (1 + tax_k^w) + \pi_k * p_k \qquad (18)$$

- The technical unitary coefficients of production which characterize the electricity sector (quantities of different fuels required to produce a unit of electricity) are determined for coal, gas and liquid fuels *(tech = [coal, gas, et])* by equation 19.

$$IC_{tech,elec,k} = \frac{\frac{prod\_elec\_techno_{tech,k}}{rho\_elec_{tech,k}}}{Q\_elec} \qquad (19)$$

- The marginal cost is increasing with the level of electricity generation through the utilization rate $\Omega_k = \frac{Q_k}{Cap_k}$. Static decreasing returns are assumed in every sector of IMACLIM-R and are associated with lower labor productivity. The electricity sector can not provide more than its annual maximum potential production Cap_k. Cap_k evolves with electrical power capacity additions.

The marginal cost of electricity generation is the aggregate supply curve of the elec- tricity sector used in static equilibrium to balance supply and demand. It incorporates information from investment and dispatch decisions through three elements: the profit markup to cover investment costs, input-output coefficients that reflect dis- patch decisions, and potential output as a function of available capacity.
Figure 6 summarises the link between macroeconomic, static equilibriums and the two electricity submodules, investment and dispatch.

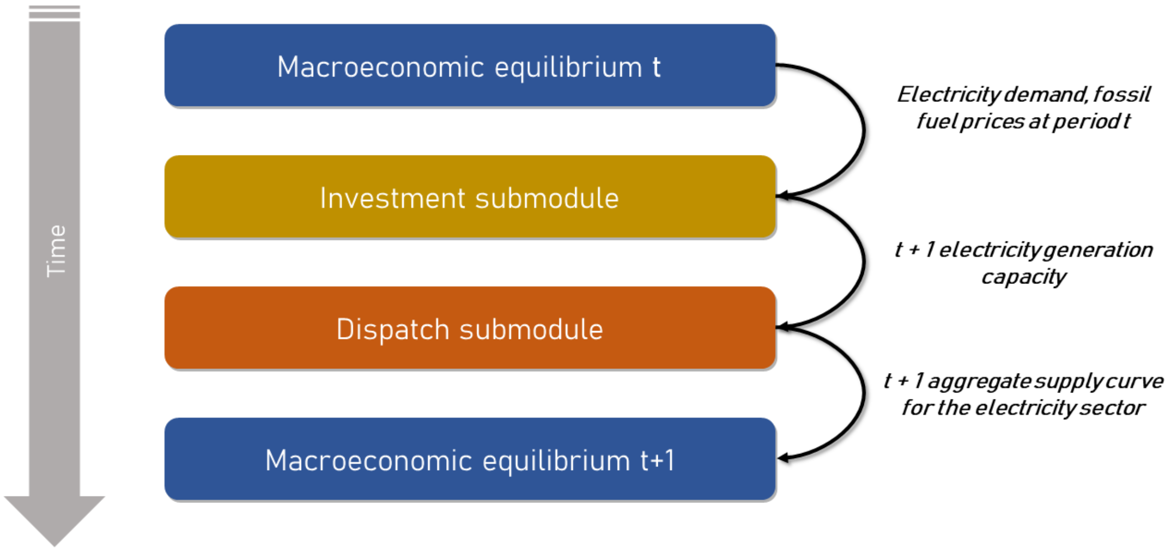


Figure 6:
Summary of the link between macroeconomic static equilibrium and the dy- namic submodules of the electricity nexus

In this section, we present the main electricity nexus outputs from 2015 to 2100 in two scenarios : a Nationally Determined Contribution scenario, following COMMIT project results (van Soest et al., 2021) and a 2°C scenario (1000 GT CO_2 budget, 2020-2100). To limit global warming at +2°C by the end of the century, a carbon tax is implemented, starting at 50$ per ton of CO_2 emission in 2020 and reaching 1500$ per ton in 2100.

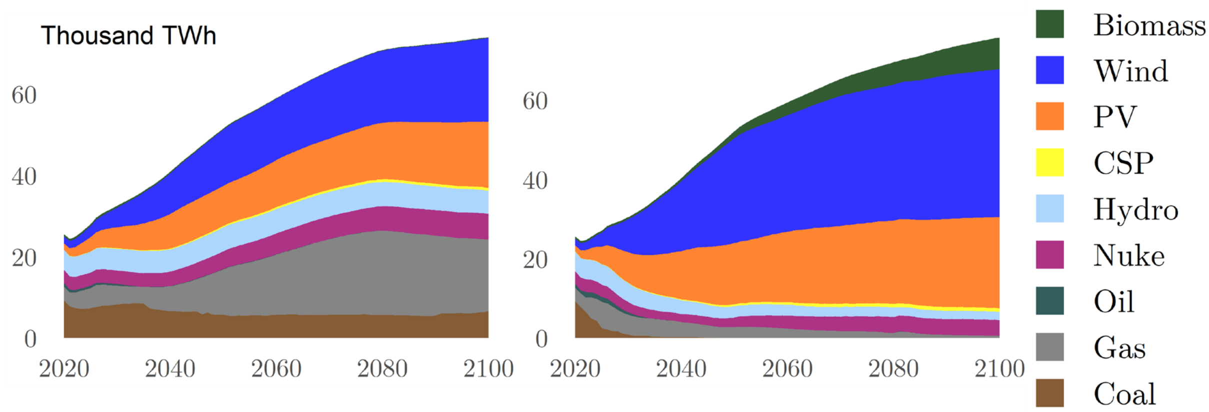


Figure 7:
World electricity generation by source, NDC (left) and 2°C (right) scenarios

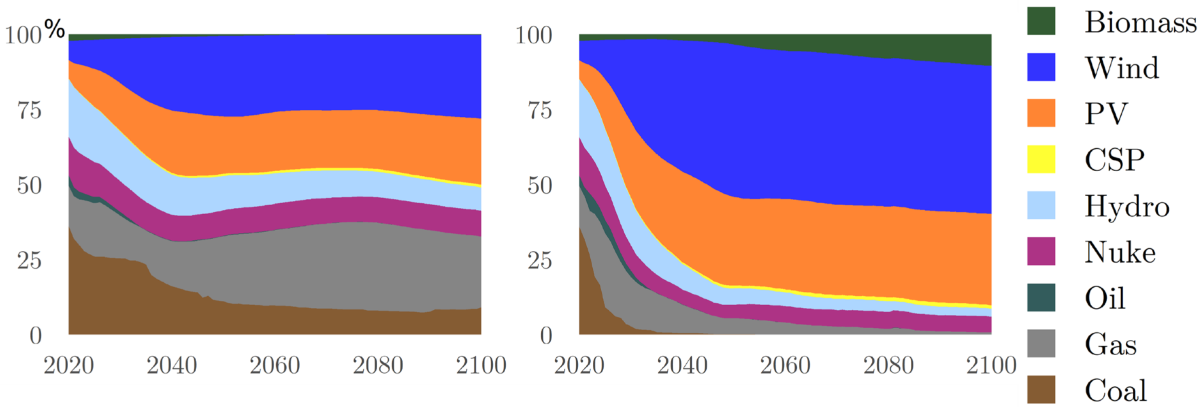


Figure 8:
World electricity market share by source, NDC (left) and 2°C (right) scenarios

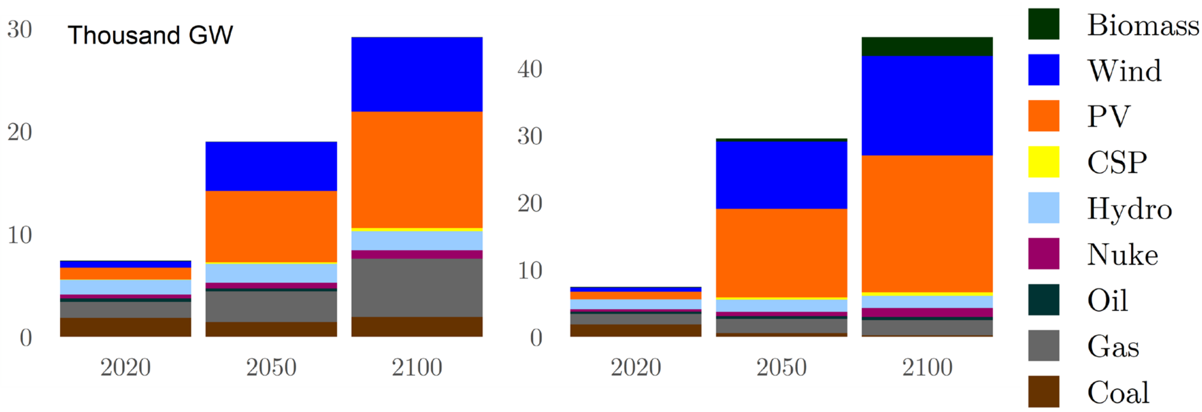


Figure 9:
World installed capacity by source, NDC (left) and 2°C (right) scenarios

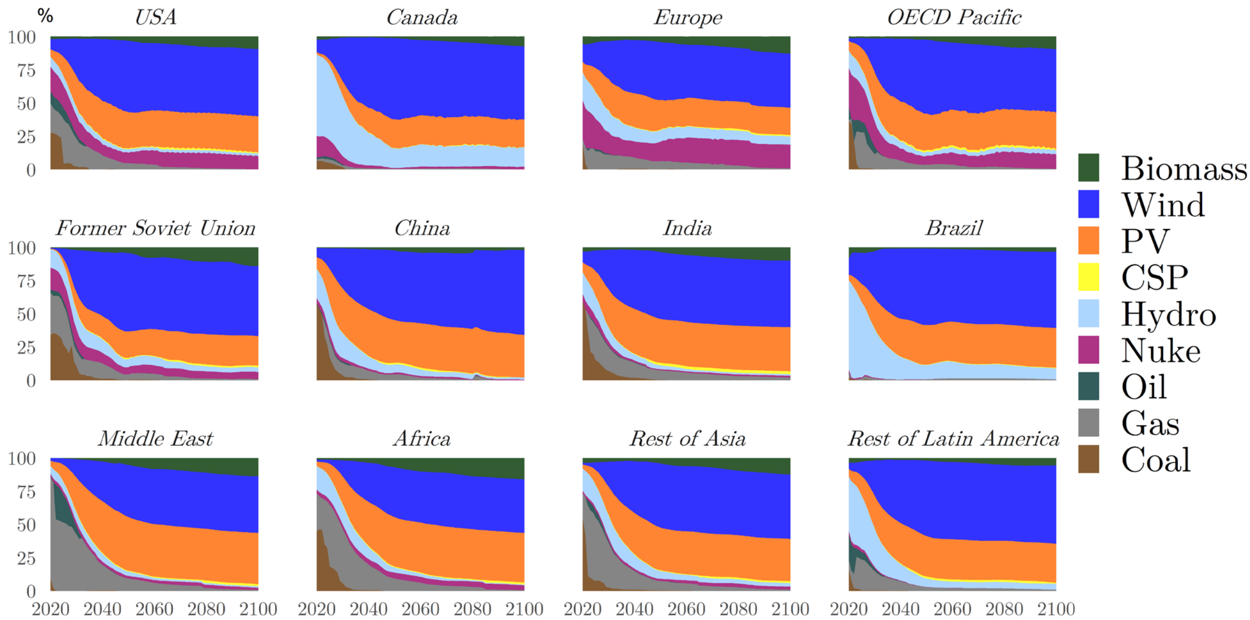


Figure 10:
World electricity market share by source, NDC scenario

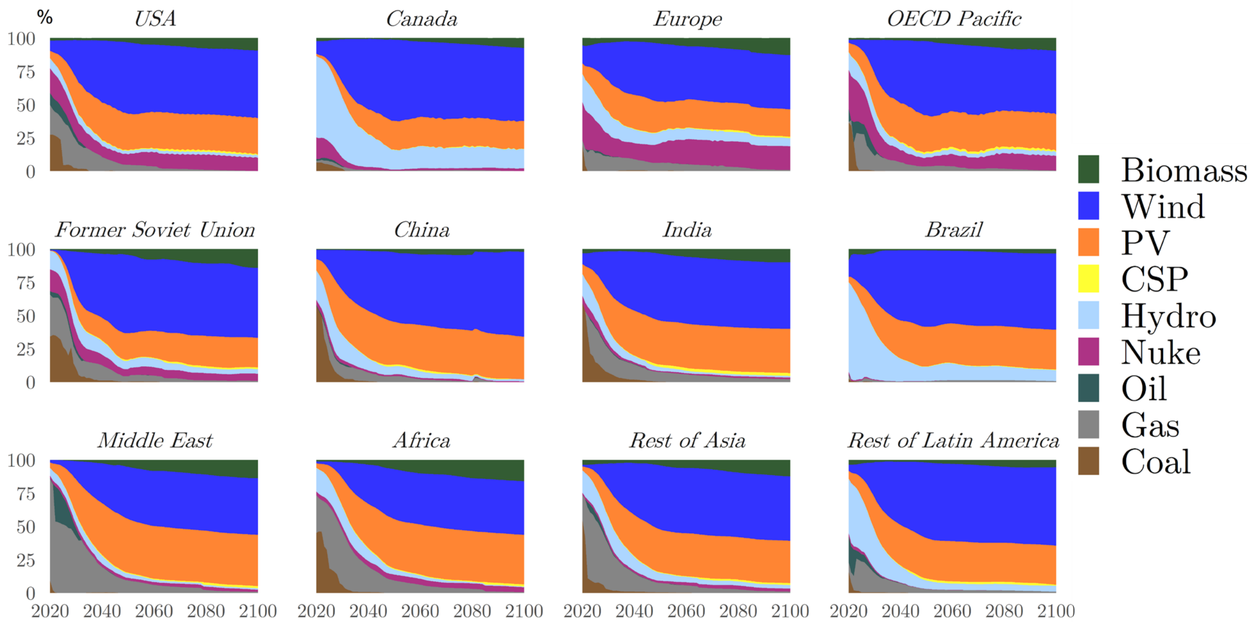


Figure 11:
World electricity market share by source, 2°C scenario

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ANNEX

Technical and economic assumptions for electricity generation

Table 1: CAPEX, in thousand 2010$ per MW

	PFC	PSS	ICG	CGS	SUB	USC	UCS	GGT	GGS	GGC	OCT	OGC	HYD	NUC	CSP	WND	WNO	CPV	RPV	BIGCC	BIGCCS
USA	1948.0	4731	2412	5195	1670.0	2134.0	4916	463.8	2783	927.6	650	991.7	2505	4638	6030	1766	5470	2676	3315	3457	6240
CAN	1948.0	4731	2412	5195	1670.0	2134.0	4916	463.8	2783	927.6	650	991.7	2505	4638	6030	2266	5470	2676	3315	3457	6240
EUR	1855.0	4638	2319	5102	1577.0	2041.0	4824	463.8	2783	927.6	650	991.7	2458	5566	5241	1865	4879	2198	2672	3457	6240
OECD	2226.0	5009	2690	5473	1948.0	2412.0	5195	463.8	2876	1020.0	650	991.7	2226	3896	6030	2708	5264	2789	2640	3457	6240
FSU	1855.0	4638	2319	5102	1577.0	2041.0	4824	417.4	2597	742.1	650	991.7	2458	3525	5241	1865	6163	2198	2672	3457	6240
CHN	649.3	3432	1020	3803	556.6	742.1	3525	324.7	2375	519.5	650	991.7	1484	2412	4545	1252	3852	1635	1541	3457	6240
IND	1113.0	3896	1484	4267	927.6	1299.0	4082	371.0	2505	649.3	650	991.7	1855	2597	5287	1316	4031	1769	1541	3457	6240
BRA	1484.0	4267	1855	4638	1206.0	1670.0	4453	371.0	2505	649.3	650	991.7	1948	3710	4963	2061	5932	3623	3438	3457	6240
MDE	1484.0	4267	1855	4638	1206.0	1484.0	4267	417.4	2597	742.1	650	991.7	1994	3247	4870	1770	5881	2157	3537	3457	6240
AFR	1484.0	4267	2041	4824	1206.0	1762.0	4545	371.0	2505	649.3	650	991.7	1948	3710	4684	1930	5701	2543	3496	3457	6240
RAS	649.3	3432	1020	3803	556.6	742.1	3525	324.7	2375	519.5	650	991.7	1484	2412	4545	1252	3852	1635	1541	3457	6240
RAL	1484.0	4267	1855	4638	1206.0	1670.0	4453	371.0	2505	649.3	650	991.7	1948	3710	4963	2061	5932	2617	2638	3457	6240

Sources: For renewables, when data for 2014 is available: IRENA, 2020. When it is not, the 2019 data is used to go backwards on the learning curve, assuming the relationship between the installed capacity and the investment costs hold for the years 2014-2019. For other technologies excepted oil and biomass: IEA, 2021. For biomass: Tidball *et al.*, 2010. For oil: Lazard, 2016.

Table 2: Fixed O&M, in thousand 2010$ per MW

	PFC	PSS	ICG	CGS	SUB	USC	UCS	GGT	GGS	GGC	OCT	OGC	HYD	NUC	CSP	WND	WNO	CPV	RPV	BIGCC	BIGCCS
USA	55.87	146.1	77.36	180.5	38.68	60.17	146.1	17.19	180.50	21.49	13.9	13.9	55.87	150.4	223.5	32.66	111.70	15.47	44.70	72.17	169.8
CAN	55.87	146.1	77.36	180.5	38.68	60.17	146.1	17.19	180.50	21.49	13.9	13.9	55.87	150.4	223.5	32.66	111.70	15.47	44.70	72.17	169.8
EUR	51.57	141.8	77.36	176.2	38.68	51.57	141.8	17.19	176.20	21.49	13.9	13.9	51.57	137.5	197.7	34.38	64.47	10.31	15.47	72.17	169.8
OECD	60.17	150.4	85.96	189.1	47.28	60.17	150.4	17.19	189.10	25.79	13.9	13.9	51.57	193.4	223.5	48.14	68.76	27.51	25.79	72.17	169.8
FSU	60.17	154.7	77.36	163.3	42.98	60.17	154.7	21.49	163.30	25.79	13.9	13.9	42.98	137.5	197.7	34.38	103.10	27.51	36.10	67.93	152.8
CHN	25.79	120.3	42.98	141.8	17.19	25.79	120.3	17.19	141.80	17.19	13.9	13.9	34.38	103.1	171.9	25.79	64.47	10.31	12.03	46.70	123.1
IND	42.98	133.2	60.17	159.0	30.08	42.98	133.2	17.19	159.00	21.49	13.9	13.9	42.98	120.3	197.7	22.35	55.87	10.31	10.31	63.68	140.1
BRA	55.87	120.3	77.36	141.8	38.68	55.87	120.3	17.19	141.80	21.49	13.9	13.9	42.98	146.1	180.5	32.66	98.85	15.47	15.47	63.68	135.9
MDE	55.87	120.3	77.36	141.8	38.68	55.87	120.3	21.49	141.80	25.79	13.9	13.9	47.28	137.5	180.5	39.54	98.85	12.03	20.63	67.93	152.8
AFR	51.57	150.4	77.36	180.5	38.68	51.57	150.4	17.19	159.00	21.49	13.9	13.9	42.98	146.1	171.9	41.26	94.55	20.63	27.51	63.68	144.3
RAS	25.79	120.3	42.98	141.8	17.19	25.79	120.3	17.19	55.87	17.19	13.9	13.9	34.38	103.1	171.9	25.79	64.47	10.31	12.03	46.70	123.1
RAL	55.87	120.3	77.36	141.8	38.68	55.87	120.3	17.19	141.80	21.49	13.9	13.9	42.98	146.1	180.5	32.66	98.85	15.47	15.47	63.68	135.9

Sources: IEA, 2020b. For oil: Lazard, 2016.

Table 3: Variable O&M, in 2010$ per MWh

PFC	PSS	ICG	CGS	SUB	USC	UCS	GGT	GGS	GGC	OCT	OGC	HYD	NUC	CSP	WND	WNO	CPV	RPV	BIGCC	BIGCCS
4.27	4.27	3.53	3.53	4.27	4.27	4.27	3.49	2.5	2.5	3.49	2.5	0	0.93	0	0	0	0	0	13.9	13.9

Sources: Author's calculation (mean value accross models): Tidball *et al.*, 2010. Hyp GGS = GGC, OCT = GGT, OGC = GGS. For biomass: Lazard, 2016.

Table 4: Energy efficiency (rho), in %

	PFC	PSS	ICG	CGS	SUB	USC	UCS	GGT	GGS	GGC	OCT	OGC	HYD	NUC	CSP	WND	WNO	CPV	RPV	BIGCC	BIGCCS
USA	0.43	0.36	0.44	0.36	0.39	0.45	0.38	0.40	0.51	0.59	0.34	0.45	1	0.36	0	0	0	0	0	0.4	0.3
CAN	0.43	0.36	0.44	0.36	0.39	0.45	0.38	0.40	0.51	0.59	0.34	0.45	1	0.36	0	0	0	0	0	0.4	0.3
EUR	0.43	0.36	0.44	0.36	0.39	0.45	0.38	0.40	0.51	0.59	0.34	0.45	1	0.36	0	0	0	0	0	0.4	0.3
OECD	0.43	0.36	0.44	0.36	0.39	0.45	0.38	0.40	0.51	0.59	0.34	0.45	1	0.36	0	0	0	0	0	0.4	0.3
FSU	0.43	0.36	0.44	0.36	0.39	0.45	0.38	0.38	0.49	0.57	0.34	0.45	1	0.36	0	0	0	0	0	0.4	0.3
CHN	0.41	0.35	0.43	0.36	0.37	0.44	0.37	0.38	0.49	0.57	0.34	0.45	1	0.36	0	0	0	0	0	0.4	0.3
IND	0.40	0.31	0.41	0.36	0.36	0.40	0.33	0.38	0.48	0.56	0.34	0.45	1	0.36	0	0	0	0	0	0.4	0.3
BRA	0.43	0.35	0.44	0.36	0.39	0.45	0.37	0.38	0.49	0.58	0.34	0.45	1	0.36	0	0	0	0	0	0.4	0.3
MDE	0.41	0.35	0.42	0.36	0.37	0.43	0.37	0.38	0.49	0.57	0.34	0.45	1	0.36	0	0	0	0	0	0.4	0.3
AFR	0.39	0.32	0.40	0.36	0.35	0.42	0.34	0.38	0.50	0.58	0.34	0.45	1	0.36	0	0	0	0	0	0.4	0.3
RAS	0.41	0.35	0.43	0.36	0.37	0.44	0.37	0.38	0.49	0.57	0.34	0.45	1	0.36	0	0	0	0	0	0.4	0.3
RAL	0.43	0.35	0.44	0.36	0.39	0.45	0.37	0.38	0.49	0.58	0.34	0.45	1	0.36	0	0	0	0	0	0.4	0.3

Sources: IEA, 2020b. For oil : Lazard, 2016.

Table 5: Availability factor (for dispatchable plants)/ Load factor (for variable renewable plants), in %

	PFC	PSS	ICG	CGS	SUB	USC	UCS	GGT	GGS	GGC	OCT	OGC	HYD	NUC	CSP	WND	WNO	CPV	RPV	BIGCC	BIGCCS
USA	0.83	0.83	0.82	0.82	0.83	0.83	0.83	0.91	0.84	0.84	0.91	0.84	0.37	1	0.28	0.42	0.41	0.21	0.16	0.83	0.83
CAN	0.83	0.83	0.82	0.82	0.83	0.83	0.83	0.91	0.84	0.84	0.91	0.84	0.56	1	0.30	0.42	0.41	0.13	0.11	0.83	0.83
EUR	0.83	0.83	0.82	0.82	0.83	0.83	0.83	0.91	0.84	0.84	0.91	0.84	0.39	1	0.30	0.28	0.49	0.13	0.11	0.83	0.83
OECD	0.83	0.83	0.82	0.82	0.83	0.83	0.83	0.91	0.84	0.84	0.91	0.84	0.34	1	0.38	0.34	0.45	0.20	0.14	0.83	0.83
FSU	0.83	0.83	0.82	0.82	0.83	0.83	0.83	0.91	0.84	0.84	0.91	0.84	0.39	1	0.30	0.25	0.37	0.12	0.09	0.83	0.83
CHN	0.83	0.83	0.82	0.82	0.83	0.83	0.83	0.91	0.84	0.84	0.91	0.84	0.39	1	0.28	0.25	0.32	0.17	0.13	0.83	0.83
IND	0.83	0.83	0.82	0.82	0.83	0.83	0.83	0.91	0.84	0.84	0.91	0.84	0.37	1	0.26	0.26	0.29	0.20	0.15	0.83	0.83
BRA	0.83	0.83	0.82	0.82	0.83	0.83	0.83	0.91	0.84	0.84	0.91	0.84	0.48	1	0.28	0.44	0.46	0.20	0.16	0.83	0.83
MDE	0.83	0.83	0.82	0.82	0.83	0.83	0.83	0.91	0.84	0.84	0.91	0.84	0.18	1	0.30	0.30	0.32	0.21	0.17	0.83	0.83
AFR	0.83	0.83	0.82	0.82	0.83	0.83	0.83	0.91	0.84	0.84	0.91	0.84	0.46	1	0.30	0.26	0.37	0.21	0.17	0.83	0.83
RAS	0.83	0.83	0.82	0.82	0.83	0.83	0.83	0.91	0.84	0.84	0.91	0.84	0.34	1	0.28	0.25	0.32	0.17	0.13	0.83	0.83
RAL	0.83	0.83	0.82	0.82	0.83	0.83	0.83	0.91	0.84	0.84	0.91	0.84	0.52	1	0.28	0.44	0.46	0.20	0.16	0.83	0.83

Sources: IEA, 2020b. Australia values used for the OECD Pacific region when available (WND,WNO,CPV,CSP): IEA, 2020a. For hydro, author's calculation: Keramidas, K. *et al.*, 2018.

Table 6: Lifetimes, in year

PFC	PSS	ICG	CGS	SUB	USC	UCS	GGT	GGS	GGC	OCT	OGC	HYD	NUC	CSP	WND	WNO	CPV	RPV	BIGCC	BIGCCS
40	40	40	40	40	40	40	30	30	30	20	20	80	60	25	25	25	25	25	50	50
40	40	40	40	40	40	40	30	30	30	20	20	80	60	25	25	25	25	25	50	50
40	40	40	40	40	40	40	30	30	30	20	20	80	60	25	25	25	25	25	50	50
40	40	40	40	40	40	40	30	30	30	20	20	80	60	25	25	25	25	25	50	50
40	40	40	40	40	40	40	30	30	30	20	20	80	60	25	25	25	25	25	50	50
40	40	40	40	40	40	40	30	30	30	20	20	80	60	25	25	25	25	25	50	50
40	40	40	40	40	40	40	30	30	30	20	20	80	60	25	25	25	25	25	50	50
40	40	40	40	40	40	40	30	30	30	20	20	80	60	25	25	25	25	25	50	50
40	40	40	40	40	40	40	30	30	30	20	20	80	60	25	25	25	25	25	50	50
40	40	40	40	40	40	40	30	30	30	20	20	80	60	25	25	25	25	25	50	50
40	40	40	40	40	40	40	30	30	30	20	20	80	60	25	25	25	25	25	50	50
40	40	40	40	40	40	40	30	30	30	20	20	80	60	25	25	25	25	25	50	50

Sources: IEA, 2020a. For biomass: Tidball *et al.*, 2010. For oil: Lazard, 2016.

Table 7: Learning rates, in %

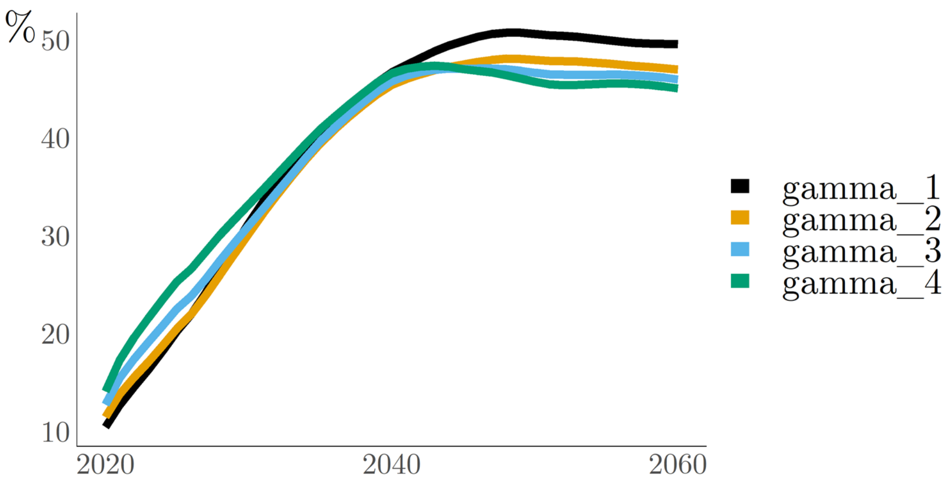
PFC	PSS	ICG	CGS	SUB	USC	UCS	GGT	GGS	GGC	OCT	OGC	HYD	NUC	CSP	WND	WNO	CPV	RPV	BIGCC	BIGCCS
0	0.1	0.1	0.1	0	0	0.1	0	0.1	0	0	0	0	0	0.1	0.05	0.15	0.2	0.2	0.1	0.1

Sources: IEA, 2021.

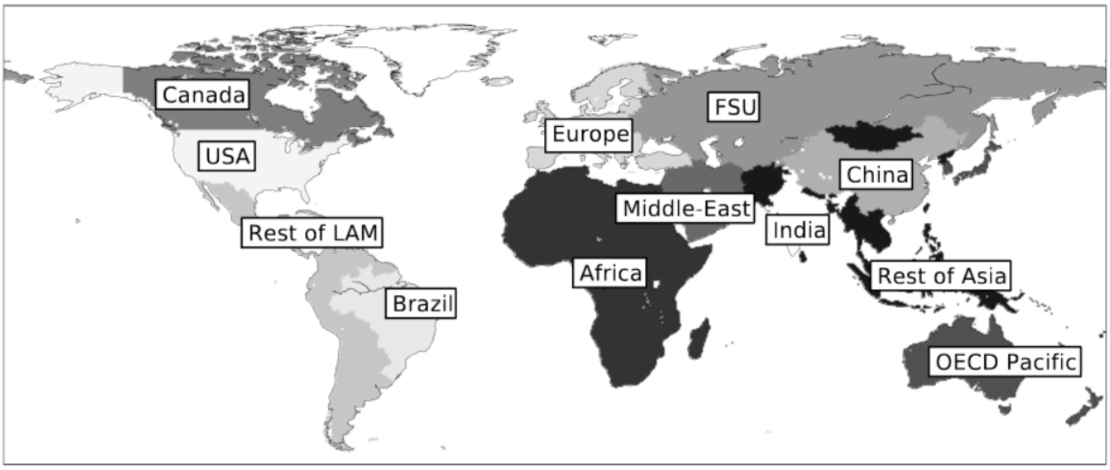
Sensibility analysis: logit exponent

Figure 12 shows the electricity market share for variable renewable energy sources (solar and wind, including CSP) under different values for the γ parameter corresponding to the exponent of the first logit nest (3). The value used by default in IMACLIM-R is $\gamma = 3$.

Figure 12: World electricity market share for renewable energy sources, NDC scenario



Regional disaggregation



OECD Pacific includes Australia, New Zealand, Japan and South Korea.
FSU = Former Soviet Union.
Rest of LAM = Rest of Latin America.

Figure 13:
Regional disaggregation of IMACLIM-R model, (Bibas et al., 2016)

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chaire modélisation prospective au service du développement durable

Les cahiers de la Chaire

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Working paper