MERCURY

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Power sector modeling improvements in the WITCH model

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Power sector modeling improvements in the WITCH model

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1. The Project

1.1 Preface

The MERCURY project – "Modeling the European power sector evolution: low-carbon generation technologies (renewables, CCS, nuclear), the electric infrastructure and their role in the EU leadership in climate policy" is a H2020-MSCA Marie Skłodowska-Curie 2015 Global Fellowship carried out by the Fellow Samuel Carrara.

The Beneficiary is Fondazione Eni Enrico Mattei (FEEM), Milan, Italy. The outgoing host is the Renewable & Appropriate Energy Laboratory (RAEL) of the University of California, Berkeley (UC Berkeley). The project Supervisor at FEEM is Prof. Massimo Tavoni, while the Supervisor at UC Berkeley is Prof. Daniel M. Kammen.

The project lasts two years. It started on January 16, 2017 and it will finish on January 15, 2019. The first year is dedicated to the outgoing phase at UC Berkeley, while the second year is dedicated to the return phase at FEEM.

1.2 Proposal Abstract

The reduction of greenhouse gas emissions is a vital target for the coming decades. From a technology perspective, power generation is the largest responsible for CO_2 emissions, therefore great mitigation efforts will be required in this area. From a policy perspective, it is common opinion that the European Union is and will remain leader in implementing clean policies.

Basing on these considerations, the power sector and the European Union will be the two key actors of this project. The main tool adopted in this work will be WITCH, the Integrated Assessment Model (IAM) developed at Fondazione Eni Enrico Mattei (FEEM).

The description of the power generation sector in WITCH is quite detailed, but needs to be integrated, especially as far as the electric infrastructure downstream the power generation system is concerned. In the first half of the project, developed at the outgoing host, the modeling of the electric sector will thus be completed and refined. In particular, four main aspects need to be assessed: i) system integration (i.e. the issues related to the non-negligible penetration of intermittent renewables in the grid), ii) electricity storage, iii) electrical grid, and iv) electricity trade.

In the second half of the project, developed at the return host, the improved WITCH model will be employed in scenario assessment calculations. Firstly, the prospects in Europe of renewables, Carbon Capture and Storage (CCS) and nuclear will be analysed. In particular, attention will be focused not so much on the pure technology aspects, but rather on policy issues such as the role of incentives in renewable diffusion, the slow CCS deployment, or the effects of the nuclear reactors ageing, or of their phase-out.

Secondly, the focus will move on assessing the role of these technologies (and the consequent evolution of the electric infrastructure) according to different mitigation scenarios, and in particular considering different levels of global participation in EU-led climate mitigation.

1.3 Note on Work Package 1 and Scope of Deliverable D1.1

According to the proposal, the first year of the MERCURY project (corresponding to Work Package 1 – "Power sector modeling improvements") is dedicated to the improvement of the power sector modeling in the WITCH model, adopting the SWITCH model as a reference. As reported in the previous section, WITCH is the Integrated Assessment Model developed at FEEM, while SWITCH is the detailed energy model developed at the Renewable & Appropriate Energy Laboratory of the University of California, Berkeley. As mentioned, four main aspects are considered in WP1: 1) system integration of Variable Renewable Energies into the electrical system (Task 1.2), 2) electricity storage (Task 1.3), 3) electrical grid (Task 1.4), and 4) electricity trade (Task 1.5). Two deliverables were planned with reference to these activities: the first one (D1.1 – "Power infrastructure modeling improvements in WITCH") was dedicated to Tasks 1.2, 1.3, and 1.4, while the second one (D1.2 – "Electricity trade in WITCH") was dedicated to Task 1.5.

During the first months of the project, however, two issues arose in this context.

First of all, it became clear that a more interactive, two-way collaboration between the two models could be more fruitful than the mere improvement of WITCH referring to SWITCH: on the one hand, as planned, WITCH was improved also taking inspiration from SWITCH (in addition to the IAM literature), but on the other hand more direct interactions between the two models, as well as the possibility to integrate SWITCH in an integrated assessment model framework, were explored.

Additionally, a more in-depth analysis of the issue questioned the actual necessity and value added of implementing electricity trade in the WITCH model. After all, this point is not considered among the priorities in the IAM research community as far as the power sector modeling is concerned.

In this light, Task 1.5 has been diverted accordingly, with a consequent, partial revision of the deliverable plan of the first year. D1.1 has remained the same in terms of content, but it has been renamed "Power sector modeling improvements in the WITCH model". D1.2 is instead dedicated to the interactions between WITCH and SWITCH and will be called “Interactions and joint applications between the WITCH and the SWITCH models”.

2. Introduction

2.1 Climate Change and its Mitigation

Climate change is one of the biggest challenges that mankind has to face in the 21st century. According to the Fifth Assessment Report (AR5) released by the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2014), there is undisputable scientific evidence that world climate is experiencing global warming. The average temperature of the atmosphere has been growing since about half of the 20th century and it has now reached 1°C higher than the pre-industrial levels. The Greenhouse Gas emissions (GHG) related to human activities, fostered by economic and population growth, have been identified as being “extremely likely” the cause of such an increase (Clarke and Kejun, 2014).

It has been evaluated that, without any structural interventions in terms of emission abatement, global temperature is likely to increase by additional 2-3°C (or even 4.5°C in the worst estimates) by the end of the century (i.e. 3°C to 5.5°C with respect the pre-industrial era), which could imply dramatic consequences both from an environmental and a socio-economic point of view. A 2°C-increase has in fact been identified as the threshold beyond which irreversible changes in natural ecosystems may occur.

This consideration has been the cornerstone of the Paris Agreement, signed at the end of 2015 at the 21st Conference of Parties (COP21), where almost all world countries agreed to “*strengthen the global response to the threat of climate change by keeping a global temperature rise this century well below 2°C above pre-industrial levels and to pursue efforts to limit the temperature increase even further to 1.5°C*” (UNFCCC, 2015a). This agreement has been translated into Intended Nationally Determined Contributions (INDCs), in which every country ratifying the protocol (175 on 195 as of March 2018) specifies which mitigation and adaptation measures is going to implement to contribute to this global goal (UNFCCC, 2015b and Rogelj et al., 2016).

Mitigation and adaptation are two concepts that refer to the fact that, in general, the actions against climate change can be twofold: on the one hand, efforts can be made to limit the extent of the phenomenon (mitigation), essentially by reducing GHG emissions, while on the other hand solutions to minimize the impacts of climate change can also be put in place (adaptation). In this work the general focus will always be the first one, however.

Carbon dioxide (CO_2) is the main contributor among GHGs, accounting for 76% of the overall greenhouse effect, among which 65% is related to fossil fuel and industry (FF&I), while the remaining 11% is related to forestry and other land use[1] (IPCC, 2014).

The power sector generates the relative majority of CO_2 emissions, accounting for about 40% of the emissions from the FF&I sector (IEA, 2017), therefore great emission abatement efforts are required in this area: the power sector is the main focus of the MERCURY project.

2.2 The Role and the Modeling of Variable Renewable Energies

Modeling the pathways to achieve emission reduction in the power sector requires integrated tools that be able to capture the multiple dimension of the climate change, since this entails implications on the economy, energy, the environment. Integrated Assessment Models are the most suitable tool for such an analysis, as they do couple representations of economic, environmental and energy systems to obtain a comprehensive picture of the impacts of different climate policies (Clarke and Kejun, 2014 and Kriegler et al., 2014). For some fifteen years, FEEM has been developing its own IAM, WITCH. This model has been used in a number of research projects and scenario exercises and it is the tool that is being adopted throughout this project. Section 3 reports a description of the model.

As discussed in Section 1, the main objective of the MERCURY project is to explore pathways of decarbonization of the power sector, especially focusing on the European Union. In order to do so, it is fundamental to have a reliable and high-level modeling tool, especially regarding the modeling of renewables.

It is now common opinion that renewable energies will be a major driver for the decarbonization of the power sector in the next decades. Variable Renewable Energies (VRE), i.e. wind and solar, have been characterized by a huge growth in recent years and, thanks to their enormous potential and technological advancements, they are deemed to be by far the main technologies in the future renewable landscape (IEA, 2017).

The penetration of high shares of VREs in the electricity mix is not a trivial matter from a technical point of view, however. It is in fact known that the correct management of the electrical grid requires that supply and demand be instantaneously in equilibrium. This is not a major issue for dispatchable technologies (such as fossil fuel plants, nuclear, or hydro), but becomes critical when the power technology is fed by a resource which is variable by nature like wind and solar radiation. A proper modeling of VRE diffusion thus requires an adequate description of this aspect.

[1] The remaining 24% is divided between methane (16%), nitrous oxide (6%), and fluorinated gases (2%).

Modeling the penetration of VREs in the electricity system is particularly awkward in Integrated Assessment Models, though. As said, these models aim at capturing in an integrated framework, over an horizon of several decades and on a global scale, the different dimensions of climate change, but this is in contrast with the very small time and space scales which characterize VRE variability (Pietzcker et al., 2017). Hence, modeling solutions which be at the same time compatible with the IAM framework and effective in describing the VRE variability must be implemented in order to generate credible energy scenarios.

In the past years, a considerable modeling effort was made to improve the VRE modeling in the WITCH model, especially in the context of the ADVANCE project[2] (Pietzcker et al., 2017 and Luderer et al., 2017) which will be described in the next section. However, as will be discussed, many issues were still to be tackled at the beginning of the MERCURY project. The objective of the first part of the work – described in this deliverable – was thus to achieve the state of the art considering the system integration modeling, and go beyond it considering the grid and storage modeling.

3. State of the Art

3.1 The WITCH Model

WITCH (World Induced Technical Change Hybrid) is an IAM aiming at studying the socio-economic impacts of climate change throughout the 21st century. It is a regionally disaggregated hybrid global model with a neoclassical Ramsey-type optimal growth structure (top-down) combined with a detailed energy input component (bottom-up) (Bosetti et al., 2006 and Emmerling et al., 2016). The energy sector is particularly detailed and hard-linked with the economy so that energy investments and resources are chosen optimally considering the trend of macroeconomic variables and policy-induced economic stimuli. Technological change is accounted for endogenously, mainly via learning curves that influence the investment cost of new technologies via dedicated R&D investments (learning-by-researching) and/or capacity deployment (learning-by-doing), see Section 3.1.3.

In its default configuration, the model is divided into thirteen regions, aggregated according to geographic and/or economic contiguity. The thirteen economic regions are USA (United States), OLDEURO (Western EU and EFTA countries), NEWEURO (Eastern EU countries), KOSAU (South Korea, South Africa and Australia), CAJAZ

[2] http://www.fp7-advance.eu/

(Canada, Japan and New Zealand), TE (Transition Economies, namely Russia and Former Soviet Union states and non-EU Eastern European countries), MENA (Middle East and North Africa), SSA (Sub-Saharan Africa except South Africa), SASIA (South Asian countries except India), EASIA (South-East Asian countries), CHINA (People's Democratic Republic of China and Taiwan), LACA (Latin America and Central America) and INDIA (India). If regions are facing a global policy target, they can either behave independently or form coalitions: in the second case, coalitions of regions optimize their total welfare as a whole.

3.1.1 The Economy

In the model, a social planner with perfect foresight maximizes a utility function as the sum of regional discounted utility of each coalition. The regional utility function at any point in time and each region is based on Constant Relative Risk Aversion (CRRA) utility function derived from consumption per capita (and log-shaped). If no coalitions are present, the model optimizes considering each region as a coalition.

Consumption, the argument of the utility function, is given by the budget constraint as the output of a single region, from which investments (in final good, energy and extraction sector, R&D, grid and adaptation) and operation and maintenance costs (O&M) are subtracted, as they represent competing claims of the economy. The economic output of each region is represented by a nested production function combining labor, capital (these two aggregated in a Cobb-Douglas function) and energy services in a Constant Elasticity of Substitution (CES) framework, plus the influence of a climate damage function, cost of fossil fuels and GHG emissions mitigation, reducing the output. All economic quantities are defined in 2005 United States Dollars.

3.1.2 The CES Framework

The CES production function is a macroeconomic functional form that sees the output as a function of a number of inputs. This function accounts for the extent to which one input (e.g. labor) can be substituted by another one (e.g. capital) to produce the final output, through the concept of elasticity of substitution. Equation 3.1 represents a general two-variable CES production function.

$$Y = A[aX_1^\rho + (1-a)X_2^\rho]^{\frac{1}{\rho}} \qquad [3.1]$$

The output Y depends on the productivity A, on the two inputs X_1 and X_2, on a, which determines the optimal distribution of inputs, and on ρ, which is in turn a function of σ, i.e. the elasticity of substitution between the two outputs, defined as σ = 1 / (1−ρ).

Therefore, if σ approaches infinite, the CES function becomes linear and the two output become perfect substitutes (i.e. the two inputs can be used equivalently to generate the same output). The more σ approaches zero, the more the two outputs become complements, so a certain amount of both should always be provided to obtain the output, and the margin to substitute one source of input with another decreases (Henningsen A. and Henningsen G., 2011).

3.1.3 The Energy Sector

The energy sector in WITCH is described with good detail, thus justifying the "hybrid" nature of the model: on the one hand, the economy is described in a very aggregated way (top-down), while on the other hand the level of detail allows to account for the different energy technologies and their performance, primary fuel requirements and pollutant emissions (bottom-up).

Referring to the CES tree reported in Figure 3.1, Energy Services (ES) are provided either with investments in efficiency improvements, that are endogenously accounted for and build the stock of energy R&D (RDEN), or via actual energy consumption (EN), that is in turn a CES combination of electric (EL) and non-electric energy (NEL). The two sub-sectors are described in detail and decomposed to the level of the single technology: the choice among different energy production options is determined by the utility maximization, where a CES-tree structure determines substitutability and complementarity between technologies, to avoid a so called "bang-bang solution", where technological choice is purely based on cost minimization and all the investments are shifted towards the most economical option, without any inertia of the energy sector. Electric sector includes both fossil-based plants, such as gas, coal and oil, and low carbon options such as nuclear, wind, solar, biomass, Carbon Capture and Storage (CCS) and hydro, plus an electric backstop technology (representing a basket of promising technological options, far from commercialization[3]). Non-electric demand regards transportation, industrial, commercial and residential sectors. Cost of production includes investments, O&M and fuel costs.

[3] It is normally thought as nuclear fusion or advanced, waste-free nuclear fission.

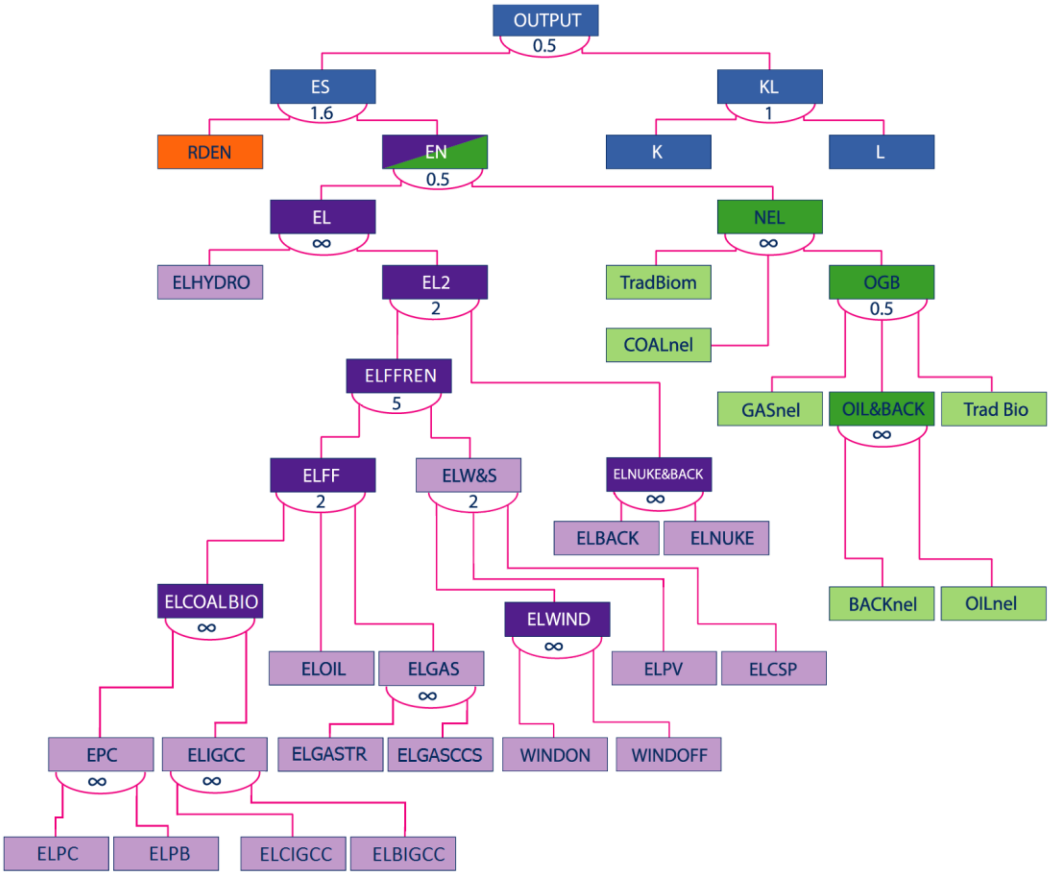

Figure 3.1 – The CES structure in WITCH.

Investment costs in traditional energy technologies (e.g. fossil fuel power plants or nuclear) are constant over time, while those of new energy technologies (e.g. backstop, wind, and solar) are subject to two different types of learning, allowing for cost improvements in the future:

- Learning by doing: investment costs decrease proportionally to cumulative installed capacity, therefore endogenously. Before this work, the technologies benefiting from this type of learning were solar, wind and advanced biofuels. Storage technologies have been added during the MERCURY project.
- Learning by researching: similarly to what is done for general energy intensity of the economy, it is possible to invest money and accumulate an R&D capital stock, whose growth determines a technology cost decrease. This is done for the two backstop technologies (electric and non-electric) and for energy efficiency improvements, that decrease the total energy demand at same output level.

The existing capital of generation technologies and grid undergoes depreciation, meaning that capital shrinks in time if no further investments are done. WITCH uses a standard exponential depreciation rule: the depreciation rate is calibrated based on a finite useful life of each technology, with a linear depreciation rate of 1% per year until the end of the lifetime and full depreciation thereafter. Based on realistic plant lifetimes, the exponential depreciation rate is found equalizing the integral of both depreciation schedules. Operation and maintenance cost are constant in time for all the technologies, while the prices of fossil fuels and exhaustible resources (oil, gas, coal, and uranium) are determined by their marginal cost of extraction, which in turn depends on current and cumulative extraction. A regional mark-up is added to mimic different regional costs including transportation costs. The regional fuel consumption takes into account the domestic extraction and fuel imports, to determine the fuel expenditure of each region.

3.1.4 Climate

GHG emissions are responsible for climate change, and can be generated by energy sector (power production, residential heating, transportation and industry) and land use. Emissions include Carbon Dioxide (CO_2), Nitrous Oxide (N_2O), Methane (CH_4) and Fluorinated gases (targets of Kyoto Protocol). The estimates of agriculture, forestry and bioenergy emissions are provided in input from Global Biosphere Management Model (GLOBIOM)[4], a land-use model soft-linked with WITCH. As regards the relation between GHG concentration in the atmosphere and temperature increase, WITCH can internally convert regional emissions or can alternatively be soft-linked with a climate model (which is the option adopted in this work): Model for the Assessment of Greenhouse-gas Induced Climate Change (MAGICC)[5].

3.2 Modeling of System Integration in Integrated Assessment Models

As discussed in Section 2.2, IAMs are useful instruments to understand the role of energy technologies in meeting long-term climate policy targets. Representing the dynamics that lie behind the existence of VRE integration cost is a challenge for IAMs, due to their high level of spatial and temporal aggregation. To compensate for this weakness, IAMs feature a stylized representation of these phenomena, with different levels of detail and accuracy (see Ueckerdt et al., 2015a and Pietzcker et al., 2017 for more information):

[4] http://www.globiom.org/

[5] http://wiki.magicc.org/index.php?title=Main_Page

- Upper bounds to maximum VRE generation share: it is a simple yet rigid measure, that neither specific literature nor real-word experience indicate as reliable.
- Integration cost markups: often defined as a cost penalty per unit of VRE generation, growing with the VRE share, it is a less rigid approach but it does not capture the influence of high VRE share on other power plants, in terms of operation and installed capacity requirement.
- Fixed investments in specific integration options: they rise with VRE share and associate the diffusion of wind and solar with a change in the energy system mix (e.g. firm capacity from gas-fired power plants, electricity storage or transmission infrastructure). Nevertheless, the mitigation option to invest in is often only one, so the model is not let freely choose the most cost-effective integration option. Moreover, VRE integration entails multiple challenges (see Section 2), that cannot be addressed by a single technical solution.
- Time slices: some models differentiate energy demand in time, representing characteristic situations in the power sector with different and often co-existing levels of temporal detail (seasonal variability, day/night, weekday/holiday). The goal is to capture demand variability with the lowest number of times slices possible, leveraging the regularity of load patterns in time, to minimize the model complexity. However, this approach does not allow capturing the correlation between load and solar/wind generation patterns, that requires a more accurate spatial and temporal definition, increasing both model complexity and computational time.
- Flexibility and capacity constraints: some models try to incorporate the concept of reliability of electricity supply in the modeling framework, elaborating on the concept of adequacy. This feature is intended both as the capability of an electric power system (grid and generation fleet) to satisfy the expected peak demand, plus some extra reserves to face possible contingencies and outages (capacity requirement), and as the possibility to adjust generation over different time scales in response to foreseen and unforeseen demand variations (flexibility requirement). Both these requirements are accounted for in a stylized, parametric way: a capacity constraint equation, representing the fact that technologies are able to cover peak demand with different degrees of reliability (depending mostly on the availability of the primary resource); a flexibility requirement, indicating if each technology is capable of providing flexibility to the system or requires additional flexible generation and ultimately imposing a balance between flexible and non-flexible options. A more detailed description of the theoretical background and the actual implementation of these two equations is provided in Section 3.3.1.

- Application of RLDCs: this innovative approach stems from the model implementation of the so-called Residual Load Duration Curves (RLDCs). RLDCs represent the duration of electricity demand non satisfied by VRE generation within a geographical area, which must be satisfied by non-VRE power sources. They can be used to estimate the capacity value of VRE technologies, the fraction of VRE curtailment, and the impacts on capacity factors of non-VRE technologies with an increasing share of renewables. They are built starting from Load Duration Curves (LDCs), a representation of the instantaneous power demand that a certain load area experiences, ordered according to the number of hours this load condition is verified (see Figure 3.2). The shape of RLDCs changes with the VRE share in the region of interest: the higher the amount of VRE generation, the steeper the slope of the RLDC, that can even assume negative values for a small amount of hours per year, meaning that renewables production exceeds demand requirement, thus being curtailed. The advantage of RLDCs is that they allow capturing key features of VRE sources, such as their low capacity credit, their effect on the reduced capacity factor of dispatchable power plants and possible VRE over-production. Nevertheless, this approach presents some shortcomings: information is lost about the temporal sequence of demand and supply, so it is not possible to represent accurately features such as short-term storage or demand-side management, that are subject to fast dynamics.

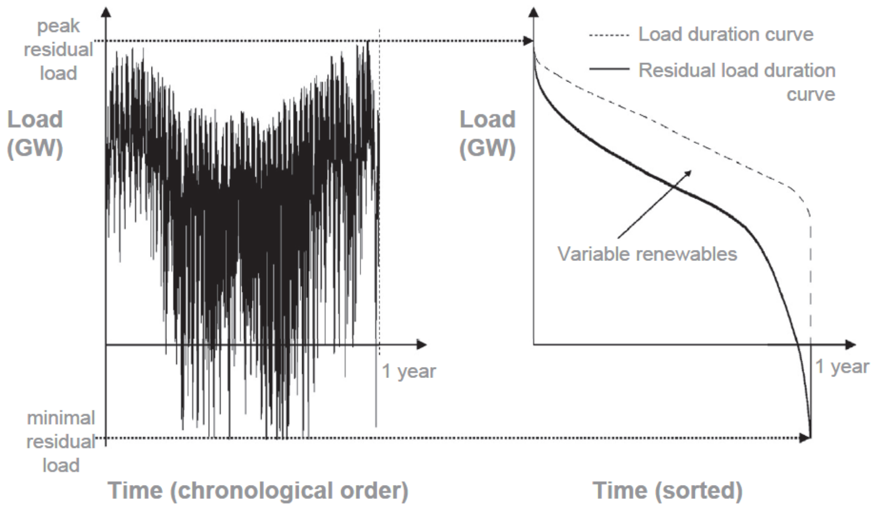

Figure 3.2 – The residual power supply time series over the year (left) is reshaped to represent the RLDC (right, solid line), while the dashed line represents the actual LDC (source: Ueckerdt et al., 2015a).

3.3 Original Modeling of System Integration, Grid, and Storage in WITCH

3.3.1 System Integration

The implemented modeling solution is based on Sullivan et al., 2013, who developed the methodology for the MESSAGE model, and it is described in Carrara and Marangoni, 2017.

The modeling scheme is based on two constraints: the flexibility and the capacity constraints.

The capacity constraint ensures that sufficient firm capacity is built to cover peak demand and reliably face contingency events. Referring to Equation 3.2, the peak load is computed as approximately twice[6] as the average annual load, which is given by the ratio between the yearly electricity demand, Q_EL_TOT, and the yearly hours, 8760. Non-VRE plants contribute with their full nameplate capacity K_EL, while storage contributes with 85% of its capacity. On the other hand, to account for their variability and unpredictability, VRE capacities are multiplied by their capacity factor CF (defined as the ratio between full production hours of a power plant over the number of hours in a year, 8760) and their capacity value CV, representing the VRE capability of actually contributing to firm requirement, which decreases with the share of wind and solar penetration.

$$\begin{aligned}\sum_{jel|non\_VRE} K\_EL(jel,t,n) \;+\; \sum_{jel|VRE} K\_EL(jel,t,n) \times CF(jel,t,n) \\ \times CV(jel,t,n) \;+\; K\_EL_{storage}(t,n) \times CC_{storage} \\ \geq firm\_req(n) \times \frac{Q\_EL\_TOT(t,n)}{yearly\_hours}\end{aligned} \qquad [3.2]$$

The flexibility constraint (Equation 3.3) ensures the operational reliability in each modeled region, by assigning each generating technology a flexibility coefficient FC (constant over time and across regions) between -1 and 1, that multiplies the electricity generation of the specific technology (Q_EL). A positive flexibility coefficient means that specific technology is able to provide flexibility to the energy system (for instance rapidly ramping up or down its production to follow the load), while a negative coefficient implies that the technology provides inflexibility to the system, or in other words it requires flexibility. Numerically, the flexibility coefficient quantifies

[6] The real values – firm_req – depends on regions and is comprised between 1.5 and 2.

the flexibility required by an additional unit of generation from that technology. Storage is assumed as a "dummy" technology that provides energy at its nameplate capacity ($K\_EL_{storage}$) for 2000 hours a year (yearly_storage_hours). The load is also assigned a negative coefficient of -0.1 (FC_load), to represent the fact that, even in absence of negative-FC technologies, some flexibility is still required to follow the load, which is not constant.

$$\sum_{jel} Q\_EL(jel,t,n) \times FC(jel) \; + \; K\_EL_{storage}(t,n) \times yearly\_storage\_hours \times FC\_storage \; + \; FC\_load \times Q\_EL\_TOT(t,n) \geq 0 \qquad [3.3]$$

Table 3.1 shows the flexibility coefficient of generation technologies in WITCH:

Technology	Flexibility coefficient
Load	-0.1
Wind	-0.08
PV	-0.05
Nuclear	0
CSP	0
Coal ST	0.15
IGCC	0.15
Coal CCS	0.15
Oil	0.3
Biomass	0.3
Combined cycle	0.5
Gas CCS	0.5
hydroelectric	0.5
Storage	1

Table 3.1 – Flexibility coefficients in the original WITCH formulation.

3.3.2 Grid

WITCH represents the electricity transmission and distribution grid as a homogeneous, generic capital with no technological distinction, undergoing depreciation, featuring the same cost all over the world and no associated electricity losses. The capital is expressed in TW-equivalent.

The modeling solution is based on two equations. The first one calculates the installed grid capacity, which is linearly proportional to the installed generation capacity, with the addition of two further contributions (Equation 3.4).

$$K\_EL\_GRID(t,n) = \sum_{jel|non\_VRE} K\_EL(jel,t,n) + \sum_{jel|VRE}\sum_{distance} K\_EL\_D(jel,t,n,distance) \times \frac{transm\_cost(jel,distance)}{grid\_cost} + \sum_{jel|VRE} K\_EL(jel,t,n) \times (1 + SHARE\_EL(jel,t,n)^{b}) \qquad [3.4]$$

Where $K\_EL(jel,t,n) = \sum_{distance} K\_EL\_D(jel,t,n,distance)\ \forall jel|VRE.$

Firstly, there are some cost markups (transm_cost) for wind and solar PV plants, depending on their distance from the load center (or from shore, in case of offshore wind). They are classified as “far”, “intermediate” and “near” in this respect. The adopted grid investment cost grid_cost was equal to 400 $2005/kW and had been obtained averaging costs over lengths and capacities of transmission lines.

Secondly, the equation features a simplified representation of the grid pooling effect, that is the tendency to improve the grid connection over large areas to smooth VRE variability by means of long-distance high voltage (DC or AC) lines or smart controls. This is included through a formulation taken from the REMIND model. The latter term was defined for each VRE technology and increased exponentially with the generation share SHARE_EL of the single VRE with an exponent b equal to 1.55 (Luderer et al., 2013).

The second equation is the capital stock equation. This equation, for every region and time step, accounts for the aging and the consequent retirement of the existing grid capacity and the capacity addition due to the yearly investments in grid.

The main weaknesses of this formulation are the lack of a distinction between transmission and distribution lines, the absence of a representation of thermal losses on the lines, and the coarse description of the grid pooling effect. This research work has naturally been directed towards solving these issues.

3.3.3 Storage

Investments in a single type of short-term storage (i.e. dealing with intra-day VRE output variability) are endogenously accounted for in WITCH. However, storage is not an actual electricity technology, but more a “dummy” technology in which the model can invest and which positively contributes to capacity and flexibility equation, without actually entering the CES or and being associated to any economic value in the production function.

As discussed in Section 3.3.1, the installed storage capacity can provide a contribution within the capacity constraint through a Capacity Coefficient (CC) equal to 0.85. Moreover, it is involved in flexibility constraint assuming 2000 yearly full production hours, to obtain a sort of "fictitious generated energy" with a flexibility coefficient FC equal to 1. Thus, investing in storage capacity represents just a measure to facilitate the installation of high capacities of VRE, characterized by a low contribution to meeting the peak load and by a negative flexibility coefficient.

However, this formulation has some clear limitations due to the insufficient description of the operation of storage technologies. In particular, the absence of an electricity input from the other generation technologies and of an electricity output to the grid, associated to an efficiency loss, represented the main weakness. Seasonal storage, that could smooth anti-correlations between supply and demand on a seasonal basis (Ueckerdt et al., 2015b) is also not represented in this version.

3.4 The ADVANCE Framework

The modeling solutions described in Section 3.3 were mostly developed in the context of the already mentioned European ADVANCE project, and in particular in the task titled "Report documenting methodological approaches for representing VRE in Energy System Models".

In particular, a list of 18 features of the fundamental dynamics and drivers of VRE system integration was defined in the ADVANCE project in order to qualitatively assess the ability of the participating models to properly model the VRE penetration in the electricity system, see Table 3.2 (Pietzcker et al., 2017). For each feature, each model is assigned a qualitative mark (0, +, ++, or +++) depending on its ability to capture the relevant dynamics. Table 3.3 shows the detailed results for the analysis in WITCH as reported in Pietzcker et al., 2017. The table also adds some information concerning specific points which have not been thoroughly discussed in the main text.

Translating the +'s into numbers (1, 2, or 3), the scores shown in Figure 3.3 are obtained for the six models participating in the ADVANCE exercise. WITCH is characterized by 15/54, quite far from the state-of-the-art level of 25-30/54 achieved by the other models.

A further modeling improvement was thus necessary: this has been the starting point for the MERCURY project.

Investment dynamics	Investment into dispatchable technologies differentiated by load band
	Investment into VRE
	Expansion dynamics
	Capital stock inertia and vintaging
	Structural shift of generation capacity mix
	Love of variety
Power system operation	Dispatch
	Flexibility and ramping
	Capacity adequacy
	Curtailment
Temporal matching of VRE and demand	Wind/solar complementarity
	Demand profile evolution
Storage	Short-term storage
	Seasonal storage
	Demand response
Grid	General transmission and distribution grid
	Grid expansion linked to VRE
	Pooling effect from grid expansion

Table 3.2 – Features of VRE system integration modeling: list.

Feature	**Description of the modeling solution in WITCH**	**Mark**
Investment into dispatchable power plants differentiated by load band	Homogeneous good; flex&cap constraints with fixed parameters creates demand for peak-load technologies	+
Investment into VRE (including feedback on the system)	Optimization accounts for feedback of VRE on flexibility constraint and capacity equation (+)	+
Expansion dynamics	Hard constraints on expansion rate	+
Capital stock inertia and vintaging	Exponential vintaging (+); early retirement (+)	++
Structural shift of generation capacity mix	Possible, but limited by CES with elasticity 5	+
Love of variety	CES	+
Dispatch	Capacity factor as upper limit allows output reduction	+
Flexibility and ramping	flexibility constraint with fixed parameters	+
Capacity adequacy	CV for each VRE type decreases with VRE share	+

(continues)

Curtailment	Implicitly contained in the CES function	+
Wind-Solar complementarity	Non-linear CES function favours mix of wind and solar	+
Demand profile evolution	N/A	0
Short-term storage	Endogenous storage investm. driven by capacity & flexibility equation with fixed coeffcients	+
Seasonal storage	N/A	0
Demand response (incl. electric vehicles and vehicle-to-grid)	Basic representation: reduction of cap. & flex. requirements from V2G	+
General transmission and distribution grid	Grid capital linearly proportional to total electricity-producing capacity	+
Grid expansion linked to VRE	Aggregated grid cost markups depending on VRE share; also included implicitly as grid capacity is calculated from capacity, not energy+	+
Pooling effect from grid expansion	N/A	0

Table 3.3 – Features of VRE system integration modeling: WITCH (original).

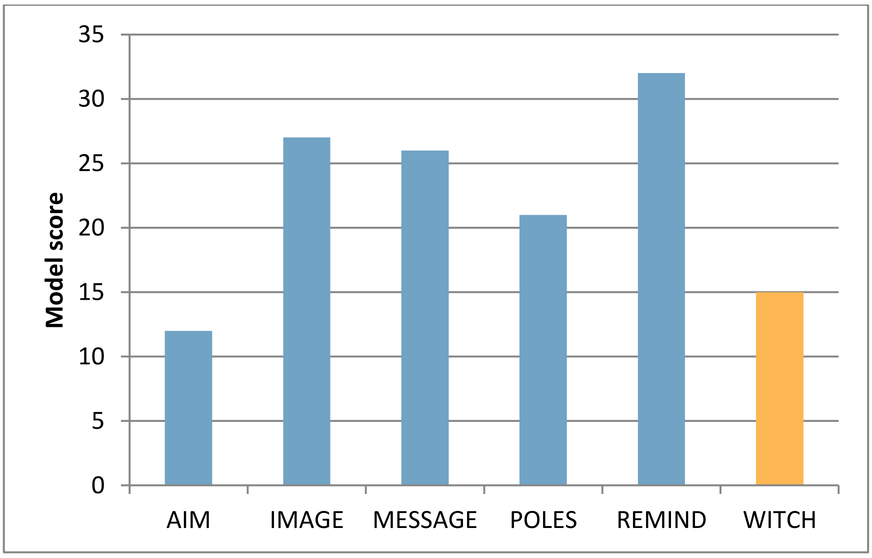

Figure 3.3 – Features of VRE system integration modeling in ADVANCE: model scores.

4. The New System Integration Modeling

4.1 Preliminary Considerations

The MESSAGE model has again been taken as a reference for the new modeling of VRE system integration (Johnson et al., 2017). The new modeling in MESSAGE does not directly implement the Residual Load Duration Curves developed during the ADVANCE project, but rather indirectly uses them to refine the formulation of the flexibility and capacity constraints, as well as to derive additional information. In the indirect MESSAGE formulation – and thus in WITCH – electricity is treated as a homogeneous good over the year, while RLDCs typically consider different load segments (e.g. peak load, intermediate load, base load, with a possible additional differentiation). This is normally unnecessary in Integrated Assessment Models, since they typically provide average yearly data with multi-year time steps. The MESSAGE modeling framework was thus deemed to be a very effective way to implement the information richness included in the RLDCs, assuring at the same time modeling simplicity and manageability.

One limitation of the approach is that the new coefficients and curves derived for the flexibility and capacity constraints are strictly valid only for a band of wind/PV shares in the electricity mix. RLDCs are in fact produced for a set of wind/PV shares, and the shape varies accordingly. On the other hand, a dynamic formulation updated in each iteration with the new wind/PV share would be practically impossible to be implemented. The MESSAGE team has thus produced the updated parameters referring to the average wind/PV shares that they normally obtained in their scenarios.

The first step was thus to check if there is at least a general compatibility between the MESSAGE and WITCH results. First of all, the 11 regions modeled in MESSAGE are practically identical to the 13 regions modeled in WITCH[7]. This allows a direct comparison between the two sets of results. Additionally, comparing the wind/PV share in average ADVANCE scenarios, one can see that in general the two models are compatible, see Figure 4.1. The MESSAGE formulation can thus be applied to the WITCH model.

Indeed, as Figure 4.2 suggests, the differences in the RLDCs are quite limited also in the "worst" cases (like India), meaning that the information derived from them would not be so different also if the wind/PV penetration shares were markedly different.

[7] Essentially, WITCH's KOSAU and CAJAZ are grouped in only one Pacific OECD region in MESSAGE, as well as WITCH's India and South Asia form a unique South Asia region in MESSAGE. This substantial coherence simplified the application to WITCH of the parameters developed for the MESSAGE regions.

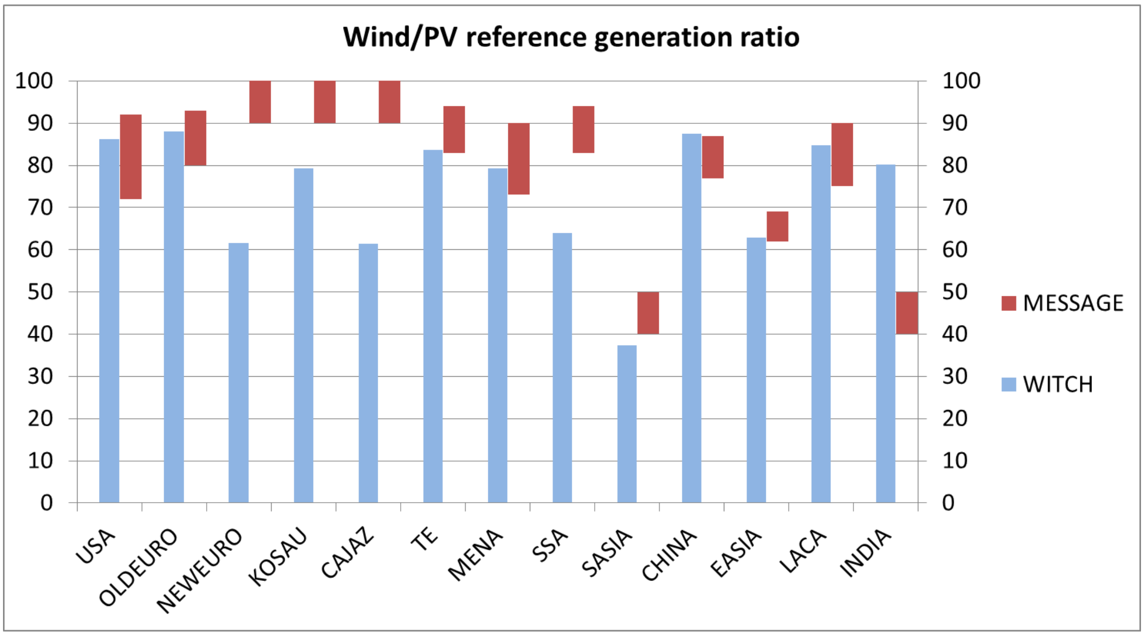

Figure 4.1 – Wind/PV reference share in MESSAGE and WITCH.

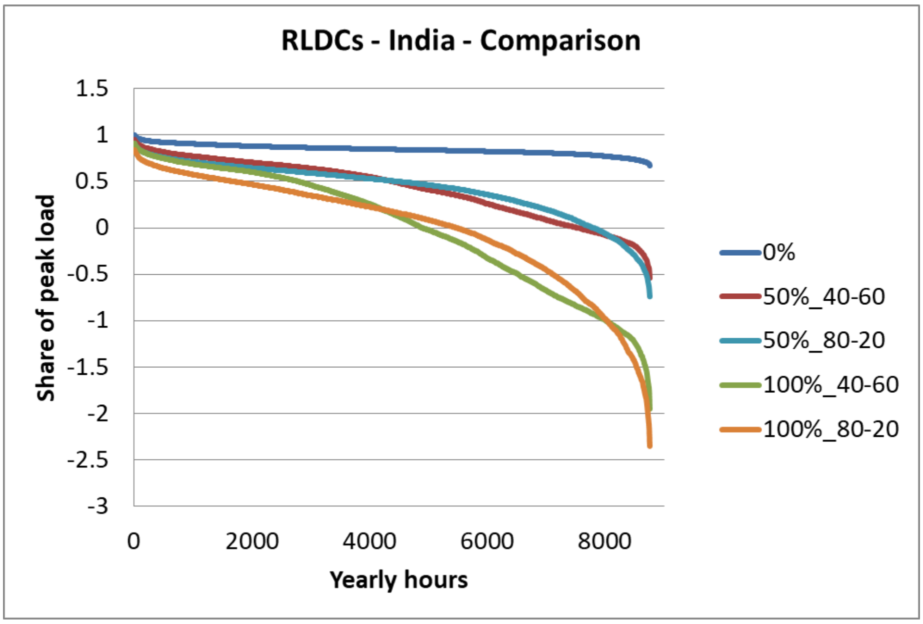

Figure 4.2 – RLDCs in India (in the caption, the percentage indicates the VRE penetration, while the second number indicates the wind/PV share).

4.2 Capacity Constraint

Starting from the capacity constraint equation in the form of Equation 3.2, some updates have been implemented basing on the findings of RLDCs-based work described in Johnson et al., 2017. As mentioned above, the relevant RLDCs had been produced in the context of the ADVANCE project (Ueckerdt et al., 2015b) for each region, for different shares of VRE generation, and for each share of wind over PV production.

First of all, it is expected that the firm capacity requirement, which represents the capacity required to meet the peak load as a multiple of the annual average load, will vary across regions and over time as electricity demand changes with development, while now it is assumed constant over time. The evolution of the firm capacity requirement over time for the different regions is calculated using a method proposed by Heinen et al., 2011, i.e. approximating the ratio between the annual peak load and the annual average load from the projected shares of residential and industrial electricity demands and adding a margin of 20% to cover contingency events. So, with this new formulation, firm_req, which was only a function of regions, has become a function of time as well. Figure 4.3 shows the previous value of the requirement and the new ones averaged over the century. The value is now (averagely) slightly lower than before (the variation over time is very low, anyways).

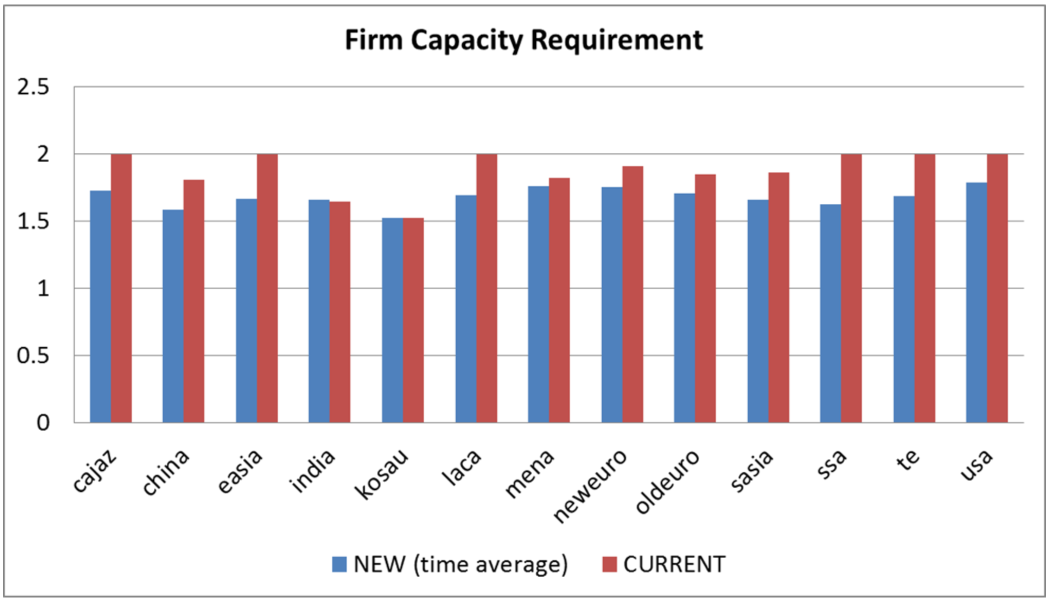

Figure 4.3 – Firm capacity requirement.

The RLDCs have also been used to quantify how the Capacity Values (CVs) of PV and wind power plants change with increasing generation shares of these technologies. The capacity value of a technology is defined as its contribution to the firm capacity requirement and so its ability to cover the peak load. The capacity value of the single VRE technology is calculated as the fraction of the technology capacity that contributes to covering peak load. To express CV as a function of VRE share, it has been derived from several different RLDCs, featuring an increasing VRE share. The overall analytic formulation of the capacity constraint equation has not changed (see Equation 3.2), but now the updated implementation identifies unique capacity values for the single VRE technology in the different regions as a function of its generation share (before considering curtailment). Therefore, the main improvement with respect to the previous implementation is the complete differentiation across regions, based on the regional RLDCs.

Figure 4.4 describes how the capacity value of wind and PV technologies decreases with an increasing generation share of these technologies in the USA. It is worth highlighting how the capacity value of PV technology starts at a much higher level than the wind one at low generation shares, but then it presents a much steeper decrease. This is due to the fact that solar PV generation is normally well-aligned with peak load at low VRE deployment, but provides very little capacity value beyond a 30% share, while the behavior of wind plants is more uniform.

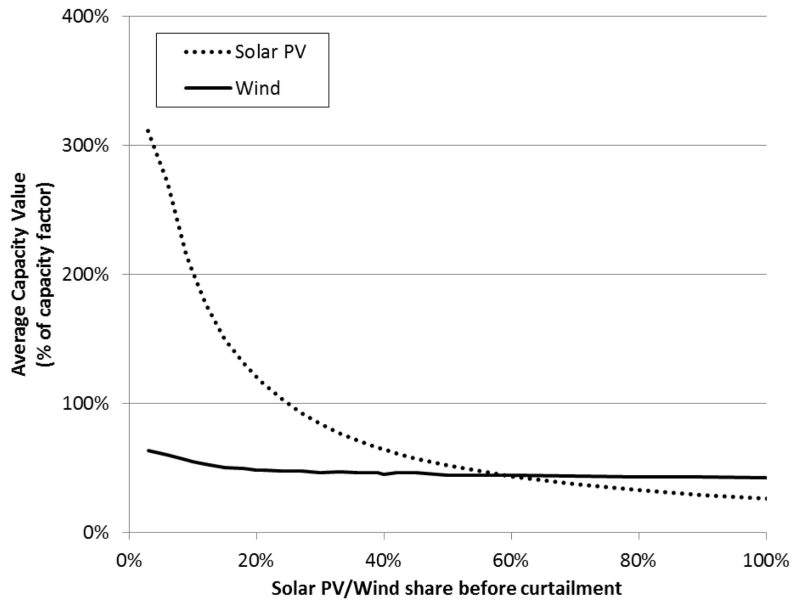

Figure 4.4 – Average capacity value of VRE technologies in the USA as a function of their generation share before curtailment (source: Johnson et al., 2017).

4.3 VRE Curtailment

Since VRE generation is intermittent and non-dispatchable, a wide deployment of these energy sources may mean a significant curtailment, especially when coupled with inflexible base load generation. Curtailment represents potentially useful electricity produced by VRE technologies that is actually wasted, because this generation would occur in a period with a lower level of load. One important feature of the RLDCs is the ability to represent the curtailed generation at the different shares of generation by VRE technologies. Curtailment can be defined as the amount of negative residual load, or VRE oversupply, in a given RLDC (Figure 3.2). A negative residual load indicates that VRE generation alone exceeds electricity demand. The average total curtailment is split into two different components:

- Short-term curtailment: the portion that can be addressed with short-term (<24 h) storage and is due to the daily mismatch between VRE production and electricity demand.
- Seasonal curtailment: the portion that can be handled with seasonal storage and is caused by the seasonal mismatch of high VRE production and high electric load. The way this quantity is estimated in Johnson et al., 2017 is based on Denholm and Hand, 2011.

In the MESSAGE model, total curtailment is defined from the regional RLDCs as a function of the VRE generation share before curtailment in that region. It is modeled equal to zero until a certain VRE share around 40-50 % (specific of the region) and then increases with the generation share. Figure 4.5 shows the behavior of the total curtailment (sum of short-term and seasonal) for the USA case. In MESSAGE this curve is approximated with a stepwise function presenting growing uniform values in 10% wide VREs shares bins.

In the WITCH model, a similar representation of curtailment has been implemented, with the difference of using a second degree function, starting from VRE share equal to zero. The reason behind this choice is twofold: the first one is the numerical structure of the model, which does not allow an easy representation of discontinuous functions or functions with discontinuous first derivative, as the one used in MESSAGE; the second one is related to the fact that considering curtailment equal to zero up to VRE shares around 40-50% appears unrealistic and not able to represent what is actually happening in systems with lower VRE shares. The behavior of WITCH short-term and seasonal curtailment is shown in Figure 4.6 for the USA case.

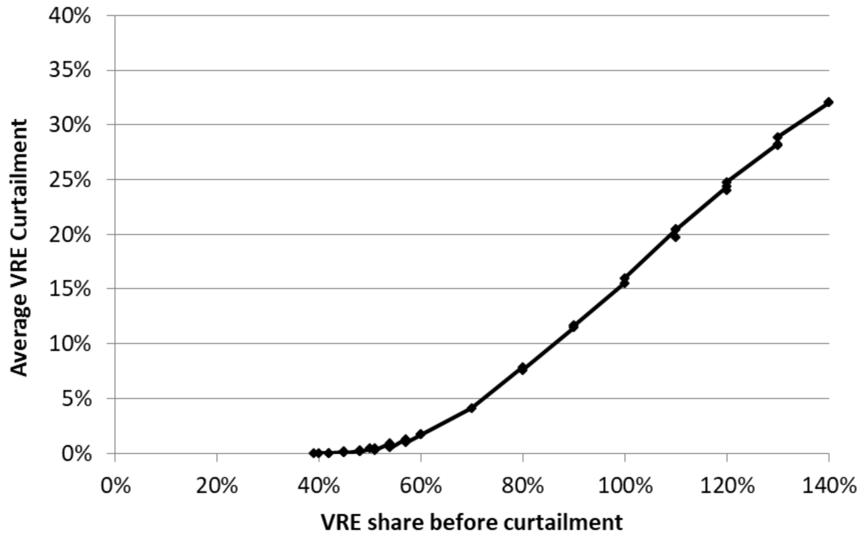

Figure 4.5 – Average total curtailment in the USA as a function of the VRE share before curtailment (source: Johnson et al., 2017).

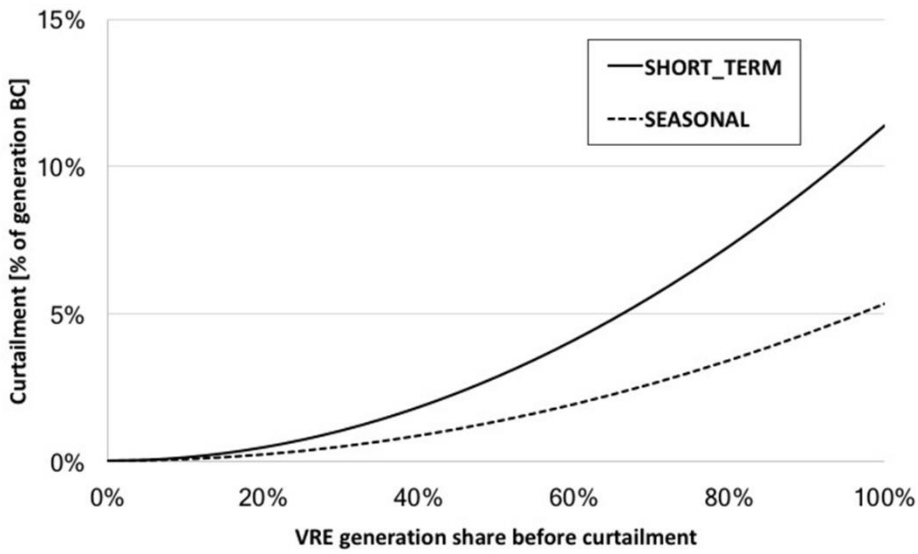

Figure 4.6 – Short-term and seasonal curtailment representation in WITCH as a function of the VRE share before curtailment for the USA.

VREs generation Q_EL after considering curtailment is calculated in the WITCH model as the difference between production before curtailment Q_EL_BC and the curtailed fraction of generation Q_EL_CURT (defined for all j_vre technology), see Equation 4.1:

$$Q\_EL(j\_vre,t,n) = Q\_EL\_BC(j\_vre,t,n) - \sum_{curt\_type} Q\_EL\_CURT(j\_vre,curt\_type,t,n) \quad [4.1]$$

4.4 Flexibility Constraint

The development of the WITCH model has followed three main guidelines set by the recent improvements in the MESSAGE model as regards the flexibility constraint (Johnson et al., 2017):

- Differentiation of the load flexibility coefficient among the different regions
- Improved representation of flexible operation in thermoelectric power plants
- Better definition of the flexibility coefficients for VRE technologies

4.4.1 Flexibility Coefficient of Load

The flexibility coefficient of load represents the flexible fraction of total generation that must be supplied to meet fluctuations and uncertainty in demand. It is derived, for each region, from the load duration curve with no VRE deployment and so, not being influenced by the supply system structure, it represents the need for flexibility of the load (Johnson et al., 2017). Figure 4.7 provides a comparison of the values of the flexibility coefficient of load for the 13 regions of the WITCH model in the current and the new formulation. As one can see, its absolute value has increased with respect to the previous formulation for all the regions except india and sasia (it was set equal to -0.1 for all the regions).

4.4.2 Flexible Operation of Thermoelectric Power Plants

Most thermoelectric power plant technologies can be managed to provide some operating reserve to the system. However, allowing for a flexible operation mode can cause significant impacts on O&M costs, efficiency and capacity factor. In the MESSAGE model two different modes of operation are accounted for: baseload and flexible. In this formulation the flexible operation provides a fraction of generation as operating reserve, but this comes with penalization in terms of higher O&M costs, lower efficiency and lower capacity factor.

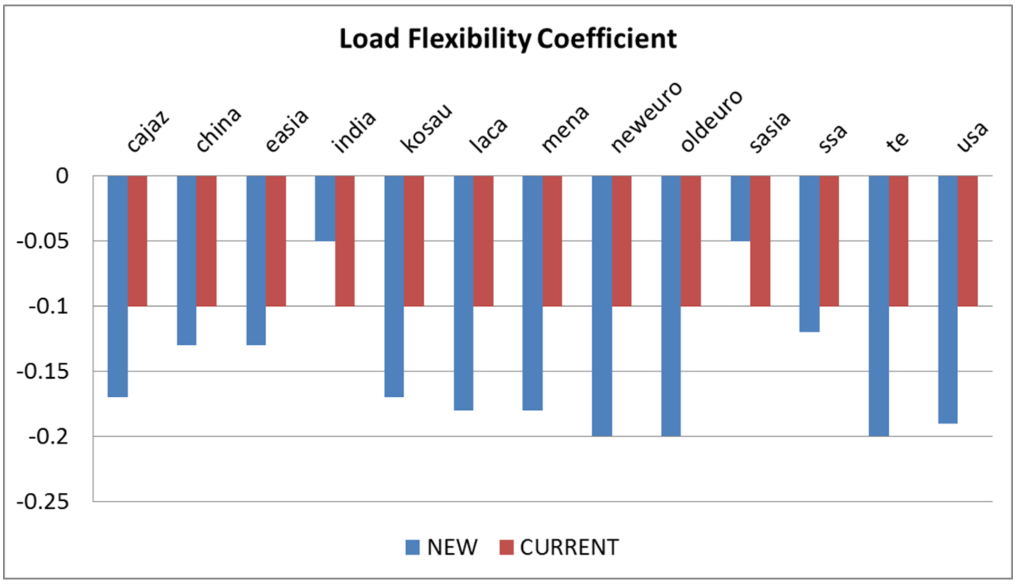

Figure 4.7 – Flexibility coefficient of load in WITCH.

Since a continuous representation is needed in WITCH, due to its numerical structure, the MESSAGE approach has been partially modified to be integrated within the model. In WITCH, the annual generation of a particular technology jel is defined by the following equation:

$$Q\_EL(jel,t,n) \leq K\_EL(jel,t,n) \cdot CF(jel) \cdot \text{yearly hours} \qquad [4.2]$$

where K_EL is the installed full nameplate capacity of the technology in that year. The capacity factor used in Equation 4.2 is defined as the typical maximum achievable capacity factor for each technology. Thus, the model is able to optimize the actual generation between zero and the maximum possible value, given the installed capacity.

The representation of the flexible operation of thermo-electric power plants is introduced adding the following equation:

$$Q\_EL(jel,t,n) = K\_EL(jel,t,n) \cdot CF\_REAL(jel) \cdot \text{yearly hours} \qquad [4.3]$$

where CF_REAL(jel) is defined as the actual capacity factor of the particular technology jel at the period t, resulting from the optimized solution. Starting from the definition of this new variable, the ratio between CF_REAL(jel) and the maximum achievable capacity factor CF(jel) is used to derive the impacts of the operation mode on O&M costs, thermal efficiency and flexibility coefficient of the thermoelectric power plants.

The implemented formulation is the following. A level equal to 40% of the maximum achievable capacity factor CF(jel) is set as the minimum load at which usually thermoelectric power plants are able to work (Kumar et al., 2012). In WITCH there is a further approximation, because the model considers the overall installed capacity of a particular technology in each region, and there is not a representation of each single power plant. At the minimum load, the increase of O&M costs is derived from Johnson et al., 2017 and the thermal efficiency reduction is determined from Kumar et al., 2012. In addition to introducing the two latter forms of penalization, the flexible operation mode has the positive effect of increasing the Flexibility Coefficient (FC) of the technology. The FC increment for the different thermo-electric technologies derived from Johnson et al., 2017 is set in correspondence of the minimum load. Then, the actual variation of these three parameters (O&M increase, efficiency reduction and FC increment) is described as a linear function of the ratio between CF_REAL(jel) and the maximum achievable capacity factor CF(jel). In particular, the variation are set equal to zero when CF_REAL(jel) = CF(jel) and so their ratio is 1 and equal to the above mentioned values (derived from literature) when the ratio is equal to 40%.

Analyzing the impact of this new formulation, some interesting insights can be derived. Without the definition of CF_REAL, the optimization results were such that in some time steps some installed capacity of non-VRE technologies was not producing at full capacity factor, or even not producing at all. This could be explained by the fact that the optimal solution included installing some non-VRE capacity at a certain point to meet the demand or satisfy the capacity or flexibility constraint equations and then, when more favorable ways of meeting the objective were reached, the capacity was just exploited less, because there were not associated penalties. With the new formulation, including CF_REAL, the results are different to what may be expected. The model never exploits non-VRE capacity at a lower capacity factor than the maximum possible one, because it appears that the higher O&M costs, lower efficiency and lost production are not economically justified by the possible higher flexibility coefficient. This behavior is explicable through the perfect foresight nature of the model, which thus is able to optimize the amount of non-VRE installed capacity to avoid that in the subsequent time steps the latter is used at lower capacity factor than the maximum possible. The general impact on the energy system is a moderate change in the overall generation of non-VRE technologies, together with a decrease in their installed capacity with respect to the case with the old formulation, because the installed capacity is always used at the highest capacity factor.

4.4.3 VRE Flexibility Coefficient

In the last updates of MESSAGE model, a series of RLDCs for the different regions with increasing VRE shares has been used to estimate how the flexible fraction of non-VRE generation varies with increasing VRE deployment. The flexibility coefficient of VRE technologies is defined as the additional amount of generation by flexible non-VRE technologies (in kWh) required for one additional kWh produced by VRE. This formulation is used in the flexibility constraint equation. It stands for the supplementary flexibility required by the system due to an extra kWh of VRE production. MESSAGE defines the marginal variation of the VRE flexibility coefficients (Marginal flexibility coefficients MFCs) that assumes different values in three different ranges of VRE generation shares. The values employed in MESSAGE for the USA are shown in Table 4.1. The values for the other regions can be retrieved in Johnson et al., 2017.

VRE share BC	Marginal VRE FC
0 - 15%	-0.03
15 - 50%	-0.39
> 50 %	0.29

Table 4.1 – Marginal Flexibility Coefficients of VRE technologies for different ranges of VRE shares before curtailment for the USA.

These values have been implemented in WITCH with a continuous formulation in full coherence with the MESSAGE formulation. In particular, the VRE flexibility coefficient corresponding to a particular share of VRE has been defined as the weighted mean of the marginal VRE flexibility coefficients derived from zero to the corresponding share. This operation has been repeated for all VRE shares between 0 and 120% and the resulting values have been then interpolated with a 3rd degree polynomial curve, ensuring compatibility with the numerical structure of the WITCH model. In Figure 4.8 the two curves for the USA case can be seen: the dotted one represents the original values calculated from the MFC values and the solid one is the derived 3rd degree polynomial curve.

The formulation of the flexibility constraint resulting from the updates described in this section is shown in the following Equation 4.4. With respect to Equation 3.3, FC_load is now different across regions; FC_non_VRE is a function of the actual capacity factor of the non-VRE technology jel; FC_VRE is a function of the VRE share before curtailment, as shown in Figure 4.8.

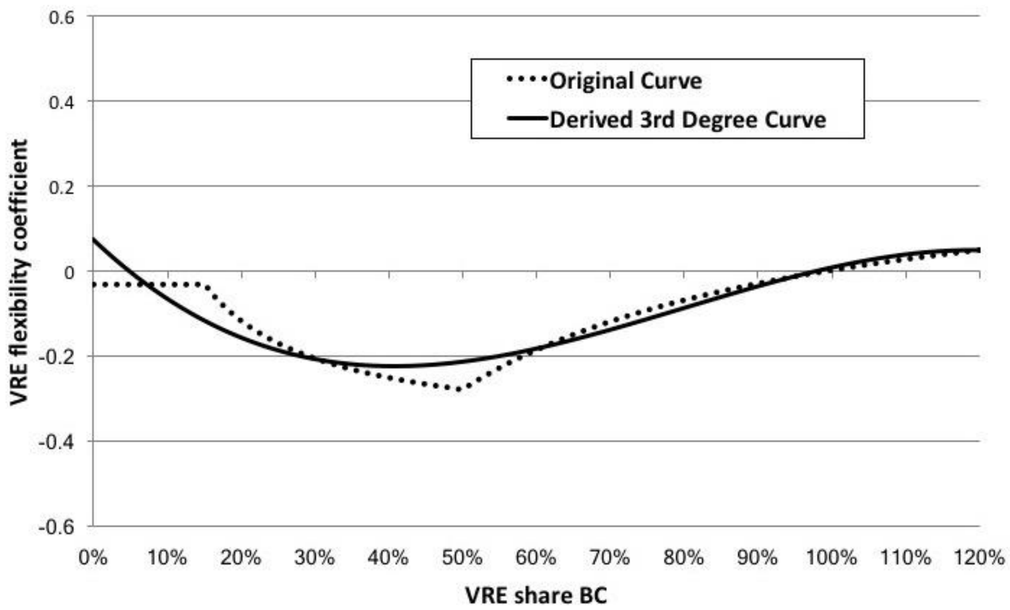

Figure 4.8 – VRE Flexibility Coefficient curve derived from the marginal VRE flexibility coefficient values in Johnson et al., 2017 for the USA case.

$$\sum_{jel|non\_VRE} Q\_EL(jel,t,n) \times FC\_non\_VRE(jel) + \sum_{jel|VRE} Q\_EL(jel,t,n) \times FC\_VRE(jel) + K\_EL_{storage}(t,n) \times CF\_storage \times yearly\_hours \times FC\_storage + FC\_load(n) \times Q\_EL\_TOT(t,n) \geq 0 \quad [4.4]$$

4.4.4 New Interpretation of VRE Flexibility Coefficient

A technical interpretation of the behavior of the flexibility coefficient shown in Figure 4.8 was deemed to be necessary. The investigation started from two considerations.

First of all, looking at the MFC values from Johnson et al., 2017, it could be noted that for some regions the value in the first VRE shares range is positive, apparently meaning that VRE could provide flexibility. The involved regions are mena, neweuro, oldeuro and ssa. Looking at the data about the electricity generation mix between 2005 and 2015 for these regions from IEA Statistics[8], it has been possible to highlight that these

[8] https://www.iea.org/statistics/

regions are currently characterized by a high share of generation provided by non-VRE flexible generation. This in contrast with other regions, whose electricity mix is dominated by baseload technologies. Thus, since the RLDCs from which these values have been derived are built for the current electricity mix of the different regions, it could be concluded that the positive value of the coefficient at low VRE shares (0-15%) comes from the higher available flexibility of the power system. Therefore this means that it is or has been possible to install low shares of VRE without increasing the production from non-VRE flexible power plants.

The second point is linked to the fact that, for all the regions, the marginal flexibility coefficient for VRE becomes positive in the third VRE deployment bin. This leads to an increase in the VRE flexibility coefficient that starts becoming less negative from the beginning of the third bin (corresponding to a VRE share of 50%) and going on with increasing VRE share, as it can be clearly seen in Figure 4.8. This behavior is the result of how the VRE MFCs have been calculated in Johnson et al., 2017.

4.4.4.1 Behind the Calculation of VRE Marginal Flexibility Coefficients

The VRE MFC in a certain range of VRE shares has been calculated as the average marginal increase of non-VRE flexible generators production per one kWh growth in VRE generation. Thus, what happens is that through the first and the second bins the growth of VRE production goes together with a higher generation from non-VRE flexible power plants, to the detriment of baseload plants generation. But with the beginning of the third VRE shares bin, a further increase in VRE production must imply also an absolute decrease of non-VRE flexible generation. This happens simply because the sum of the production shares of all the technologies is 100% and to have a further increase of VRE share, the share of flexible generators has to decrease accordingly. Nonetheless, this should not mean that VREs, alone, are capable of requiring less flexibility, because the need for flexibility is intrinsically dependent on the nature of the VRE technologies and on their reliance on an intermittent natural energy source. Therefore, it is concluded that the shape of the curve resulting from VRE MFCs shown in Figure 4.8 could not represent the flexibility coefficients of VRE technologies alone, but there should be another contribution that allows the VRE technologies to ask for less flexibility at high shares. A personal communication with Nils Johnson, the corresponding author of Johnson et al. 2017, clarified that, in the MESSAGE model, the contribution of grid upgrades to the integration of VREs is not explicitly modeled, but it is intrinsically included in the existing formulation. Thus, it was concluded that a contribution related to the "smartening" and pooling of the grid is the one that allows the VREs to require less flexibility per unit of electricity generated, i.e. their flexibility coefficient becomes less negative. This contribution becomes significant at VREs shares higher than 50% (that corresponds to the third MESSAGE deployment bin) because higher VREs shares are not likely to be achieved without the above mentioned interventions on the grid.

4.4.4.2 Flexibility Coefficient Curve as Sum of Two Contributions

Based on the considerations reported in the previous section, it is concluded that the VRE flexibility coefficients curve in Figure 4.8 are the results of the sum of two different contributions:

- A curve representing the "actual" flexibility coefficient of VRE technologies, as they are installed and interact with the rest of the power system. This contribution has been modeled as a 3rd degree polynomial curve function of the VRE share before curtailment that behaves as the overall FC curve in the first two VRE shares bins and then remains constant at the value assumed in correspondence of the beginning of the third bin.
- A curve representing the contribution of grid pooling, that stands for the whole set of technology options (such as area monitoring and control or integration of VRE and distributed generation) which could increase the electric grid connection and reliability and allow high shares of VRE generation. This contribution has been modeled as a 2nd degree positive polynomial curve function of the VRE share before curtailment, starting from 0 null VRE share and then increase reaching significant values at the beginning of the third VRE shares bin. To find this curve, a difference between the curve interpolated from the original MFCs values and the curve of VRE alone FC above mentioned has been performed. Then, the obtained values have been interpolated with a 2rd degree positive polynomial curve, starting from the origin and reaching the actual value for a VRE share of 100%. The effect of grid pooling is represented with the grid pooling coefficient POOLING that assumes the values of the curve and whose meaning and use will be explained in Section 5.

Figure 4.9 shows the curves representing the two different contributions and the overall resulting FC curve could be seen for the USA case, while Figure 4.10 shows a comparison between the 3rd degree polynomial curve of the overall VRE FC implemented in WITCH and resulting from the sum of the two abovementioned contributions, and the VRE FC 3rd degree polynomial curve derived from the original MFCs values and also visible in Figure 4.8. The comparison highlights that the implemented curves constitute a good approximation of the originally interpolated ones. More details, and in particular the polynomial coefficients used in the WITCH model for representing the different curves described in this section, can be found in Marni and Prato, 2017.

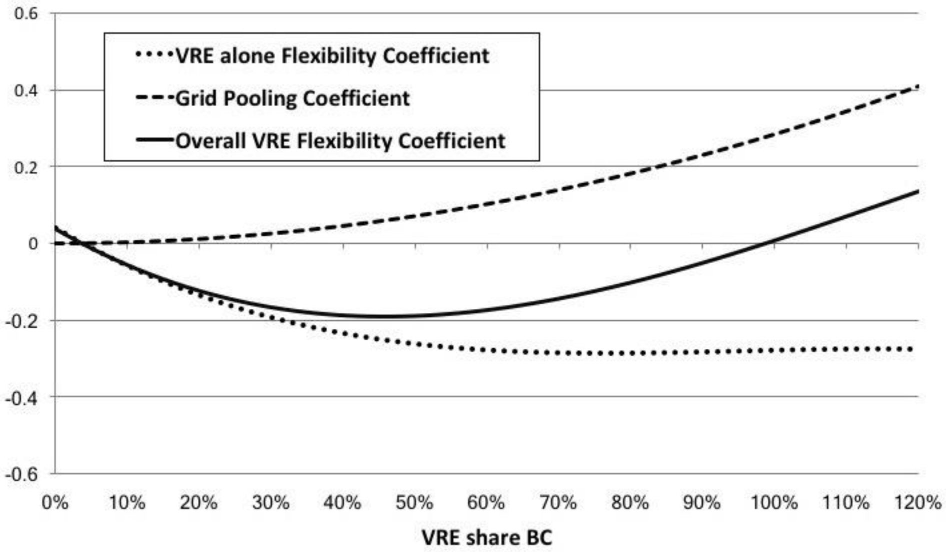

Figure 4.9 – VRE alone FC curve, grid pooling curve, and overall VRE FC curve for the USA.

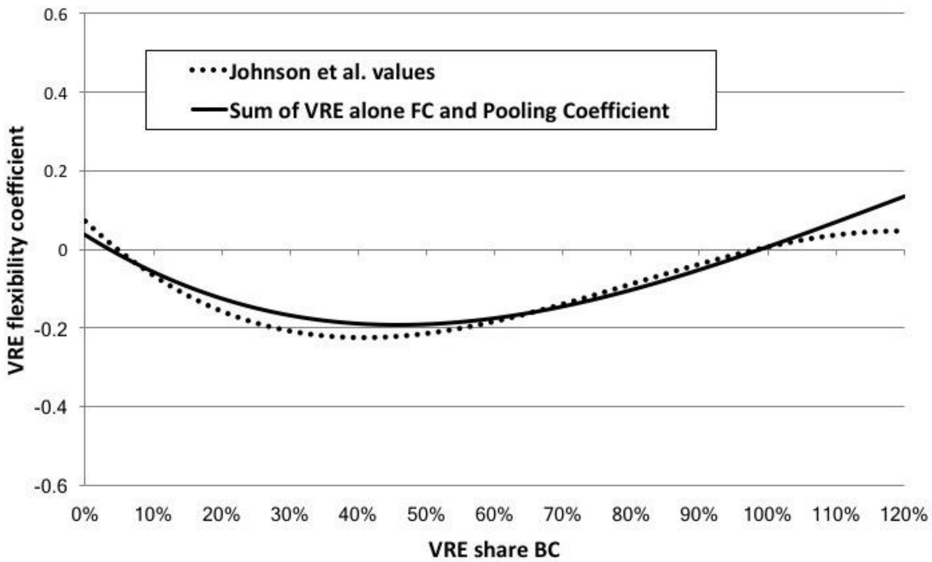

Figure 4.10 – Comparison between the overall VRE FC curve implemented in WITCH and the curve interpolated from the original MFCs values taken from Johnson et al., 2017.

5. The New Electric Grid Modeling

The improvement of the electric grid modeling in WITCH has proceeded along four directions:

- Better definition of installed grid capacity.
- Distinction between two different types of electric grid: transmission and distribution lines, characterized by different extensions and investment costs.
- Refinement of the grid pooling modeling.
- Introduction of losses on electric grid lines to differentiate between electricity input to the grid and the output to the demand.

5.1 Better Definition of Installed Grid Capacity

Installed grid capacity is still considered linearly proportional to the installed generation capacity. Nevertheless, the conversion factor grid requirement grid_req was introduced, expressed in terms of km of installed grid per Terawatt (TW) of installed generation capacity. This was done in order to translate the installed grid capacity into km instead of TW. The reason behind this choice is that the km are a measurement unit broadly used in the related literature and with respect to which it is much easier to derive literature data on the grid investment costs.

5.2 Distinction between Transmission and Distribution Lines

A general distinction among transmission and distribution lines has been introduced. A more detailed differentiation, based on the different lines voltages, has been taken into consideration, but eventually considered not to be within the scope of an IAM like the WITCH model. Moreover, the representation of grid has to be based on strong approximations in a model without a detailed geographical representation of load locations and grid extensions.

The distinction between transmission and distribution lines pursues the objective of highlighting the specific investments required in the two different types of grid, based on the fact that different types of VRE technologies (depending on the distance from load centers) and of storage technologies ask for different types of grid. The differences between the two technologies can be summed up as in the following:

- <u>Different lifetime</u>: 60 years for transmission and 50 years for distribution lines.
- <u>Distinct grid requirement</u>: For transmission lines, the ranges of values is between about 2 million and 7 million km/TW, while for distribution lines the ranges of values is between about 4 million and 14 million km/TW. The higher values for distribution lines are due to the fact that these are usually much

shorter than transmission lines, but the distribution grid is much more widespread.

- Different grid investment costs: around 7 M$2005/km for transmission lines and 250 k$2005/km for distribution lines.
- Different power technologies: all non-VRE generation technologies require both transmission and distribution lines, while for VRE technologies we applied some distinctions based on distance from load centers. Solar and wind capacity with intermediate or far distance necessitates both transmission and distribution since the electricity they produce need to be firstly transmitted to the load centers and then distributed. Besides, for far VRE plants a markup is set by multiplying the transmission grid requirement by a factor of 4 (assumed as the ratio between mean distance of “far” VRE plants and “average” VRE plants), to consider the additional grid needed to connect solar and wind plants very far from the load centers, often characterized by geographical obstacles and difficulties. On the other hand, solar and wind capacity characterized by near distance (<50 km) requires just distribution line because they are close to the electricity consumption points and they can also represent VRE capacity at the residential level.
- Concerning storage capacity, it was assumed that PHES and CAES technologies only require transmission lines because they are usually used as centralized electric storage systems connected to the high voltage lines. Conversely it was assumed that batteries and fuel cells only need distribution lines because they are widely thought as distributed electric storage systems. Naturally, these indications will become clearer after the description of the storage technologies in Section 6.

As a result, the following equations describing the electric grid were introduced. The capital stock Equation 5.1 has the same shape as in the pre-existing formulation but now it is differentiated for the two grid types (the exponent 5 is related to the WITCH time steps). Equation 5.2 represents the definition of installed transmission grid capacity from installed generation and storage capacity, while Equation 5.3 is the analogous for distribution grid capacity. In the two latter, the new formulation of the installed capacities K_STOR and K_FUEL_CELL of electric storage technologies (in TW) is introduced. Again, please refer to Section 6 to fully understand its meaning.

$$K\_EL\_GRID(grid\_type, t + 1, n) = K\_EL\_GRID(grid\_type, t, n) \times (1 - \delta\_grid)^5 + 5 \times \frac{I\_GRID(grid\_type, t, n)}{grid\_inv\_cost(grid\_type)} \quad [5.1]$$

$$K\_EL\_GRID_{transmission}(t, n) = grid\_req_{trasmission} \times \Bigg[\sum_{jel|non\_VRE} K\_EL(jel, t, n) + \sum_{jel|VRE_{intermediate}} K\_EL(jel, t, n) + 4 \times \sum_{jel|VRE_{far}} K\_EL(jel, t, n) + K\_STOR_{phes}(t, n) + K\_STOR_{caes}(t, n) \Bigg] \quad [5.2]$$

$$K\_EL\_GRID_{distribution}(t, n) = grid\_req_{distribution} \times \Bigg[\sum_{jel|non\_VRE} K\_EL(jel, t, n) + \sum_{jel|VRE_{near}} K\_EL(jel, t, n,) + K\_STOR_{batteries}(t, n) + K\_FUEL\_CELL(, t, n) \Bigg] \quad [5.3]$$

5.3 Refinement of the Grid Pooling Modeling

Representing the concept of grid smartening and pooling[9] in an IAM is not an easy task. Eventually it was decided to represent grid pooling as additional investments that are required to upgrade the existing grid or build more connections. Therefore, there is not an installed capacity associated to pooling. Because of the variegate nature of the actual grid smartening and pooling solutions, representing its economic values only is a good approximation in a model like WITCH.

This additional amount of investments needed for grid pooling and to integrate VRE into the grid has been considered proportional to the sum of the investments I_GRID in transmission and distribution lines, as visible in Equation 5.4. The rationale is that the more transmission and distribution lines are built, the more investments will be required to smarten and connect them at international level. The factor of proportionality is precisely the variable POOLING that is represented by the 2nd degree positive polynomial curve function of the VRE share before curtailment introduced in Section 4.4.4.2. Thus, the variable POOLING grows quadratically with the VRE share before curtailment (Figure 5.1 for the USA case).

[9] For the sake of simplicity, in the following it will be referred to simply as ”pooling”.

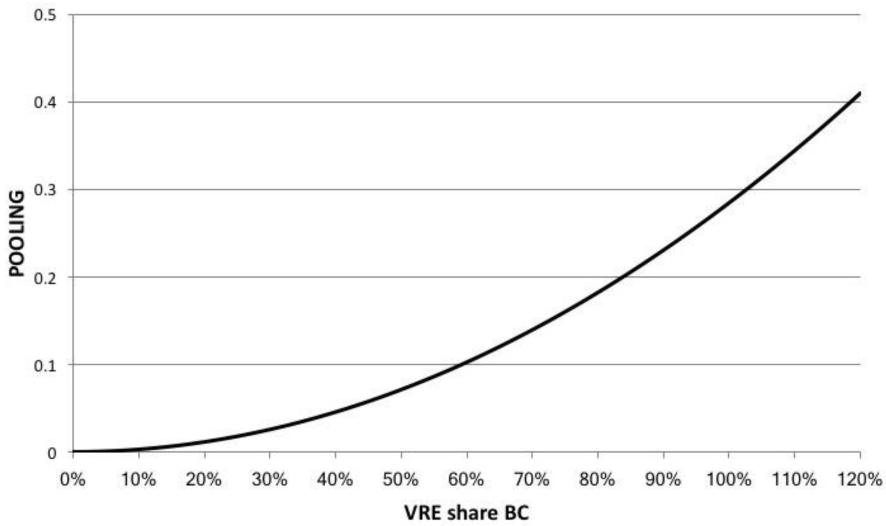

Figure 5.1 – POOLING quadratic behavior as a function of SHARE_EL_VRE_BC for the USA case.

$$I\_GRID\_POOLING(t,n) = pooling\_req \times POOLING(t,n) \times \sum_{grid\_type} I\_GRID(t,n) \qquad [5.4]$$

where POOLING is a function of SHARE_EL_VRE_BC(t,n).[10]

5.4 Grid Losses

The lack of a description of thermal losses on electric lines can be considered a weakness of the previous formulation of the electric grid, because these losses constitute a non-negligible fraction of the electricity generation all around the world. Introducing these losses allows adding the distinction between the electricity generated that is the input into the electric grid and the electricity that can actually be consumed. This aspect has been modeled representing the grid thermal losses just as a portion of the economic value of electricity that is lost. It is reminded, in fact, that the WITCH model calculates the overall generation by the energy sector and converts it into its economic value, that enters the utility function together with capital and labor. This conversion is done through the energy factor productivity, a parameter that translates the TWh of electricity produced into its monetary value. The loss is thus modeled at this level.

[10] The "pooling requirement" coefficient pooling_req has a default value of 1. It has been defined to perform a sensitivity analysis on the link between investments in pooling and the overall investments in grid. For the sake of brevity this will not be discussed in this document.

6. The New Storage Modeling

The objective in this area was to introduce a formulation that would allow representing the general operation of storage, in terms of input (charge) and output (discharge) electricity and related losses, due to non-unitary round-trip efficiency.

Two different types of storage, with different input sources and uses, have been modeled:

- Short-term storage: it represents the storage technologies used for daily shifting of electricity generation to meet peak load, that does not happen in coincidence with high VRE production, or to exploit daily differences in electricity prices. In the new modeling, it can receive the electricity input from three different types of sources: non-VRE power plants, VRE short-term curtailment and non-curtailed VRE generation.
- Seasonal storage: it stands for the set of technologies used to implement a shifting of generation between different seasons. It could be exploited particularly in regions where high electricity demand is strongly decoupled from high VRE generation among different seasons. In the modeling, it can receive input from one source only, i.e. VRE seasonal curtailment.

6.1 Short-term Storage

The technologies chosen to be considered in modeling short-term electric storage in WITCH are:

- Pumped Hydro Energy Storage (PHES): it is the only commercially-proven large-scale storage technology, with more than 300 plants and almost 100 GW of installed capacity worldwide; the working principle of this technology is very simple, as it stores electrical energy in the form of hydraulic potential energy, pumping water from lower to higher reservoirs, thus increasing its geodetic height.
- Compressed Air Energy Storage (CAES): it is a mechanical storage technology that works converting electricity into air high pressure through a compressor, storing the air in a reservoir (most commonly an underground cavern) and then heating up the air and expanding it in a turbine to generate electricity when needed.
- Lithium-ion batteries (LiB): it is a relatively old technology that has widespread applications in electronics (laptops, tablets, smartphones), Plug-In Hybrid and Full-Electric Vehicles and power grid applications.

Commercial maturity, future prospects, completeness in storage representation as well as analogy with other IAMs were the basis for this choice.

As regards the installed capacity, the storage technologies have been considered under both the dimensions that characterize storage: the power conversion system and the energy reservoir. Accordingly, two different capacities have been defined: K_STOR, that is the installed power capacity (in TW), and K_STOR_RES, that is the installed energy capacity (in TWh). For each technology, an investment cost per unit of TW for the power conversion system and an investment cost per unit of TWh for the energy reservoir have been considered. Thus, the overall investment cost in short-term storage I_STOR includes both the investments in power and energy capacities.

Since there was not the possibility to model the ratio installed storage TWh/TW as based on optimization of charge-discharge cycles (due to temporal and geographical aggregation of the WITCH model), it was decided to fix the ratio between K_STOR and K_STOR_RES of each technology through the parameter avg_EtoP_ratio (average energy-to-power ratio). The following Equation 6.1 defines the link between the two installed capacities of storage technologies:

$$K\_STOR\_RES(j\ stor,t,n) = avg\_EtoP\_ratio(j\ stor) \cdot K\_STOR(j\ stor,t,n) \qquad [6.1]$$

The overall investment cost has been derived through the sum of the two distinct cost components, for the power and energy capacity of the technology. It has been expressed in terms of installed power by converting the cost in TWh through the avg_EtoP_ratio specific of each technology. Moreover, for LiB and CAES, the overall capital cost decreases with growing cumulative installed power capacity, through Learning by Doing, and therefore it is a function of time.

Consequently, for each short-term storage technology j_stor, a capital stock equation has been defined as shown in Equation 6.2:

$$\begin{aligned} K\_STOR(j\_stor, t+1, n) = {} & K\_STOR(j\_stor,t,n) \times (1 - \delta\_stor(j\_stor))^5 \\ & + 5 \times \frac{I\_STOR(j\_stor,t,n)}{INV\_COST\_STOR(j\_stor,t)} \end{aligned} \qquad [6.2]$$

As specified above, the short-term storage technologies can receive electricity as input from three different sources:

- non-VRE power plants
- VRE short-term curtailment
- non-curtailed VRE generation

The first two can supply a fraction of installed storage capacity called K_STOR_CURT, while the latter can supply the second fraction of storage capacity called K_STOR_PEAK. Thus, the overall installed capacity of each short-term storage technology j_stor and the relevant yearly investments are defined as follows:

K_STOR(j_stor,t,n) = K_STOR_CURT(j_stor,t,n) + K_STOR_PEAK(j_stor,t,n) [6.3]

I_STOR(j_stor,t,n) = I_STOR_CURT(j_stor,t,n) + I_STOR_PEAK(j_stor,t,n) [6.4]

The following Table 6.1 summarizes the main economic and technical assumptions for the short-term storage technologies.

Technology	Energy cost $\frac{\$05}{kWh}$			Power cost $\frac{\$05}{kW}$			O&M cost	
	min	mid	max	min	mid	max	var $\frac{\$05}{kWh}$	fix $\frac{\$05}{kW}$
PHES	41.51	68.85	116.44	424.26	534.63	837.38	0.00032	4.66
CAES	30.38	40.50	47.59	704.74	853.58	939.65	0.0045	3.95
LiB	684.49	804.98	1158.36	403.00	461.81	536.65	0.0030	6.99

Technology	RTE	Lifetime (yrs)	Lifetime (cyc)	Cycle disch. time
PHES	0.775	55	30000	-
CAES	0.54	35	20000	2.6
LiB	0.85	12.5	3000-6500	2
	Full prod h	**E2P ratio**	**FlexC**	**CapC**
PHES	457-1202	9.8	0.75	1
CAES	1486	7.8	0.75	1
LiB	480-1040	2	1	0.8
	Learning rate	**Floor cost**		
PHES	0	-		
CAES	5%	half initial cost		
LiB	12%	half initial cost		

Table 6.1 – Main assumptions for the short-term storage technologies.

6.2 Seasonal Storage

Seasonal storage can receive electricity input from one source only: seasonal curtailment of VRE generation.

Seasonal storage has been modeled with the production and subsequent consumption of hydrogen. The reason behind this choice is that hydrogen can be considered a good solution in terms of long-term storable and dispatchable energy carrier and because the implemented technologies are already in their commercial phase. In particular, hydrogen is produced through a generic electrolyzer technology that is fed by the electricity input from seasonal VRE curtailment. Then, hydrogen is stored and transported: the economic impact of these operations has been considered through an overall storage and transport cost per unit of kWh of hydrogen produced. Finally, hydrogen represents the fuel input into a generic fuel cell technology modeled as a Polymeric Electrolyte Membrane Fuel Cell (PEMFC) which in turn re-converts hydrogen into electricity. Again, this technology has been chosen due to its commercial maturity and prospects.

6.2.1 Hydrogen Production

First of all, the maximum hydrogen production Q_ELH2 in terms of TWh in each time step and in each region is defined by the seasonal curtailed fraction of VREs generation reduced through the assumed efficiency of the electrolyzer technology (Equation 6.5).

$$Q\_ELH2(j\_vre,t,n) \leq Q\_EN\ Cseasonal(j\_vre,t,n) \cdot \eta\ electrolyzer \qquad [6.5]$$

After that, in Equation 6.6 the hydrogen production is linked to the installed electrolyzer capacity K_ELH2 (in TW). In particular, the hydrogen production must be lower than the product between the electrolyzer installed capacity and an average number of annual operating hours, that is directly related to an average number of full production hours (avg_CF(j_vre) × yearly hours) of the single j_vre. In particular, the annual operating hours that the electrolyzer can dedicate to the input from a particular j_vre is derived from the average number of full production hours of this j_vre multiplied by the share of the overall VREs seasonal curtailment represented by this specific j_vre technology. This is obviously an approximation, but it appears to be a consistent way to define the real annual operating hours of the electrolyzer technology and hence derive the installed capacity K_ELH2 through the hydrogen production Q_ELH2(j_vre,t,n) (which derives from Equation 6.5). The reason behind this modeling choice is that the installed electrolyzer capacity should not be derived from its hydrogen production through some annual operating hours defined a priori. On the contrary, the electrolyzer can work just in the hours when there is available electricity from VREs seasonal curtailment.

$$Q\_ELH2(j\_vre,t,n) \leq K\_ELH2(t,n) \times avg\_full\_prod\_hours_{VRE}(j\_vre,n) \times \frac{Q\_EN\_C_{seasonal}(j_v re,t,n)}{\sum_{j\_vre} Q\_EN\_C_{seasonal}(j_v re,t,n)} \quad [6.6]$$

The last equation (Equation 6.7) is the capital stock equation that links installed capacity and investments for the electrolyzer technology:

$$K\_ELH2(t+1,n) = K\_ELH2(t,n) \times (1 - \delta\_electrolyzer)^5 + 5 \times \frac{I\_ELH2(t,n)}{INV\_COST\_ELH2} \quad [6.7]$$

6.2.2 Fuel Cells Capacity and Generation

The first equation (Equation 6.8) modeling the fuel cell technology links its electricity generation Q_FUEL_CELL to the available amount of exploitable energy in terms of TWh of hydrogen Q_ELH2 through the efficiency of the fuel cell.

$$Q\_FUEL\_CELL(j\_vre,t,n) = Q\_ELH2(j\_vre,t,n) \cdot \eta_{fuel\_cell} \quad [6.8]$$

The second equation (Equation 6.9) expresses the relationship between the fuel cell technology annual generation Q_FUEL_CELL and its installed capacity K_FUEL_CELL in TW, through the parameter $full\_prod\_hours_{fuel\_cell}$ indicating the annual full production hours that characterize the fuel cell technology operation.

$$Q\_FUEL\_CELL(j\_vre,t,n) \leq K\_FUEL\_CELL(t,n) \cdot full\_prod\_hours_{fuel\_cell} \quad [6.9]$$

Finally, Equation 6.10 is the capital stock equation for the fuel cell technology.

$$K\_FUEL\_CELL(t+1,n) = K\_FUEL\_CELL(t,n) \times (1 - \delta\_fuel\_cell)^5 + 5 \times \frac{I\_FUEL\_CELL(t,n)}{INV\_COST\_FUEL\_CELL} \quad [6.10]$$

The following Table 6.2 reports the main assumptions for the seasonal storage technologies.

Technology	Capital cost $\frac{\$05}{kW\,year}$ min	mid	max	O&M cost $\frac{\$05}{kW}$	Storage cost $\frac{\$05}{kWh}$
Electrolyser	-	997.2	-	-	-
PEM Fuel Cell	625.5	1454.3	2862.9	24.81	-
H_2	-	-	-	-	0.0338

Technology	Efficiency	Lifetime (yrs)	Full prod h	
Electrolyser	0.70	21	(see Section 4.4.2)	
PEM Fuel Cell	0.50	24	2465	
	FlexC	CapC	Learning rate	Floor cost
Electrolyser	-	-	18%	half initial cost
PEM Fuel Cell	0.9	1	18%	half initial cost

Table 6.2 – Main assumptions for the seasonal storage technologies.

6.3 Wrap up

Figure 6.1 summarizes the modeling scheme of the new storage modeling in WITCH.

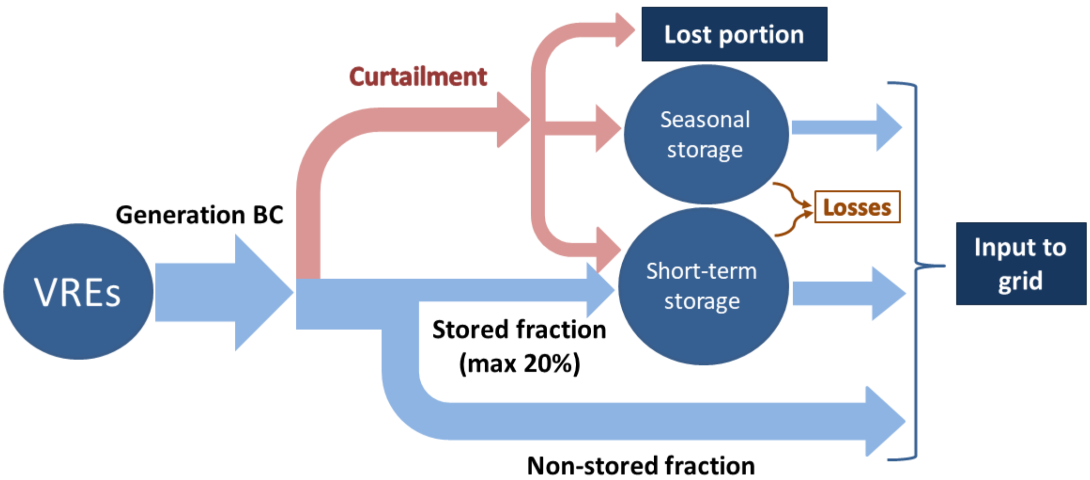

Figure 6.1 – The new storage modeling in WITCH: summary.

6.4 Effect of the New Formulation on Pre-Existing Equations

The effects of the new formulation of electric storage is particularly visible on three pre-existing equations in WITCH:

- The definition of VREs generation Q_EL after considering curtailment
- The capacity constraint equation
- The flexibility constraint equation

6.4.1 Definition of VREs Generation after Curtailment

The VRE generation after considering curtailment Q_EL (Equation 6.11) is the one that enters in the calculation of the monetary value of energy, to consider its effect on the utility function. Thus, the positive effect of the additional contributions of short-term and seasonal curtailment fractions that are stored and then produced must be taken into consideration, along with the negative effect of the losses related to the non-curtailed portion of VRE generation that is stored. The resulting equation has the following aspect (defined ∀ j_vre technology):

$$
\begin{aligned}
Q\_EL(j\_vre,t,n) = {} & Q\_EL\_BC(j\_vre,t,n) \\
& - \sum_{curt\_type} Q\_EL\_CURT(j\_vre,curt\_type,t,n) \\
& + \sum_{j\_stor} Q\_OUT\_STOR\_CURT(j\_vre,j\_stor,t,n) \\
& - \sum_{j\_stor} K\_STOR\_PEAK(j\_vre,j\_stor,t,n) \\
& \qquad \times full\_prod\_hours(j\_stor,t,n) \times \left(\frac{1}{\eta_{stor}(j\_stor)} - 1\right) \\
& + Q\_FUEL\_CELL(j\_vre,t,n)
\end{aligned}
\tag{6.11}
$$

6.4.2 Capacity Constraint Equation

Compared to Equation 3.2, the new formulation of the capacity constraint equation presents differences in the definition of terms referring to capacities of storage technologies (Equation 6.12). First of all, there is the contribution of installed capacity of every short-term storage technology K_STOR, each multiplied by its capacity coefficient CC_{stor}(j_stor) (1 for PHES and CAES, 0.8 for LiB). Then, the component related to the installed fuel cell technology capacity K FUEL CELL is visible with a capacity coefficient CC_{fuel_cell} of 1. Again, the positive contributions of generation plants and storage technologies must be greater or equal than the product of firm requirement and annual average load for each time step and region.

$$\begin{aligned}
&\sum_{jel|non_VRE} K_EL(jel,t,n) \;+\; \sum_{jel|VRE} K_EL(jel,t,n) \times CF(jel,t,n) \times CV(jel,t,n) \\
&+ \sum_{j_stor} K_STOR(j_stor,t,n) \times CC_{stor}(j_stor) \\
&+ K_FUEL_CELL(t,n) \times CC_{fuel_cell} \\
&\geq \; firm_req(n) \times \frac{Q_EL_TOT(t,n) \;-\; LOSS(t,n)}{yearly_hours}
\end{aligned} \qquad [6.12]$$

where

$$LOSS(t,n) = \sum_{jel|non-VRE} \sum_{j\_stor} Q\_EL\_STORED(jel,j\_stor,t,n) \times (1-\eta_{stor}(j\_stor))$$

The LOSS term is subtracted from the overall electricity generation Q_EL_TOT(t,n) to consider the losses in storage related to the input from non-VRE technologies.

6.4.3 Flexibility Constraint Equation

The flexibility equation is the one that presents the addition of the highest number of terms (refer to Equation 4.4). Let us start focusing on the first term between square brackets, that is multiplied by FC_VRE (second, third and fourth rows of the following Equation 6.13). Here, the overall generation of a single VRE technology after considering curtailment Q_EL has to be reduced by the fractions that are actually produced by short-term storage technologies (the first and second term) and by fuel cell technology (the third term). This is done because these terms were included in the calculation of the Q_EL of each j_vre technology (Equation 6.11) in order to have the right value entering the calculation of the monetary value of energy.

Then, the second term between square brackets, that is all multiplied by FC_{stor} (fifth, sixth and seventh rows of Equation 6.13) represents the contribution of short-term storage technologies. For each short-term storage technology j_stor, all the three storage outputs (each one related to a different input source) are multiplied by the proper flexibility coefficient FC_{stor} (0.75 for PHES and CAES, 1 for LiB). The last new term is the one related to the fuel cell technology: its annual generation multiplied by a flexibility coefficient FC_{fuel} cell equal to 0.9. Finally, the term related to the flexibility requirement of load appears.

$$
\begin{aligned}
&\sum_{jel|non\_VRE} Q\_EL\_NON\_STORED(jel,t,n) \;\times FC\_non\_VRE(jel) \\
&+ \sum_{jel|VRE} \Bigg[Q\_EL(jel,t,n) - \sum_{j\_stor} \Bigg(Q\_OUT\_STOR\_CURT(j\_vre, j\_stor, t, n) \\
&\qquad - \frac{K\_STOR\_PEAK(j\_stor,t,n) \times full\_prod\_hours(j\_stor,t,n)}{\eta_{stor}(j\_stor)} \Bigg) \\
&\qquad - Q\_FUEL\_CELL(j\_vre,t,n) \Bigg] \times FC\_VRE(jel) \\
&+ \sum_{j\_stor} \Bigg[\sum_{j\_vre} \Bigg(Q\_OUT\_STOR\_CURT(j\_vre, j\_stor, t, n) \\
&\qquad + K\_STOR\_PEAK(j\_vre, j\_stor, t, n) \\
&\qquad\qquad \times full\_prod\_hours(j\_stor,t,n) \Bigg) \\
&\qquad + \sum_{jel|non-VRE} Q\_EL\_STORED(jel, j\_stor, t, n) \Bigg] \times FC_{stor}(j\_stor) \\
&+ Q\_FUEL\_CELL(j\_vre,t,n) \times FC_{fuel\_cell} \\
&+ FC\_load(n) \times \big(Q\_EL\_TOT(t,n) \; - \; LOSS(t,n) \big) \;\geq\; 0
\end{aligned}
\qquad [6.13]
$$

7. Assessment of the New Modeling Scheme

In the light of the new modeling features added or modified in WITCH, the previously reported Table 3.3 can be updated as follows (Table 7.1): the added +'s are underscored.

Feature	Changes in the modeling solution in WITCH	Mark
Investment into dispatchable power plants differentiated by load band	Flex&cap constraints updated to fit the constraints to the region-specific ADVANCE RLDCs, in order to more accurately represent the effect of VRE on the RLDC.	+<u>+</u>
Investment into VRE (including feedback on the system)	Flexibility and capacity coefficients are now VRE-share-dependent.	+<u>+</u>
Expansion dynamics	-	+

(continues)

Capital stock inertia and vintaging	-	++
Structural shift of generation capacity mix	-	+
Love of variety	-	+
Dispatch	Flexible operation of thermoelectric power plants	++
Flexibility and ramping	VRE share dependent flexible coefficients coupled with the flexible operation of the non-VRE plants	++
Capacity adequacy	RLDC-derived CV for VREs	++
Curtailment	Based on region-specific RLDC	++
Wind-Solar complementarity	Wind-solar RLDC (+++); relies on single wind-solar mix per region to parameterize flex. & cap. equations (-)	++
Demand profile evolution	-	0
Short-term storage	Endogenous storage investments driven by capacity & flexibility equation with fixed coefficients and by VRE-share-dependent effect on curtailment	++
Seasonal storage	Hydrogen electrolysis, fuel cell to convert hydrogen into electricity, linkage with seasonal curtailment	++
Demand response (incl. electric vehicles and vehicle-to-grid)	-	+
General transmission and distribution grid	Distinction between transmission and distribution, installed capacity expressed in kilometers, regional grid requirement (km/TW), introduction of grid thermal losses	+++
Grid expansion linked to VRE	Better differentiation between near, intermediate and far VREs in terms of transmission and distribution requirements	++
Pooling effect from grid expansion	Region-wide pooling is implicitly contained in the RLDCs, plus an explicit formulation has been added	++

Table 7.1 – Features of VRE system integration modeling: WITCH (new).

The sum of the +'s now gives 30, exactly twice as the level reached at the beginning of the work. This has allowed WITCH to reach the state-of-the-art level in the IAM community in modeling the VRE penetration in the electricity mix, with some beyond-state-of-the art solutions concerning grid and storage.

8. Results

8.1 Introduction

The main objective of this deliverable is to present the new modeling of system integration, grid, and storage in the WITCH model. Naturally this formulation has been tested in a series of scenarios, but the relevant results are not of capital importance per se. This will be the focus of the second half of the MERCURY project. Rather, it is interesting to compare the new results with those obtained in the previous model version. This section will thus report some results with this purpose. For more details the reader is referred to Marni and Prato, 2017.

8.2 Scenario Details

The scenarios reported in the graphs refer to the following scheme.
In terms of climate policy:

- BAU (Business-as-Usual): no policy scenario;
- CTAX: a moderate carbon tax, starting from 30 $2005/tCO2eq in 2020 and increasing at an annual rate of 3.5%, is applied to carbon emissions;
- CTAX2DEG: a carbon tax is applied to carbon emissions in order to achieve a temperature increase of 2°C in 2100 with respect to the pre-industrial levels with a likely chance. In order to compare it to the previous scenario, this entails an annual growth rate of about 7%.

In terms of model configuration:

- MASTER: the ADVANCE model version at the beginning of this work;
- SYST_INT: MASTER with the new system integration modeling;
- +GRID: SYST_INT with the new grid modeling;
- +STORAGE: +GRID with the new storage modeling → final model configuration.

In terms of technology availability:

- nukeccs_ON: full portfolio of technologies available;
- nukeccs_OFF: no CCS and progressive nuclear phase-out (this scenario is meant to boost renewable expansion).

8.3 Results Overview

Raising the value of a global carbon tax to achieve increasingly ambitious temperature reduction targets has a positive effect both on the deployment of VRE technologies and of electricity storage technologies if compared to the Business-as-Usual scenario. While VRE technologies represent just 24% of global net generation in 2100 in the BAU scenario, if the tax is raised to achieve the 2°C target indicated by the Paris Agreement (CTAX2DEG), VREs become the most widespread technology options, accounting for 51% of global net electricity generation (Figure 8.1).

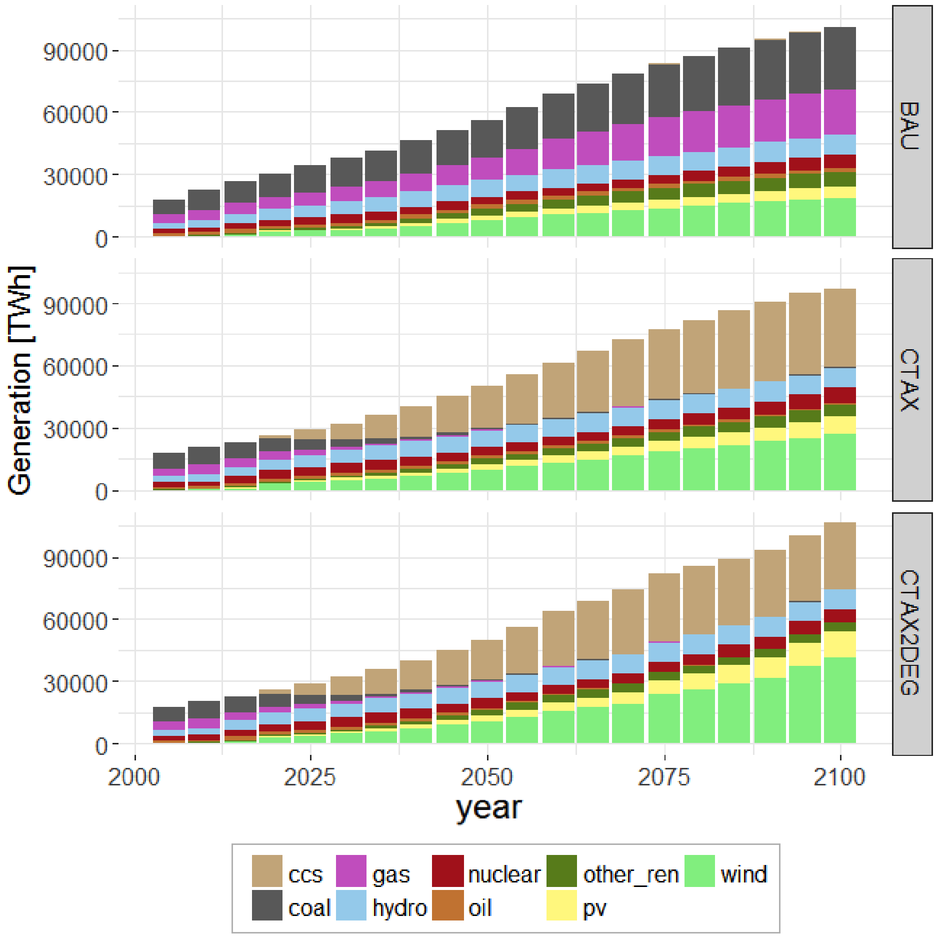

Figure 8.1 – Global electricity generation.

Yearly grid investments increase in time in all the scenarios from 2015 to 2100 and grow with increasing value of carbon tax: investments in transmission grid decrease from BAU to CTAX and CTAX2DEG, while investments in distribution, smartening and pooling of the grid behave the other way around, more than compensating the transmission reduction (Figure 8.2).

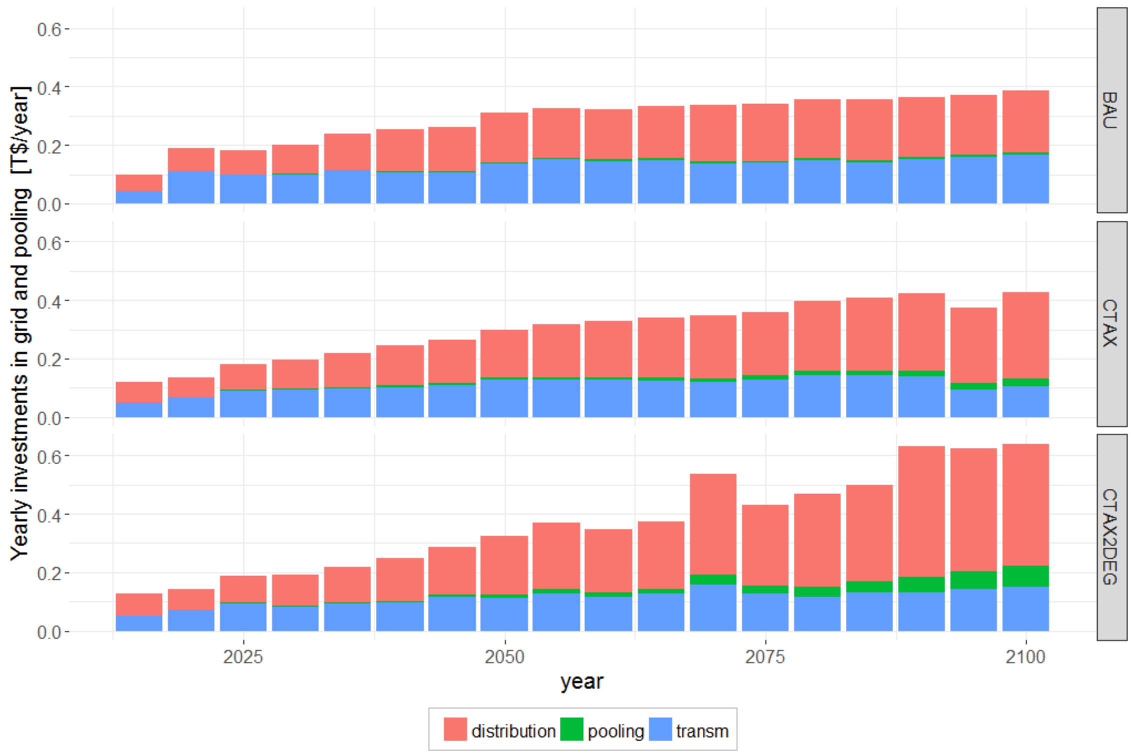

Figure 8.2 – Global investments in grid.

Concerning storage capacity (Figure 8.3), it grows with increasing carbon tax and with the share of VRE generation. PHES is the dominant technology in the BAU scenario, while the introduction of a carbon tax benefits CAES and batteries, that leverage on cost reductions from learning effect to become the dominant technologies. Considering the energy capacity, CAES is the dominant option in CTAX and CTAX2DEG, followed by batteries, while if we consider the power capacity (a proxy for the number of single installation required), batteries are the most widespread technologies in both scenarios, due to their lower energy-to-power ratio. Overall, CAES is the preferred short-term storage option in regions with very high VRE shares, due to its higher capability to provide firm capacity compared to batteries. Seasonal storage deployment is almost an order of magnitude lower than short-term one in the most favorable CTAX2DEG scenario (and so are yearly investments), slowed mostly by the high costs of electrolyzers and fuel cells.

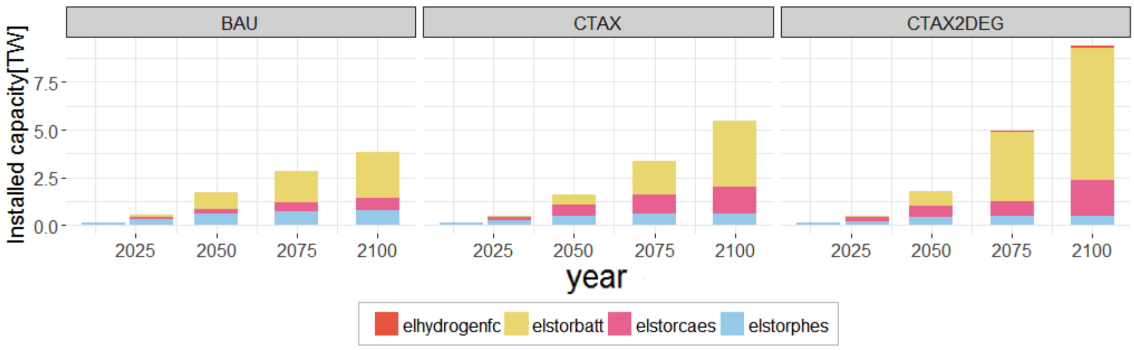

Figure 8.3 – Global storage capacity.

Figure 8.4 shows that, whereas the whole available energy from short-term storage is exploited, the same does not applies to seasonal storage.

Figure 8.4 – Global curtailed energy conversion.

Global yearly investments in short-term storage experience a considerable growth in time, particularly in presence of a carbon tax: at the end of the century investments have the same order of magnitude of investments in transmission plus grid smartening and pooling.

The main effect of the more detailed representation of electric grid is an overall increase in VRE generation with respect to the previous grid modeling, across all policy scenarios. This is due to the fact that the “near” VRE technologies require only investments in distribution lines, and this decreases their integration cost with respect to the previous WITCH implementation. On the other side, the new storage modeling has the opposite effect on VREs, whose global generation level decreases in all policy scenarios (whereas other technologies are not affected by these changes). This is mainly due to the fact that an efficiency loss due to storage, previously absent, has been introduced that penalizes net wind and solar generation. The combined effect of grid and storage yields different results according to the policy scenario considered. Overall, with the new formulation, the model is more responsive to price signals and technology availability options.

If we compare the new WITCH version with the old MASTER version, featuring a less detailed representation of system integration, grid, and storage, it is clear that a better modeling of the VRE system integration challenges, along with more detailed electric grid and storage formulations, compensates for the previous underestimation of VRE integration costs and entails a reduction of the global net VRE share of 4% in the CTAX2DEG scenario.

Interestingly, the model is able to reach a 100% renewable scenario if no investments towards nuclear and CCS are allowed (simulating social or political obstacles to the adoption of these technologies) and a 2°C target via carbon tax is imposed. This scenario entails a fourfold increase in the installed CAES capacity, becoming the dominant storage option and responding to the high firm capacity and flexibility requirements of this electricity mix (Figures 8.5 and 8.6).

The fully renewable scenario, however, requires higher expenditures in the energy sector than the normal 2°C scenario and this is reflected on global economic growth, with an undiscounted GDP loss of 16% with respect to BAU in 2100. The loss for the same scenario is lower, and in particular equal to 10%, if CCS and nuclear are available (Figure 8.7).

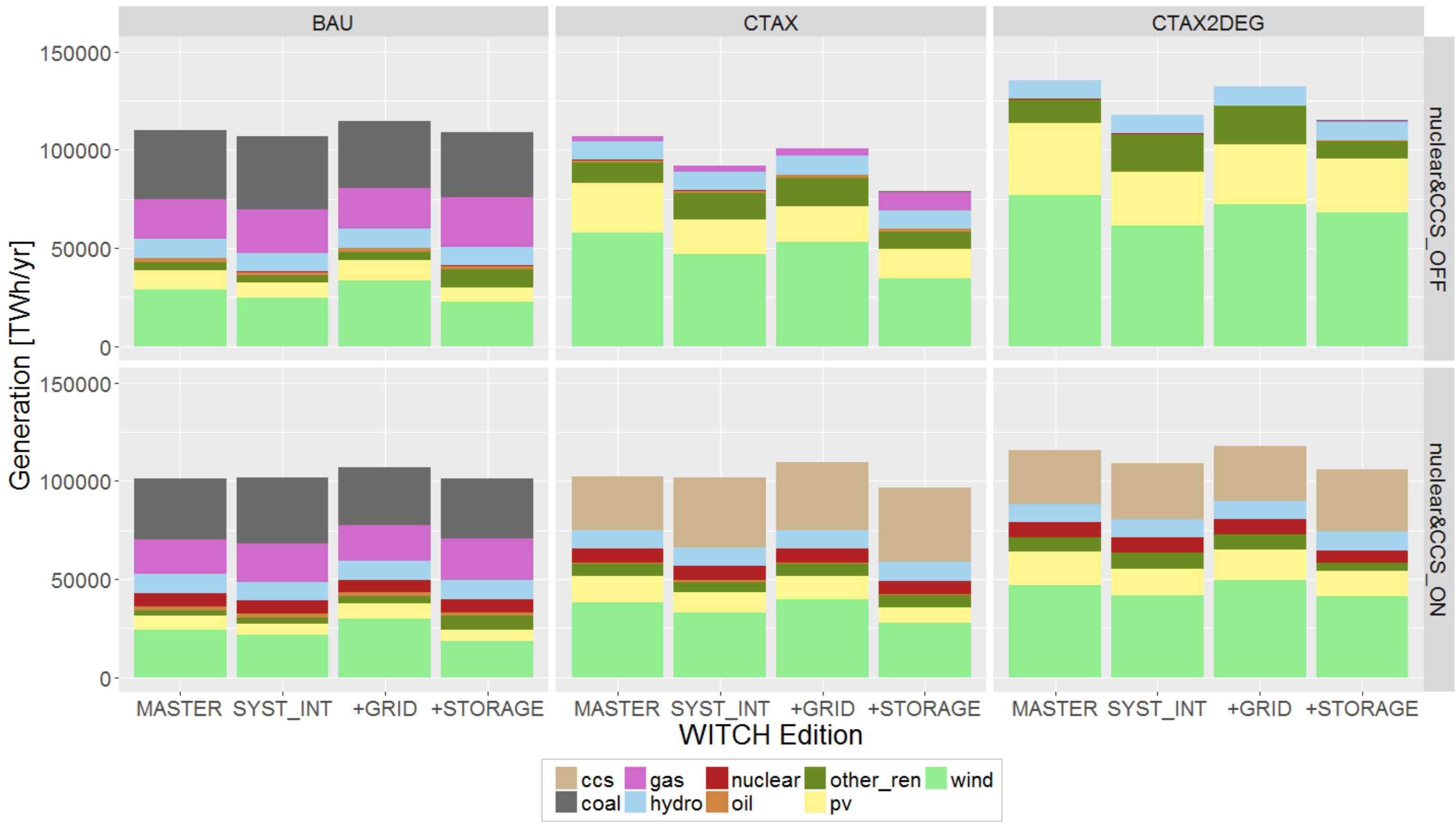

Figure 8.5 – Global electricity mix in 2100 (generation).

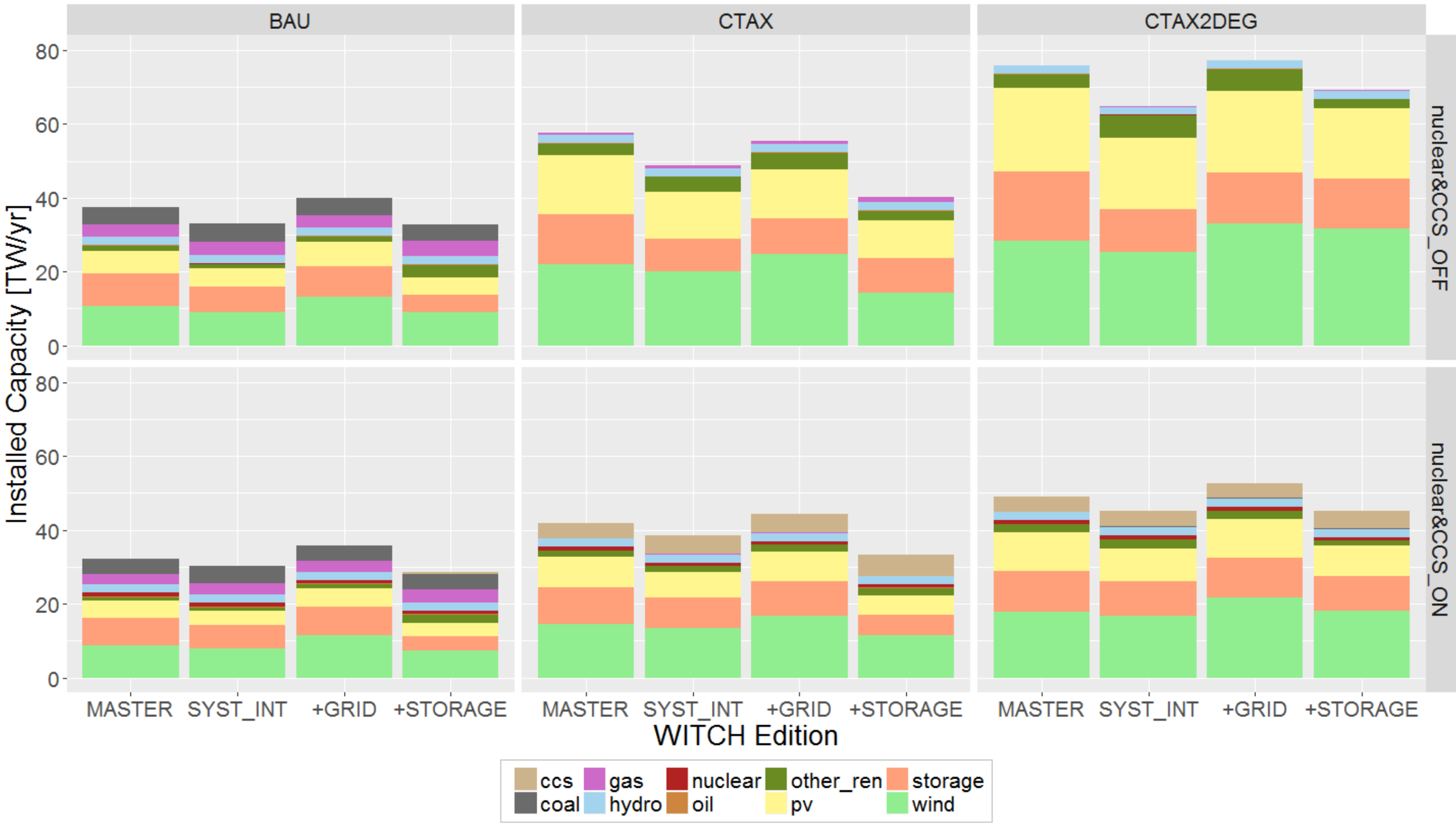

Figure 8.6 – Global electricity mix in 2100 (capacity).

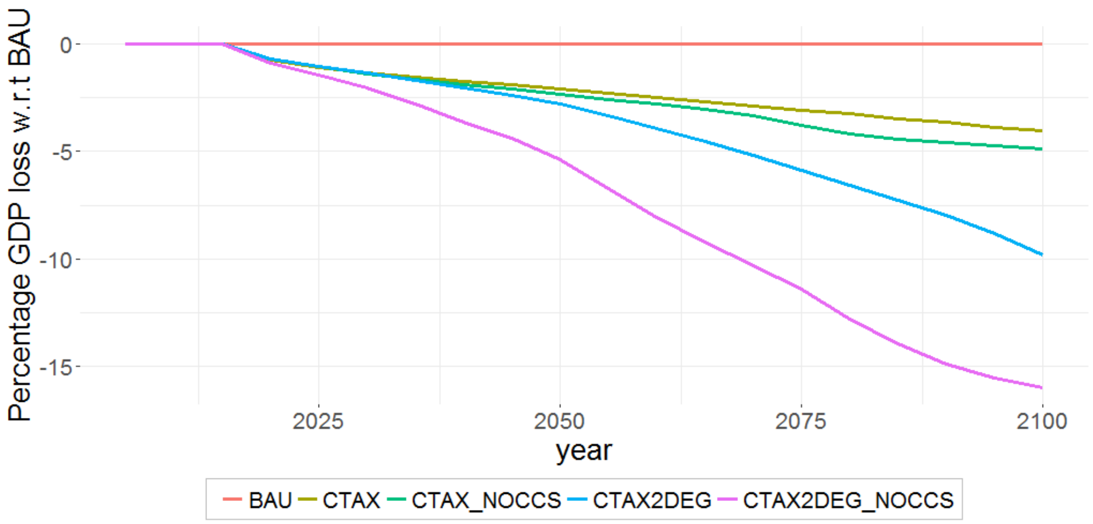

Figure 8.7 – Percentage undiscounted GDP loss for different scenarios.

WITCH results indicate that without the installation of storage capacity, it is not possible to reach high shares of VRE generation. In a counter-factual scenario in which storage technologies are not present in the model, the role of VREs is considerably undermined: world net VRE shares achieve at best about 20% in 2100, even in the presence of a high carbon tax aimed at achieving the 2°C target (Figure 8.8). The model compensates the limitation on VRE installing more biomass plants, CSP and CCS and decreasing global generation. This, in turn, affects economic growth, entailing, for the CTAX2DEG scenario, an additional 0.6% undiscounted GDP loss in 2100 with respect to BAU. As regards the effect of the grid, VRE plants that are closer to load centers are favored, as they only necessitate distribution line investments and no transmission lines. Concerning the requirements for VRE system integration, it can be said that the need for firm capacity has more influence on VRE and storage investment options than the flexibility requirement in the first years, while increasing the carbon tax entails a growing influence of the flexibility requirement, also in time.

As concerns the translation of storage and grid installation into integration costs, the effect on the LCOE of VREs technologies has been investigated (Figure 8.9). Taking Europe as an example, the impact becomes visible in 2050 with a LCOE increment of 1.5% for PV and 4% for wind. In 2100 the increase is the largest: 7% for PV and 17% for wind. If the effect on LCOE of the shadow costs related to the VRE additional flexibility and firm capacity requirement is also taken into account, their impact on integration costs is much larger: LCOE of wind is increased by half in 2050 and almost tripled in 2100.

Finally, results indicate that if a price on emissions is present, distribution grid and short-term storage (especially CAES and Li-ion battery) complement each other from an economic point of view, meaning that investments in both of them are necessary to increase VRE generation.

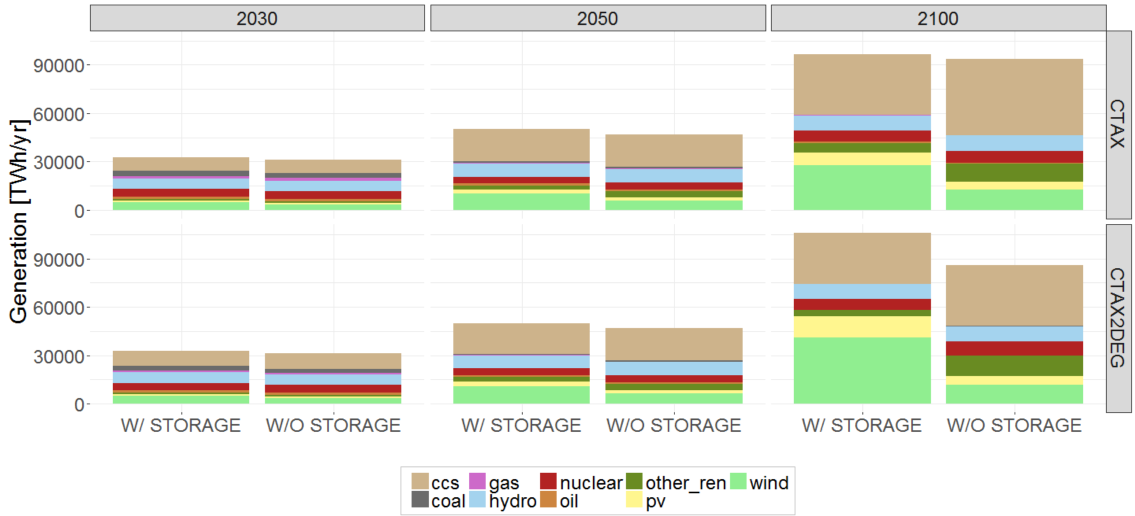

Figure 8.8 – Global electricity mix (generation) in 2030, 2050, and 2100 with and without storage.

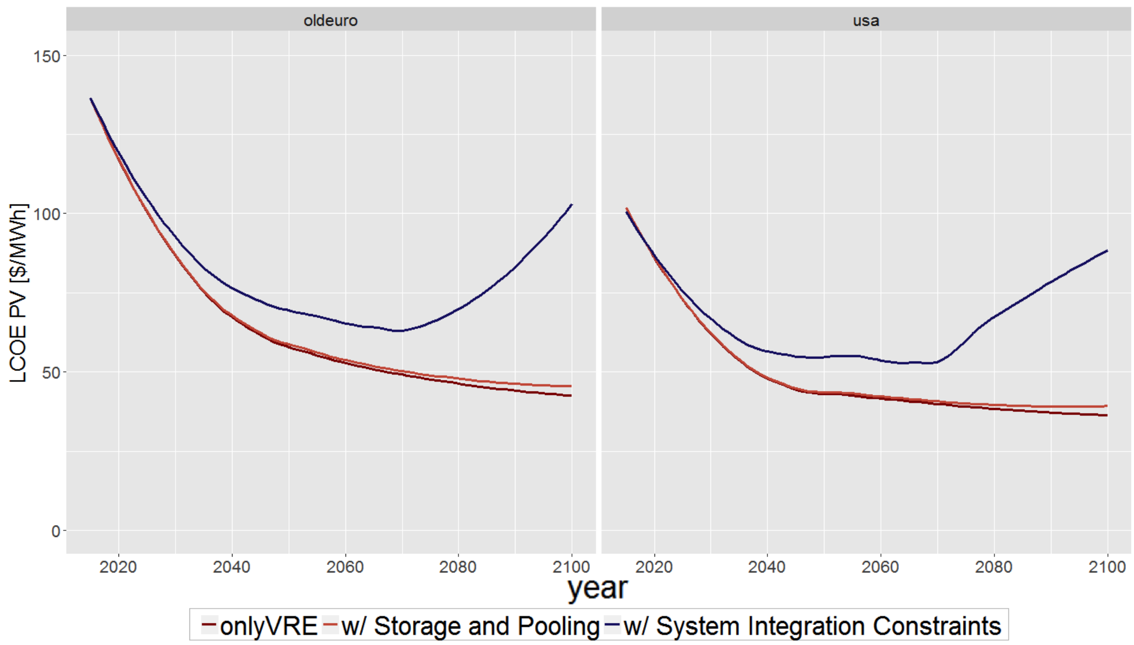

Figure 8.9 – LCOE of solar PV in Europe and USA.

The sensitivity analysis on grid cost and grid requirement per unit of generation capacity installed shows that these parameters hold a great influence on average grid investments. However, they do not show a significant impact on the installed generation capacity. Concerning the pooling requirement coefficient, the analysis suggests that the choice of its value, even if subject to uncertainty, does not affect results in a relevant way.

As regards storage parameters, decreasing the capability of storage to provide flexibility and firm capacity (through the correspondent coefficients) dramatically affects both VRE share and storage investments. This confirms that, on the one hand, the satisfaction of flexibility and firm capacity requirements plays a central role in the diffusion of VRE technologies and, on the other hand, storage is instrumental in providing this flexibility and firm capacity to the system, benefitting wind and solar installations.

The costs of short-term storage technologies, both the initial and the minimum one (floor cost) that they can achieve through learning-induced cost reduction, are two additional important drivers of VRE share growth and overall storage investments, while varying learning rate and storage efficiency (especially increasing them) does not influence much these two global variables. Looking at the impact of storage parameters on the single technologies, efficiency improvements may considerably enhance the diffusion of CAES, and higher values of Full Production Hours for both CAES and batteries technologies could play an important role as well, while their impact on PHES is minor.

Finally, WITCH results for VRE share, grid investments, and storage capacity have undergone comparison with other models in the context of the already mentioned ADVANCE IAM modeling framework. In particular, a group of six models (including WITCH) that feature similar structure, level of aggregation, and purpose participated in the exercise. WITCH results for VRE share and storage installed capacity (all obtained under the same carbon tax policy scenario) are similar to the ones obtained with POLES (Figures 8.10 and 8.11). This is the only other model of the ADVANCE group featuring a detailed technological representation of short-term and seasonal storage technologies, the same technological choice for both of them and also a better representation of VRE supply-load matching throughout the year, considered a very important piece of information for representing the typical dynamics of VRE integration, grid, and storage investments. Moreover, storage results for the EU countries are analogous for the two models. Considering that investment and generation decisions for the EU countries in POLES rely on a temporally and spatially detailed unit commitment and dispatch model (EUCAD), a matching between our and POLES results represents an important ex post validation of our work. As regards global grid investments, not present in POLES, they are in line with two out of the three IAMs considered in this comparison.

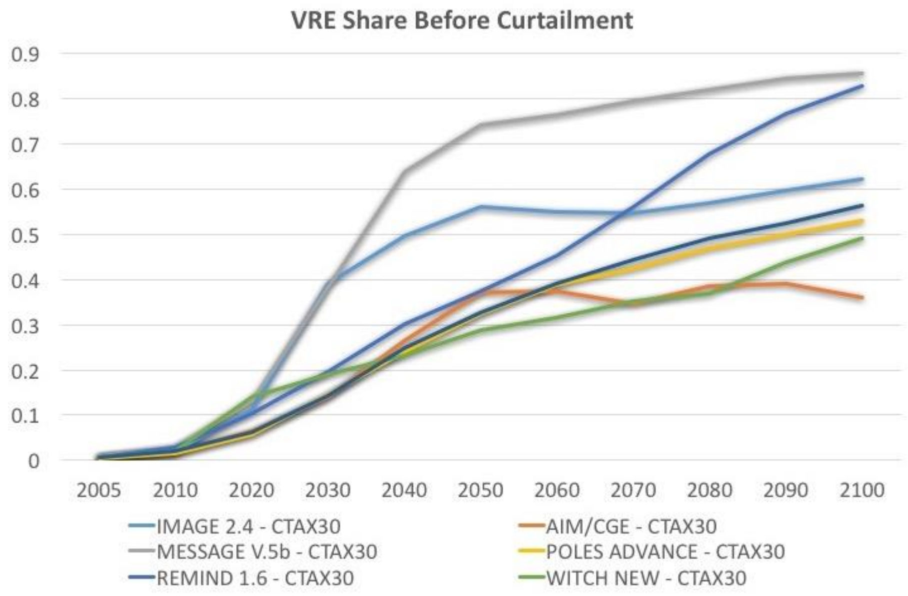

Figure 8.10 – Global VRE share before curtailment: WITCH and the other ADVANCE models.

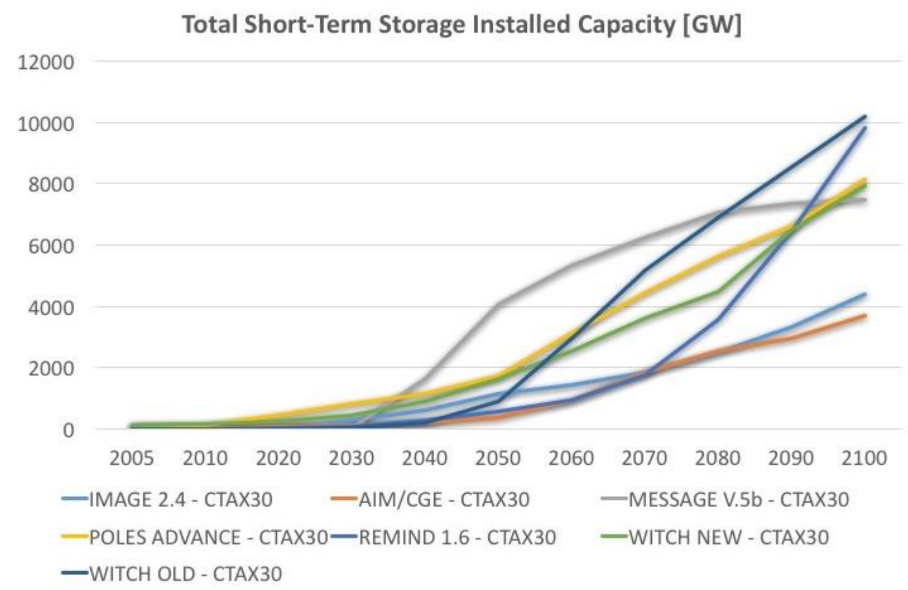

Figure 8.11 – Global short-term storage installed capacity: WITCH and the other ADVANCE models.

A further comparison has been performed with the SWITCH model application to the Chinese power sector, but this will be discussed in Deliverable 1.2, which is explicitly dedicated to the interactions between the WITCH and SWITCH models.

9. Conclusions and Future Developments

The first part of the MERCURY project has been dedicated to the improvement of the power sector modeling in WITCH, focusing in particular on i) the system integration of Variable Renewable Energies in the electricity system, ii) the electric grid, and iii) electric storage. At the beginning of this work, the WITCH model was quite behind the state of the art reached by most of the models in the Integrated Assessment Model Community (IAMC). Concerning system integration, the developments have followed the scheme applied in the MESSAGE model (which had been taken as a reference also in the previous model version of WITCH), improving the formulation based on the flexibility and the capacity constraints by indirectly implementing the information included in the Residual Load Duration Curves (RLDCs) while keeping the modeling structure based on treating electricity as a homogeneous good over the year. Concerning grid and storage, instead, a thorough and very detailed modeling has been implemented, allowing WITCH to achieve a beyond-state-of-the-art modeling level in these areas.

The new WITCH model has been tested in a series of diagnostic runs. The main outcomes can be summarized as follows. Imposing a global carbon tax in order to achieve the 2°C target, VREs become the most widespread technology options, accounting for 51% of global net electricity generation in 2100 (against 24% in the Business-as-Usual case). This deployment requires higher investments in distribution, smartening and pooling of the grid. Concerning storage capacity, the introduction of a carbon tax benefits Compressed Air Storage and Lithium-ion batteries, that leverage on cost reductions from learning effect to become the dominant technologies. Conversely, results indicate that without the installation of storage capacity, it is not possible to reach high shares of VRE generation. Grid cost and grid requirement per unit of generation capacity installed show a great influence on average grid investments. However, they do not show a significant impact on the installed generation capacity. As regards storage parameters, decreasing the capability of storage to provide flexibility and firm capacity dramatically affects both VRE share and storage investments. Moreover, the costs of storage technologies, both the initial and the minimum one that they can achieve, are two other important drivers of VRE share growth and overall storage investments.

As specified in Section 1, the improved version of the WITCH model as described in these pages will be adopted in the second part of the MERCURY project to carry out the scenario assessment exercises concerning the prospects of the low-carbon technologies, especially in the European Union.

No further modeling improvements are envisioned in MERCURY. However, a number of future developments are obviously possible. These include, among others, i) a more detailed representation of battery technology options, ii) a possible learning spillover between utility-scale and automotive Li-ion batteries, iii) a more rigorous assessment of compressed air storage geographical potential, iv) the modeling of hydrogen as a secondary energy source that can affect also the transportation and CHP sectors, v) explicit representations of Demand Response and Vehicle-to-Grid options to complete the picture of VRE system integration.

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