Modeling the optimal energy mix in 2030

Impact of the integration of renewable energy sources

ARTHUR CAMU
The European Council has recently set objectives in the matter of energy and climate policies and thus the interest in renewable energies is more than ever at stake. However, the introduction of renewable energies in an energy mix is also accelerated and altered by political targets. The two most widespread renewable technologies, photovoltaic and wind farms, have specific characteristics - decentralized, intermittency, uncertain production forecast up until a few hours ahead - that oblige to adapt the network and the current conventional generator control.

By using optimization techniques, it is possible to characterize the optimal energy mix (i.e. the optimal share of every power technology in all the countries considered). In this paper, the optimization function is defined as the sum of the yearly fixed cost of deploying a certain amount of installed capacity with the cost of electricity generation over the while year. Then the aim of the model is to evaluate the energy mix of least cost.

One can imagine multiple applications for this model, depending on which issue is to solve. Two case studies are developed in this report as examples. Renewable technologies are modifying the organization of the electricity market because of their specific characteristics. The first case study aims at quantifying the additional cost due to the integration of renewable energies. The second is targeted to characterize the impact of the integration of green energy sources on the deployment of Demand Response.
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Disclaimer

The views expressed in this thesis are those of the student and do not necessarily express the views of either RTE (Réseau de Transport d’Électricité) or the Royal Institute of Technology.
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## Abbreviations

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<th>Full Form</th>
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</thead>
<tbody>
<tr>
<td>RTE</td>
<td>Réseau de Transport d’Électricité</td>
</tr>
<tr>
<td>TSO</td>
<td>Transmission System Operator</td>
</tr>
<tr>
<td>EDF</td>
<td>Électricité De France (the French largest electricity producer)</td>
</tr>
<tr>
<td>RES</td>
<td>Renewable Energy Sources</td>
</tr>
<tr>
<td>DM</td>
<td>&quot;Département Marché&quot; i.e Electricity Markets Departement</td>
</tr>
<tr>
<td>ME²</td>
<td>&quot;Modèles de Marchés et Études Économiques&quot; i.e the Markets’ Models and Economic Studies Division in the Electricity Markets Departement</td>
</tr>
<tr>
<td>MICadO</td>
<td>Name of the computer tool used to perform the studies</td>
</tr>
<tr>
<td>DR</td>
<td>Demand Response</td>
</tr>
<tr>
<td>OPL</td>
<td>Optimization Programming Language</td>
</tr>
<tr>
<td>LDC</td>
<td>Load Duration Curve</td>
</tr>
<tr>
<td>NLDC</td>
<td>Net Load Duration Curve</td>
</tr>
<tr>
<td>PV</td>
<td>Photovoltaic</td>
</tr>
<tr>
<td>CCG</td>
<td>Combined Cycle Gas Turbine</td>
</tr>
<tr>
<td>OCGT</td>
<td>Open Cycle Gas Turbine</td>
</tr>
</tbody>
</table>
Chapter 1

Introduction

1.1 Presentation of RTE

RTE (Réseau de Transport d’Électricité) is the French Transmission System Operator (TSO). It takes care of all transmissions of high and very high voltages from generation plants to local electricity distribution operators within the French territory. Thus RTE contributes to public policy in that field as well.

RTE has been created in 2000 by detaching itself from EDF (Électricité de France) for legal purposes. It followed the European decision to open up the European market to competition; EDF had no longer the right to be both a producer and a TSO.

With its 100 000 km of lines, RTE is one of the largest TSOs in Europe. The company employs more than 8500 persons and its turnover was of 4.46 bn Euros in 2014. This Master Thesis is the result of a 6 months study performed at the Electricity Markets Department (DM) and, more precisely, of the Markets’ Models and Economic Studies Division (ME²) of RTE. The aim is to develop an optimization model able to compute the optimal energy mix in one or several countries for a given set of parameters. This tool can have multiple applications, two case studies are developed at the end of this report in order to present possible utilizations.
1.2 Context of this study

The European Council has recently set objectives in the matter of energy and climate policies. By 2030, 27% of the consumed energy will have to come from renewable energy sources. The tools for this transition are, to a certain extent, left to the choice of each country. Thus the goal of the French government is to introduce these new types of energies in an optimal way (i.e. minimizing the overall cost) so that the end consumers will not endure too much difference on their bill because of these newly introduced policies.

RTE is the system operator and, therefore, a stakeholder in these discussions. Indeed, RTE is responsible for the stability of the system and thus must give its expertise on the feasibility of introducing large amount of photovoltaic (PV) panels or wind farms.

The installed capacity of renewable energy sources is in a stage of significant expansion. It is mostly due to the fact that these power plants are based on a free and renewable energy sources (wind and solar radiations). As a result, the generation cost of renewable energy power plants is not increased with the quantity of electricity generated. Another consequence is that RES do not produce CO\textsubscript{2} during the process of electricity generation. That is why renewable energies are spreading over the world.

However, the introduction of renewable energies in an energy mix is also accelerated and altered by political targets. Because other types of power plants (i.e. thermal power plants) are either non CO\textsubscript{2} free plants or produce unwanted waste (e.g. nuclear power plants), public incentives on developing renewable generations has increased in the last decades. Even though RES plants are not always cost effective compared to thermal plants, they can receive subsidies in order to complete their development. In the meantime, the thermal generation is less and less profitable as the cost of releasing CO\textsubscript{2} (which is a greenhouse gas) rises. For these reasons, one can take into account the fact that RES introduction does not necessarily follow the perfect competitiveness.

The two most widespread renewable technologies, photovoltaic and wind farms, have specific characteristics - decentralized, intermittency, uncertain production forecast up until a few hours ahead - that oblige to adapt the network and the current standard generators.
By modeling the electricity market, it becomes possible to quantify the cost of transforming the energy mix (i.e. cost of integrating RES) by studying the evolution of the "optimal" energy mix (i.e. the one of least cost) while imposing a given quantity of renewable energy in the production portfolio.

1.3 Scope and purpose of this study

1.3.1 Objectives

In France, the installed capacity of renewable energies is rather low for now. But in a mid-term forecast, this situation is going to change considerably. This Master Thesis made in partnership with the ME$^2$ Division at RTE intends to characterize the optimal generation mix with a stronger penetration of RES. This kind of study has to be made while keeping in mind that there is a necessity of back-up power plants in case of a lack of wind and/or sun power for instance.

A high share of renewable energies requires more "flexible" energy sources with a good time response in case of sudden variation of production. These "flexibilities" can be handled by different energy sources: thermal power plants, hydropower plants (storage capacities), demand response or imports and exports.

1.3.2 Simplifications

Solving this kind of gigantic problem in its whole is not feasible (due to its high number of variables and its complexity), thus it requires defining some simplifications. The results of this problem strongly depend on the simplifications made and the chosen approach for the resolution.

As this study is integrated in a long term approach, it has been chosen to focus on finding an optimal energy mix for a given year and a given set of constraints. Nevertheless, finding the best investment policies in order to get to the optimal energy mix from the current one is not included in the scope of this study.

Due to the rather strong simplifications made during the problem formulation, it is concluded to be more consistent and relevant not to focus on the costs of integration
of RES per se, but to devote the attention to the evolution of this cost with input parameters’ variations.

1.4 Approach for the studies

1.4.1 Screening Curves Method

All power plants have different characteristics in terms of costs. One can model them in the two following categories:

- Fixed costs in \( \text{ €/MW}_\text{year} \) in order to install some generation capacity that must be paid upfront and are independent of the generation (design, construction, etc.)
- Variable costs in \( \text{ €/MWh} \) which represent the additional costs of producing one MWh of electric energy (costs for operating the power plant)

Power plants are spread out between two extreme categories:

- High fixed cost and low variable cost (e.g. nuclear)
- Low fixed cost and high variable cost (e.g. combustion turbines)

The screening curves method is a tool that helps finding the best trade-off, that is to say the best combination, between all types of power plants, according to their fixed and variable costs. The obtained combinations corresponds to the one that minimizes the overall cost of installing and generating the electricity during the period considered.

This method relies on the fixed and variables costs and on the load duration curve of the time period that is considered in the problem. One can draw a linear function for each type of power plant with the fixed cost value as the Y-intercept and the variable cost as the slope of the function.

Table 1.1 gives an example for power plant costs.
Chapter 1. Introduction

<table>
<thead>
<tr>
<th></th>
<th>Fixed Cost (€/MW/year)</th>
<th>Variable Cost (€/MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nuclear</td>
<td>285,000</td>
<td>10.23</td>
</tr>
<tr>
<td>CCG (Combined Cycle Gas)</td>
<td>79,000</td>
<td>86.66</td>
</tr>
<tr>
<td>Combustion Turbines</td>
<td>65,000</td>
<td>183.26</td>
</tr>
</tbody>
</table>

Table 1.1: Cost hypotheses for three exemplary power plants

The solution of three power plant example is given in Figure 1.1.

![Figure 1.1: Simple application of the screening curves method with three power plants](image)
For a given number of hours of usage, the generation mean of least cost is kept. This results in a piecewise linear function formed by the three lowest parts of the three linear functions. This function represents the combination of the three power plants with the least overall system cost of producing electricity. The installed capacity can be obtained by transposing the hours of use of each power plant in the load duration curve. Then the load duration curve is divided in three zones for which each width corresponds to the optimal installed capacity.

The results obtained in this example are given in table 1.2.

<table>
<thead>
<tr>
<th></th>
<th>Installed capacity (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nuclear</td>
<td>61,270</td>
</tr>
<tr>
<td>CCG</td>
<td>25,350</td>
</tr>
<tr>
<td>Combustion Turbines</td>
<td>9,860</td>
</tr>
</tbody>
</table>

Table 1.2: Optimal installed capacities for the three plants example

This results represents an optimal energy mix (i.e. the one of least cost) for the given set of technologies.

Even though it is possible to extend this method to bigger problems it becomes rapidly too restrictive. Major limitations on the possible computations are direct consequences of this characteristic:

- This method is limited to one area/country
- The load duration curve (LDC) takes away any information of the time (and area) of production within the year
- The installed capacity of must-run renewable technologies cannot be directly optimized
- Storages facilities or power plants with flexible generation such as hydro storage cannot be taken into account
- Flexible generation means with adjournments (e.g. Demand Response) cannot be taken into account
1.4.2 Optimization problem

As explained earlier in this report, the screening curves method is easy to implement but it is too rudimentary. On the contrary, optimization problems are more flexible. One can imagine a model that characterizes the optimal deployment of several technologies. Such a model can be based on finding the energy mix of least cost for the overall system. Thus the optimization function is defined as the cost of producing electricity during one year. This method is thus significantly more flexible and enables the user to adapt the model to its needs.

This is the method that has already been used in a study on the decarbonization of the electricity sector, performed by the University of Cologne [2]. It is based on the modeling of the overall electricity market while keeping the installed capacities of power plants as variables. A similar type of approach is developed in this report.

Chapter 2 exposes the modeling choices while chapter 3 concerns the upfront work on the data reorganization. Chapter 4 and 5 are examples of application for this model, in the form of two case studies.
Chapter 2

Modeling the electricity market

This chapter tends to specify how the electricity market can be modeled. The aim of this model is to characterize the optimal deployment of each technology. The optimization model described in this chapter is the one that has been used to perform the two case studies presented in chapters 4 and 5. The computation is done for a given data set and a given set of constraints on the deployment of some technologies and countries. The optimal mix is defined as the one of least yearly installation and production cost.

Some simplifications choices had to be made in order to obtain a simple but accurate model.

2.1 General organization

To complete the desired studies, it is necessary to develop a reliable and efficient computer tool. Since the study is divided in different sub-studies and that the model is aimed at being used for further studies by other users, the tool needs to be flexible. One must be able to easily change the hypothesis of the problem to solve. Inside the ME$^2$ division, this computer tool has been named $MICadO$.

$MICadO$ refers to a user interface that is developed on Microsoft Excel for simplification purposes. This interface is used to choose parameters and constraints easily. $MICadO$ manages the import of the raw data set and processes it to make it readable for the optimization solver. Finally, the analysis of the results is monitored from the same Excel file.
2.1.1 Model organization

The model is formulated in a text file (with the extension .mod) and is following the OPL (Optimization Programming Language) syntax.

In the first place, it includes the name definition of:

- Sets
- Parameters
- Variables

Then, and more importantly, it is followed by the definition of:

- The optimization function
- A large set of constraints between parameters and variables

OPL is a pseudocode that enables to formulate easily an optimization model to a solver (i.e. in equation form). From this language, a modeler is used to convert the equations into a set of first order equations (in matrix form). This first order linear problem is then solved.

And optimization model aims at minimizing or maximizing an optimization function, which represents the key point of the model. For this model, the optimal energy mix can be designated as the one of least cost. Thus one can define the optimization function as the yearly overall cost of producing electricity for all countries considered. Hence the goal is to minimize this function while following some external constraints due to e.g. the structure of the generation plants portfolio or due to political choices.

2.1.2 Principle of the approach

For the following studies, it has been chosen to optimize the electricity production over a year in all the considered countries. For practical reasons, it has been chosen to consider a year as an even number of weeks. Thus the considered problems are comprised of 52 weeks (364 days). The optimization model is solved for a unique year, that tends to characterize at its best the year 2030. One can refer to chapter 3 for data organization.
This model has been developed in order to characterize the optimal energy mix to produce the required energy for a year, considering a given set of parameters. This means that the goal is to minimize the cost of:

- Installing the capacity of production of each technology (annualized value)
- Producing enough energy to cover the load at each hour

In order to optimize the deployment of each technology, the installed capacities of power plants are considered as variables of the optimization problem. This means that the model optimizes the energy production of a year, but it also optimizes the installed capacity of each technology for the year [2].

This modeling formulation enables to study the evolution of the installed capacities with some parameters and flexibilities of the system. But it also raises two main problems:

- The optimization problem becomes significantly bigger and thus takes much more time to be solved
- A special attention needs to be given on the constraints’ formulation, as one must avoid to multiply variables between each other in order to keep a linear problem

2.1.3 Modeling choices

As it not possible to elaborate a exact model for electricity markets, one must introduce simplifications choices. The size of such a model cannot be too high in order to keep a reasonable solving time.

2.1.3.1 Electricity markets organization

One can model the electricity markets with different level of precision. The model exposed in this chapter is designed to focus at the optimal deployment of each technology according to a least cost objective function and in order to characterize an optimal dispatch.

The key points of the model’s structure are listed below:
• The model equalizes electricity generation and consumption at every hour.

• The model is divided in zones. Each zone corresponds to a country.

• Interconnections are represented by hourly transmission capacity limits.

• A technology represents all power plants of a given type (e.g. solar, nuclear, CCG etc.). Each technology is represented in every zones.

• There is no sub-zones within a country. Thus the deployment of a technology is seen in MW for the whole country without localization considerations.

• There is no considerations for:
  – Reserves (for frequency control).
  – Minimum up and down time for power plants
  – Minimum activation or turn-off time for power plants
  – Start up, turning off or idling costs

The different technologies of the model are listed in table 2.1.

<table>
<thead>
<tr>
<th>RES technologies</th>
<th>Solar power (must-run)</th>
<th>Run-of-the-river hydro (must-run)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Wind power (must-run)</td>
<td>Hydro storage (weekly dispatchable)</td>
</tr>
<tr>
<td>Thermal technologies</td>
<td>Nuclear</td>
<td>Hard Coal</td>
</tr>
<tr>
<td></td>
<td>CCG</td>
<td>Lignite</td>
</tr>
<tr>
<td></td>
<td>OCGT</td>
<td>Combustion turbine</td>
</tr>
</tbody>
</table>

Table 2.1: Technologies of the optimization model

All these power plants are modeled in the same way. This means that they all have the same set of parameters and variables. However some of them are subjected to different constraints due to their specific characteristics. In MICadO it is possible to add additional constraints to the energy mix, i.e. add an upper and/or lower limit to the installed capacity of a technology in a specific country. It can be useful in order to model different scenarios with the same data set.
2.1.3.2 Load shedding

For the studies it is considered that there must be a maximum of 3 hours of load shedding within the year. This criterion is fulfilled by considering the load shedding as a power plant with no installation cost (i.e. in €/MW/year) but with a high variable cost for production (i.e. in €/MWh). In the model, this load shedding power plant has the highest variable cost among all power plants. Thus it represents the last power plant that can be dispatched in the merit order.

When plotted among the screening curves, the load shedding technology is then a linear function crossing the origin of the coordinate system. Its slope is the highest among all. The variable cost (i.e. the slope) can be tuned in order to meet the 3 hours criterion. This is achieved when the intersection of this linear function with the one with the second highest slope is situated at the abscissa of 3 hours.

The number of hours of load shedding is directly related to the variable cost of the load shedding power plant. Thus the variable cost of this power plant is set before the solving to a value that make the use of the load shedding power plant limited to 3 hours over the year.

2.1.3.3 Hydro storage dispatch

The modeling of hydro storage requires a special attention. Indeed, the specific characteristic of hydro storage is that it can be dispatched within the time frame of the study.

However, it does not seem realistic to model the hydro storage dispatch perfectly among the whole year. This power plant depends on several parameters such as:

- The country
- The time period
- The day to day meteorology

The local inflows in hydro storage facilities cannot be forecasted several days ahead with a good accuracy. That is why, in this model, it is considered that the dispatch is
optimized within each week separately. This is performed by using an energy equivalent of
the stored water that can be dispatched during a given week. This amount of energy is then
dispatched in an optimal way for the week considered. This modeling technique
enables to take into account the impact of hydro storage on the optimal energy mix.

For such a power plant, it is not reasonable to model their optimal deployment for two
main reasons:

- The maximal installed capacity that can be deployed in every country is almost
  or already reached in most European countries.
- They represent a flexible and cheap (low variable cost of production) electricity
generation source

However, it is interesting to model their optimal dispatch. For these reasons, hydro
storage is not considered as a technology to optimize in the energy mix. Its installed
capacity is defined as fixed in every country. However, it is modeled as every other
technology for simplification purposes. This means that the installed capacity of hydro
storage is considered as a variable (as for any other type of power plant) but an additional
optimization constraint is added in order to set the installed capacity to a given value.

### 2.1.3.4 Demand Response

When modeling electricity markets, demand is often considered as *inelastic*. This means
that electricity consumers are not adapting their consumption with the electricity price
modulations. However, electricity generation and consumption must remain in balance
in real time. One can easily understand that in order to do so, it is required to continu-
ously modulate at least one of these two values.

As demand is considered as inelastic, the major part of this modulation is performed by
adapting the production of power plants in order to meet demand. However one can also
wonder if it could be possible to modulate electricity consumption as well. This means
that instead of increasing the electricity generation, energy users are paid in order to
reduce their consumption. Depending on the actors, the corresponding amount of energy
can be adjourned or not.
Demand Response allows actors to reduce their energy bill by being active on the balance market. It represents a flexibility factor for the system, as dispatchable hydro resources for instance, and enables to perform curtailments with or without adjournments (which can be interpreted as a certain type of storage facility).

DR can be of several types, depending on the structure of the energy users that are performing it. The three major types, that have been modeled in this study are:

- Industrial
- Residential
- Tertiary (also called commercial)

Industrial DR refers to significant industrial actors that can cut their electricity consumption by stopping some of their activities. They mostly are strong electro-intensive industries, requiring large amounts of power for the process of their activity (e.g. metal or paper industries).

Tertiary DR refers to public buildings, offices and all service facilities. It mostly concerns heating and cooling systems. All these facilities are easier to monitor than private ones. There are less actors to deal with. It can also include all spread out cold rooms (e.g. supermarkets, etc.). Heating and cooling systems can be used as an active consumption as they are characterized with a strong inertia for heating up and cooling down the systems. By smartly connecting the thermostat, it is possible to postpone the electricity consumption in order to avoid consumption and thus price peaks.

Finally, residential DR refers to private consumers that have installed smart meters in their home and have the will to adapt their consumption in order to reduce their energy bill.

All three types of DR have been modeled in MICadO. They have been handled by using a large amount of simplifications, some of them are exposed further ahead in this report.

One can foresee that the modeling of DR is more challenging than the other parts of the model. In the further exposed model, DR is not considered in the consumer part of the real time electricity balance but in the producer part instead. Indeed, DR can be considered as a power plant having generation which is either negative or positive.
When a consumer reduces its consumption, the amount of shed energy can be considered as an additional production instead of a decrease in consumption. The generation value and sign of a DR power plant depend on the amount of DR activated for the given hour and the amount of adjournment remaining from the previous hours. A DR power plant has a positive generation when the activation results in a shed consumption and it has a negative generation when adjournments are creating a compensating over consumption. Thus the modeling of Demand Response is more challenging than for the other power plants. Some additional information is given in chapter 5.

2.2 The input data set: New Mix

In order to perform economic studies, RTE produces data sets for all parameters such as load, RES production, storage hydro power etc. on a regular basis. These data sets are published by the "Economics, Forecasting and Transparency" Department at RTE. They are the result of statistical considerations which are not in the scope of this Master Thesis. Four data sets are produced for four different prospective scenarios. All these scenarios aim at characterizing the year 2030 in 12 countries of Europe.

The studies made in this Master Thesis are based on a data set called New Mix, also used by RTE in its Generation adequacy report [1]. It is one of the prospective scenarios used for long-term studies made by RTE. New Mix is the most optimistic data set of the four. It relies on energy temperance, which enable to reduce electricity consumption and to consider an important deployment of renewable energies. The main characteristics of this scenario are depicted in Figure 2.1.

In this scenario, it is planned that the share of nuclear energy in the energy mix will strongly reduce due to political incentives. It is partly compensated by the introduction of renewable energies. According to the goals set by the energy transition towards green growth bill [3], the share of nuclear power in France’s generation mix has to reduced to 50%. This goal as been set for 2025 in the bill but this scenario considers that this objective will be met 5 years behind schedule. Moreover, it counts on a significant increase in the energy efficiency and plans on a high price for CO₂ emissions (95 €/tonsCO₂). The maximal exchange capacities for imports and exports are considered as significantly
higher than the current ones. This scenario considers important development plans for interconnections until 2030.

Moreover, it is considered that a demand-side management enables to reduce electricity consumption. Hence the annual load is considered to be more or less stable between now and 2030, settling at 481 TWh in 2030. The main drivers of electricity demand between 2013 and 2030 are shown in Figure 2.2.

One can notice that the significant increase in energy efficiency constitutes the main
Chapter 2. Modeling the electricity market

driver for electricity demand stability for the years to come, according to the *New Mix* scenario.

One can refer to the *Generation adequacy report* for more information on the scenarios developed by RTE.

### 2.3 Data organization

The data organization for several parameters is explained in the following subsections. The general idea for the data set is that the number of values per parameter is high and allows a Monte Carlo type of approach. This means that the data set is separated in several subsets that characterize different possible inputs for the same parameter.

The scenarios presented in the *Generation adequacy report* [1], including the *New Mix* scenario, are considering the installed capacities of each power plant as fixed. The following parameters are given in the data set at each hour of the year (except for hydro storage):

- Load (in MWh)
- Renewable energy generations
  - Solar power (in MWh)
  - Wind power (in MWh)
  - Run-of-the-river hydro (in MWh)
- Thermal power plants’ available capacity (in MW)
- Hydro storage (in MWh) given for each month

These parameter values are given at each hour of the year in order to complete a subset. Several subsets are available in order to characterize more precisely the possible outcomes of 2030. Usually, a great number of scenarios (a hundred in that case) are available for a given parameter. Figure 2.3 is illustrating the described data hierarchy.

In the data considered in this report, the year starts on July, 1st and ends on June, 30th. Each subset represents a parameter during the whole year with a step of one hour.
Figure 2.3: Illustration of the data organization: subset & data set

(i.e. 24 hours × 365 days = 8,760 values). In order to perform more precise studies, a hundred subsets are generated to represent, with reasonable accuracy, the possible parameter values of one future year.

All of these parameters are obtained by statistical reasoning, which is not in the scope of this study. Moreover, these tables of data are produced for each country separately.

2.3.1 Load

In the raw data sets, the load is represented by the electricity consumption at each hour during one year. Thus, each yearly consumption set is made of 8,760 values (i.e. 24 hours × 365 days of hourly load). A typical set of load during a week is shown in Figure 2.4. The first day of the week is set on a Saturday at midnight.

This week of load is part of the 5200 making the data set. One can easily notice the daily and weekly patterns for electricity consumption. The load is on average higher during the weekdays. Moreover, two major consumption peaks are observed within the day (one in the morning and one in the evening).

The whole load data set is then made of a hundred possible yearly consumption sets, in order to represent the electricity consumption of one future year.
2.3.2 Renewable energy sources

In the raw data sets, the generations of RES are also given at every hour (8,760 values) and for one hundred possible yearly generations.

The generation profile of renewable energy sources depends on meteorological factors and the location of the RES farms. The yearly sets for all RES generations considered in this report are given for a whole country. Thus, there is no zonal approach within a given country. The fact that volatility created by RES power plants can be shared between different zones within a country and then flattened (balancing effect) is not considered in the model presented further ahead in this chapter.

In Figure 2.5, a typical generation of solar farms during a week in France has been represented.

One can easily notice the pattern of generation related to the hours with daylight.

Wind power plants do not have the same generation characteristics as solar farms. One example of weekly generations is shown in Figure 2.6.
Figure 2.5: A typical week for the generation of solar panels in France in the *New Mix* scenario.

Figure 2.6: A typical week for the generation of wind farms in France in the *New Mix* scenario.
Generations can vary significantly between days. As for solar panels, wind farms are considered as must-run power plants. Indeed, the optimal use of these generations is when there is no energy spillage (as the variable cost of these must-run power plants considered to be equal to zero). However, the must-run generations are intermittent. Thus the generation data sets are made of several possible years of generation and tend to represent with a reasonable precision the intermittency of these generation sources.

The generation of RES in given in MWh. This means that it is given for a fixed installed capacity for each type of power plants. Indeed, this data set has been designed for the prospective scenario New Mix of the Generation Adequacy Report [1]. This scenario comes with a forecast on the installed capacity of each power plant, including renewable energy sources. As the aim of this study is to evaluate the impact of renewable energies in the energy mix, a key requirement is to be able to change the installed capacity of all power plants. A new parameter has been created from this data set, which is the availability of the power plant. The availability is a factor between 0 and 1 that characterizes the share of installed capacity that is available for generation at hour $t$. Thus, the maximum possible generation at an hour $t$ is given by the availability times the installed capacity. As the generation is given in MWh for most of the technologies in the New Mix data set, in order to obtain the availability one must divide the generation by the installed capacity. This factor is used to characterize the availability of each power plant.

### 2.3.3 Available capacity for thermal power plants

From the raw data set, it is also possible to obtain the available capacity of thermal power plants. It represents the amount of power (in MW) available for generation at a given hour. This quantity is less than or equal to the installed capacity of the power plant.

This available capacity is statistically generated and takes into account the maintenance schedule as well as the possible technical problems. The historical data of such parameter is also available on the website of RTE.

An example of yearly available capacity for the French nuclear power plants (with an installed capacity of 37,634 MW) is shown in Figure 2.7.
Figure 2.7 shows that the available capacity seldom reach the installed capacity. One must recall that the first hour of the year is set to the July, 1st. As one can notice, the nuclear power plants are usually almost fully available during the load-peak season in France (i.e. during the winter). Maintenance are mainly operated during the summer, that is why the available capacity is mostly reduced during these periods.

2.3.4 Equivalent energy for stored water

Thanks to its peculiar characteristics (dispatchable, quick response, low variable cost), the hydro storage is a type of power plant which adds a significant amount of balancing power to the system. It can have a great influence on the overall cost of electricity and can enable to avoid periods of high prices. The modeling of this type of technology can be complex if done precisely. It also requires a high number of parameters that cannot be obtained with reasonable precision for a long-term study.

Thus, for this type of studies, RTE uses statistically produced values of energy dispatchable throughout each week of the year. As for the load and RES generations, a hundred scenarios of this weekly amount have been generated. These weekly energy values are
then used in the model in order to optimize the dispatch of hydro storage resources within the weeks. Further details are given in the following chapter.

2.4 Sets, Parameters and variables

In the following subsections, sets, parameters and variables are detailed. They correspond to the model that has been implemented in relation with RTE and then used to perform the case studies. Special subsections have been used for Demand Response, given the fact that its modeling requires several new parameters, variables and constraints that are not directly related to the rest of the optimization problem.

2.4.1 Sets

Sets represent all indices that have been used in order to represent all states of a given parameter or variable.

Table 2.2 lists all the sets used in the model.

<table>
<thead>
<tr>
<th>Sets</th>
<th>Description</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>⨁\text{hourly}^\text{year}</td>
<td>Hourly time index over the whole year</td>
<td>1..8,736</td>
</tr>
<tr>
<td>⨁\text{hourly}^\text{week}</td>
<td>Hourly time index within a week</td>
<td>1..168</td>
</tr>
<tr>
<td>⨁\text{weekly}^\text{year}</td>
<td>Weekly time index within the whole year</td>
<td>1..52</td>
</tr>
<tr>
<td>⨁\text{daily}^\text{year}</td>
<td>Daily time index within the whole year</td>
<td>1..364</td>
</tr>
<tr>
<td>Zones</td>
<td>Every countries considered</td>
<td></td>
</tr>
<tr>
<td>RES</td>
<td>Every must-run energy power plant</td>
<td></td>
</tr>
<tr>
<td>Thermal</td>
<td>Every thermal power plant</td>
<td></td>
</tr>
<tr>
<td>DR</td>
<td>Every Demand Response power plant (i.e. every type of DR)</td>
<td></td>
</tr>
<tr>
<td>Plants</td>
<td>RES $\cup$ Thermal $\cup$ DR</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.2: Sets of the optimisation problem

2.4.2 Parameters

In the following subsections, the optimization parameters will be listed. Parameters are inputs of the model and are of different types, depending of its nature. The ones
specifically used for the modeling of demand response have been separated from the others for clarity purposes.

2.4.2.1 General parameters of the problem

All needed general parameters are listed in table 2.3:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$VC_p$</td>
<td>Variable cost ($\text{\euro}/\text{MWh}$) $p$ in Plants</td>
</tr>
<tr>
<td>$FC_p$</td>
<td>Fixed cost ($\text{\euro}/\text{MWh}$) $p$ in Plants</td>
</tr>
<tr>
<td>$NTC_{t,z_1,z_2}$</td>
<td>Net Transfer Capacity (MWh) $t$ in $\Omega_{\text{year}}^{\text{hourly}}$; $z_1, z_2$ in Zones</td>
</tr>
<tr>
<td>$Load_{t,z}$</td>
<td>Load (MWh) $t$ in $\Omega_{\text{year}}^{\text{hourly}}$; $z$ in Zones</td>
</tr>
<tr>
<td>$Avail_{t,p,z}$</td>
<td>Availability of a plant ($\in [0;1]$) $t$ in $\Omega_{\text{year}}^{\text{hourly}}$; $p$ in Plants; $z$ in Zones</td>
</tr>
<tr>
<td>$Storage_{w,z}$</td>
<td>Energy equivalent of the stored water for a week (MWh) $w$ in $\Omega_{\text{year}}^{\text{weekly}}$; $z$ in Zones</td>
</tr>
<tr>
<td>$C_{\text{spillage}}$</td>
<td>Spillage cost ($\text{\euro}/\text{MWh}$)</td>
</tr>
</tbody>
</table>

Table 2.3: Parameters of the optimization problem

The variable cost $VC_p$ of a power plant $p$ represents the cost of producing an extra MWh of energy with this power plant, according to the fact that enough installed capacity remains for it. Values for $VC_p$ are given in appendix A.

The fixed cost $FC_p$ of a power plant $p$ represents the annualized cost of installing an extra MW of generation capacity for $p$. Values for $FC_p$ are given in appendix A.

The energy consumption ($Load_{t,z}$) at hour $t$ and in zone $z$ is obtained after extraction of the results obtained by week selection (further explanations are given in chapter 3).

The capacity transfers between two countries is represented by the maximal amount of energy that can be transferred between two countries. $NTC_{t,z_1,z_2}$ is either equal to zero if $z_1$ is supposed to be disconnected to $z_2$ or equal to the value at hour $t$ of transfer capacity from $z_1$ to $z_2$, obtained by extraction from the data set.

The availability of a power plant, $Avail_{t,p,z}$, is real number between 0 and 1 and represents a percentage of the installed capacity:
• For RES plants it represents the share of the installed capacity that is generated at a given hour. This value is obtained from the data set at each hour $t$ and for each zone $z$.

• For thermal power plants, it is usually close to one. However installed capacities are seldom fully available as one must take into account unavailabilities such as:
  
  − Maintenance cycles
  − Technical failures

These two characteristics are taken into account in the model by introducing a statistical distribution of the availabilities of this power plants. This statistical reasoning is not part of this study since the repartition of the availability is generated for the whole New Mix raw data set. The obtained factors take into account possible maintenance scenarios (e.g. loss of available installed capacities for nuclear power plants mostly concentrated during summer). In addition, a statistical repartition of technical failures is added to each power plant. The corresponding availability of each technology is then extracted from the raw data set.

• For DR plants, the availability factor depend on the DR type:

  − For industrial DR, the factor is considered either equal to 0 or 1 and allows (or not) the activation of the DR at different periods of the day. It can also characterize the availability of a DR plant on weekends. In the end, it becomes possible to constrain the availability of the installed capacity of industrial DR during working hours for instance.

  − For residential and tertiary DRs, the factor is available in the raw data set and it is possible to extract the needed values. It represents the heating power that can be shed by standard users. Its computation is made by taking into account meteorological scenarios with the corresponding load and are not in the scope of this study.

The energy equivalent of the stored water, $\text{Storage}_{w,z}$, represents the amount of energy that can be dispatched during a given week $w$. This value characterizes a national energy-giving amount of the stored water in the reservoirs.
2.4.2.2 DR specific parameters

Table 2.4 contains the additional needed parameters for DR:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_p^{adjour}$</td>
<td>Number of hours with possible adjournments p in DR</td>
</tr>
<tr>
<td></td>
<td>(Nonzero integer)</td>
</tr>
<tr>
<td>$Profile_{t,p}^{adjour}$</td>
<td>Commitment/adjournment profile ($\in [-1,1]$) t in $[1:N_p^{adjour}]$ p in DR</td>
</tr>
<tr>
<td>$HasStock_p$</td>
<td>Maximum possible daily activations (Binary) p in DR</td>
</tr>
<tr>
<td>$Stock_p$</td>
<td>Number of possible daily activations p in DR</td>
</tr>
</tbody>
</table>

Table 2.4: DR specific parameters

$N_p^{adjour}$ represents the maximum number of hours, for power plant p, during which the adjournment of the activated quantity of DR can spread out.

$Profile_{t,p}^{adjour}$ quantify the adjournment ratio within the hours from the activation of the DR and until $N_p^{adjour}$.

These parameters have been detailed in Figure 2.8 for clarity purposes.

![Example of a adjournment profile for a demand response power plant](image)

Figure 2.8: Example of a adjournment profile for a demand response power plant

Figure 2.8 represents $Profile_{t,p}^{adjour}$ with $N_p^{adjour} = 7$ and for a given DR type. In this special case, the sum of the last six $Profile_{t,p}^{adjour}$ is equal to 100%. It means that this
specific DR type considers that for a certain amount of energy shed at a given hour, 100% of this avoided consumption is adjourned within the next six hours. Thus, the overall energy consumed with and without this DR type are equal. However, it allows to perform energy transfers between different hours. Of course, one can imagine another DR type which has another adjournment profile.

### 2.4.3 Variables

Table 2.5 lists the needed variables for the optimization problem:

<table>
<thead>
<tr>
<th>G_{p,z}</th>
<th>Installed capacity (MW)</th>
<th>p in Plants ; z in Zones</th>
</tr>
</thead>
<tbody>
<tr>
<td>G_{t,p,z}</td>
<td>Generation (MWh)</td>
<td>t in Ω_{hourly}; p in Plants ; z in Zones</td>
</tr>
<tr>
<td>T_{t,z_1,z_2}</td>
<td>Energy Transfer from $z_1$ to $z_2$ (MWh)</td>
<td>t in Ω_{hourly}; $z_1$, $z_2$ in Zones</td>
</tr>
<tr>
<td>G_{t,z}^{spilled}</td>
<td>Spilled generation at t in z (MWh)</td>
<td>t in Ω_{hourly}; z in Zones</td>
</tr>
<tr>
<td>Activ_{t,p,z}^{DR}</td>
<td>Generation of DR activated at t (MWh)</td>
<td>t in Ω_{hourly}; p in DR ; z in Zones</td>
</tr>
</tbody>
</table>

**Table 2.5: Variables of the optimization problem**

One can notice that the installed capacity of each power plant $G_{p,z}$ is defined as a variable in this model. It is the key of the whole approach developed in this Master Thesis. This formulation will enable to obtain the *optimal* energy mix for the selected countries. Depending on the load and the prices of each technology, the solution of the optimization problem will tend to characterize the *optimal* deployment of each technology in the energy mix of each country.

Moreover, one can notice that for simplification purposes no imports have been defined. Energy transfers $T_{t,z_1,z_2}$ represent exports from country $z_1$ to the country $z_2$.

When the must-run power plants produce more energy than required (e.g. if the net load is negative in a one zone problem), the real-time energy balance must be still kept. That is why, one must introduce a spilled generation variable $G_{t,z}^{spilled}$. This variable contains the energy that must be spilled in zone $z$ at hour $t$. This spillage can be considered of certain cost $C_{spillage}$ if necessary.

Finally, the energy activated by a given DR type $Activ_{t,p,z}^{DR}$ at hour $t$ in zone $z$ represents the generation that is deployed at hour $t$, without any considerations of adjournments.
Thus, the generation $G_{t,p,z}$ for DR power plants are different from $Activ^{DR}_{t,p,z}$ because $G_{t,p,z}$ represents generation at hour $t$ withdrawn from all adjournments from previous activations. Further explanations are given with equation 2.9.

### 2.5 Optimization function

The goal of this model is to characterize the optimal energy mix (i.e. the optimal share of every power technology in all the countries considered). In order to do so, the optimization function can be defined as the cost of producing the electricity during one year. Then the aim of the model is equivalent to evaluate the energy mix of least cost. That is why, one must define the overall cost of producing electricity. In this report, the latter takes into account (for each power plant):

- The yearly fixed cost of deploying a certain amount of installed capacity
- The cost of electricity generation over the whole year

Thus the optimization function can be written as follow:

$$
\text{minimize} \quad OverallCost = \sum_{p \in \text{Plants}, z \in \text{Zones}} \left( \sum_{z \in \text{Zones}} G_{t,p,z} \cdot FC_p \right) \quad (2.1)
$$

The optimization model minimizes this objective function according to a given set of possible values for each variable. This set is highly constrained in order to characterize the behavior of the electricity market. All constraints are detailed in the following section.

### 2.6 Constraints

Several constraints need to be added to this model in order to model the electricity system. These constraints are detailed in the following subsections.
2.6.1 General Constraints

These constraints are often found in the electricity markets models and represent the cornerstone of the model.

As explained earlier in this report, a real-time balance between generation & consumption must be kept in the electricity system. It is represented in the model by equation 2.2.

\[
\forall t \in \Omega^\text{hourly}_\text{year}; \forall z_1 \in \text{Zones} : \sum_{p \in \text{Plants}} G_{t,p,z_1} = \text{Load}_{t,z_1} + \sum_{z_2 \in \text{Zones}} T_{t,z_1,z_2} + G_{t,z}^\text{spilled} \tag{2.2}
\]

The hourly generation of each power plant are constrained between minimum and maximum possible generations. Equations 2.3 and 2.4 give the minimum and maximum generation constraints for both RES and Thermal plants.

\[
\forall t \in \Omega^\text{hourly}_\text{year}; \forall p \in \text{RES}; \forall z \in \text{Zones} : G_{t,p,z} = \overline{G}_{p,z} \cdot \text{Avail}_{t,p,z} \tag{2.3}
\]

One can notice that in equation 2.3, the must-run generations are systematically equal to the available installed capacity. This formulation of RES generation is the reason why the model requires a spillage variable in the real-time energy balance (cf. 2.2).

\[
\forall t \in \Omega^\text{hourly}_\text{year}; \forall p \in \text{Thermal}; \forall z \in \text{Zones} : 0 \leq G_{t,p,z} \leq \overline{G}_{p,z} \cdot \text{Avail}_{t,p,z} \tag{2.4}
\]

A special attention can be given to the fact that the minimum generation of a power plant is set to zero. There is no minimum positive generation when the power plant is committed.

Transfer capacities have been defined as parameters, but the exports and imports are variables and depend on the hour of the year. Imports have been defined as negative exports (antisymmetric matrix) as shown in equation 2.5.

\[
\forall t \in \Omega^\text{hourly}_\text{year}; \forall z_1, z_2 \in \text{Zones} : T_{t,z_1,z_2} + T_{t,z_2,z_1} = 0 \tag{2.5}
\]
2.6.2 Specific constraint to storage hydro power

The modeling of hydro storage power plants requires a special attention. Storage facilities enable to perform a repartition of the hydro resources in an optimal manner. However, it would not be realistic to optimize the repartition of the storage resources throughout the whole year (or even throughout a month) since one cannot plan the load and the availability of other power plants a long time in advance. Thus it seems reasonable and it has been decided to model a perfect dispatch of this resource during one week (a week starts on Saturday and ends on Friday).

From a previous treatment on the available data about storage facilities (found in the raw data set New Mix), it is possible to obtain the energy equivalent of the stored water that can be dispatched during one week. This parameter is referred as $Storage_{w,z}$.

Then, from this parameter, the dispatch constraint can be written as shown in equation 2.6.

$$\forall w \in \Omega_{\text{year}}, \forall z \in \text{Zones} : \sum_{t \in \Omega_{\text{hour}}^{\text{weekly}}} G_{24 \cdot 7 \cdot (w-1) + t, \text{hydro}, z} \leq Storage_{w,z} \quad (2.6)$$

This equation means that the hydro storage generations are only constrained on a week basis. The sum of all generations during the current week must be less than or equal to the equivalent energy of the water stored in the reservoir for the week. Thus the dispatch of the energy $Storage_{w,z}$ is optimized within each week $w$. Thanks to equation 2.4, the hydro generation at each hour is also less than or equal to the maximum real-time generation of the hydro power plant.

2.6.3 Specific constraints to DR

So far in this model, DR have been considered as power plants (same modeling for the installed capacity and the generation). However, demand response has to be treated separately from the other power plants because of its specific characteristics which are exposed in this subsection.
2.6.3.1 Minimum and maximum generations

As for any other type of power plants, the generation of DR plants are limited by their installed capacity. However, as explained earlier in this report, the electricity generation of power plants can be negative because of the possible adjournments of these power plants. Equations 2.7 and 2.8 show the minimum and maximum constraints on generation and activated energy for DR power plants.

\[ \forall t \in \Omega^{\text{hourly}}_{\text{year}}, \forall p \in \text{DR}; \forall z \in \text{Zones} : G_{t,p,z} \leq \overline{C}_{p,z} \cdot \text{Avail}_{t,p,z} \quad (2.7) \]

One can notice that, contrary to thermal power plants, there is no minimum limitation for the generation of DR plants \((G_{t,p,z} \text{ can be negative for } p \in \text{DR})\). Indeed, the adjournments are considered as negative generations (i.e. increase in the load) and the generation of DR power plants is represented by the net activation from all possible adjournments from previous activations. Thus the generation variable for DR can be negative (cf. equation 2.9).

However, the activated energy of DR in zone \(z\) at hour \(t\), \(\text{Activ}^{\text{DR}}_{t,p,z}\), has the same type of minimum and maximum constraints as thermal power plants.

\[ \forall t \in \Omega^{\text{hourly}}_{\text{year}}, \forall p \in \text{DR}; \forall z \in \text{Zones} : 0 \leq \text{Activ}^{\text{DR}}_{t,p,z} \leq \overline{C}_{p,z} \cdot \text{Avail}_{t,p,z} \quad (2.8) \]

For simplification purposes, which are explained in chapter 3, the load is given as 52 weeks which are uncorrelated from one to another. This week organization raises problems on the adjournments at the weeks’ junctions. This kind of considerations have already been faced in another department of RTE in one of their model. The solution they implemented, and which is used here, is to loop the adjournments with the beginning of the same week.

A illustrative representation of the looping method is presented in Figure 2.9.

Thanks to this technique, the valorization of the DR is not made on the load gap between joined weeks. This approximation can arouse questioning on its influence on the end solution of the overall problem. It has been assessed by RTE that there is no significant impact on the overall deployment of DR by using this technique.
2.6.3.2 Net generation from possible adjourments

The generation of DR plants can be obtained by adding all the adjourned values of previous activations of the DR during the past hours. Then, the net generation is obtained by using equation 2.9.

\[
\forall w \in \Omega_{year}^{weekly}; \forall t \in \Omega_{week}^{hourly}; p \in DR; z \in Zones:
\]

\[
G_{168 \cdot (w-1) + t, p, z} = \sum_{t_a \in \Omega_{year}^{hourly} \cup 1 - N_{adjour}}^{1 - N_{adjour}} \sum_{t-t_a \geq 1 \& t-t_a \leq N_{adjour}}^{1} \text{Activ}^{DR}_{t, p, z} \cdot \text{Profile}^{adjour}_{t-t_a, p}
\]

(2.9)

with \(\tau = 168 \cdot (w - 1) + (t_a + 168) \mod 168 + 1\)

\(t_a\) represent an index that goes through the \(N_{adjour}\) previous hours before \(t\) so that it is possible to evaluate the energy activated during these hours.

\(\tau\) takes into account, in the value of \(t_a\), the fact that it is necessary to loop within the same week when \(t_a\) is pointing outside of the current week.

As explained earlier in this report, \(\text{Activ}^{DR}_{t, p, z}\) represents the amount of deployed energy of the considered type of DR at the hour \(t\). For some types of DR, for instance residential or tertiary ones, some energy has to be adjourned on the hours following the activation.
Thus, $\text{Activ}^{DR}_{t,p,z}$ represent the energy deployed at $t$ and $G_{t,p,z}$ represents the net energy at $t$ i.e. the sum of the activation (if any) and the adjourned energies at $t$.

For clarification purposes, figures 2.10 and 2.11 show the activated energy and the generation of a DR power plant with adjournments. First, figure 2.10 enlights the relationship between the activated energy $\text{Activ}^{DR}_{t,p,z}$ and the generation $G_{t,p,z}$ for DR power plants.

![Figure 2.10: Example of electricity activation and generation for DR with adjournments](image)

There are two consecutive activations of respectively 200MWh (in green) and 150MWh (in blue) for this power plant. One must understand from figure 2.10 that the electricity generation for DR power plants is obtained by multiplying the energy activated with the adjournment profile (by ways of shifting the activated energy from 1 to $N^\text{adjour}_p$).

Then the net generation for the example introduced in figure 2.10 is shown in Figure 2.11.

2.6.3.3 DR’s activation limitations

The DR also needs to be constrained on its activated generation within the preceding $N^\text{adjour}_p$ hours. The activated energy of a DR plant within the last $N^\text{adjour}_p$ hours...
must not exceed the maximum availability of the DR deposit during these hours. It is characterized by the equation 2.10.

\[ \forall w \in \Omega_{\text{year}}^{\text{weekly}}; \forall t \in \Omega_{\text{week}}^{\text{hourly}}; p \in \text{DR}; z \in \text{Zones} : \]

\[ \sum_{t_a \in \Omega_{\text{hourly}}^{\text{hourly}}, 1 - N_{\text{adjour}}, 0} \text{Activ}_{t,p,z}^{\text{DR}} \leq \max_{t_a \in \Omega_{\text{hourly}}^{\text{hourly}}, 1 - N_{\text{adjour}}, 0} \left( \text{Avail}_{t,p,z} \cdot \overline{G}_{p,z} \right) \]  

(2.10)

with \( \tau = 168 \cdot (w - 1) + (t_a + 168) \mod 168 + 1 \)

Equation 2.10 means that a DR deposit cannot be re-committed to the system until the adjournments are fully taken care of.

Finally, one last constraint can be added to the model. It takes into account the fact that DR power plants can be limited in their number of activation per day. This constraint is expressed in equation 2.11.

If \( \text{HasStock}_p = 1 \) then:

\[ \forall d \in \Omega_{\text{year}}^{\text{daily}}, p \in \text{DR}; z \in \text{Zones} : \]

\[ \sum_{t \in \Omega_{\text{hourly}}^{\text{hourly}}, 0} \text{Activ}_{t,p,z}^{\text{DR}} \leq \text{Stock}_p \cdot \overline{G}_{p,z} \]  

(2.11)
2.7 Performances & limitations

All equations have been written in a way that this problem is linear (LP). This has a significant importance since for these problems, when a solution exists, it is always possible to exactly determine it. Moreover, LP optimization problems are faster to solve. It has been chosen not to use binary variables in order to reduce the complexity of the problem to a minimum while keeping a trustworthy modeling. Nevertheless, solving one problem with this model can take around 45 minutes. Studies can therefore be time consuming.

A direct consequence of the non-use of binary variables is that it is, for instance, no more possible to characterize the unit commitment of power plants. This represents one limitation of this model. This variable enables to consider for instance start-up, turning-off and idling costs for power plants. All these costs could not be taken into account in this model. Moreover, thermal power plants such as nuclear ones have a low variable cost and are one of the first plants dispatched using the merit order list. But in practice nuclear power plants are constrained by other characteristics such as minimal up and down time, limited generation changes etc. These features are not taken into account in this model as well.

In the electricity markets, some capacity reserves must be performed in order to ensure the security of the system and prevent failures (frequency control). This model does not take into account any type of capacity reserves.

The weeks selection method presented in chapter 3 represent a significant factor of accuracy uncertainty. One must keep in mind that all results should be put into perspective.
Chapter 3

Reducing the size of the data set

The computing time of the models is a recurrent problem in most studies made by the ME$^2$ Division involving optimisation problems. In this study, the Monte Carlo approach is avoided and thus a reduction of the size of the input data set is performed. The implemented technique is exposed in this chapter. One can refer to 2 in order to have a general overview of the data set organization.

3.1 Reducing the size of the data set by week selection

A high number of yearly subsets in a data set tends to quantify in a better way the uncertainties of the forecasted load (by using a Monte Carlo type of approach), but it increases considerably the computing time, especially while solving a big and highly constrained model. The optimisation model that has been developed minimizes the cost of producing electricity during one year. As the model, detailed in chapter 2, is already complex and takes up to 45 minutes to be computed, it is not feasible to solve it for each of the hundred years available in the data sets within the Monte Carlo approach. Thus, a preliminary study has been made. It aims at reducing the number of input data while keeping the loss of accuracy to a minimum.

It has been decided to perform the studies by solving this model for one year only. However, a full year (52 weeks) is available in each of the hundred subsets, thus 5,200 weeks are representing one data set. A contraction method for the data sets is implemented
by selecting series of electricity consumption on a weekly basis. The used approach is to select representative weeks among all the weeks represented in the data sets and aggregate them all together to build a year.

A full data set characterizes all possible outcomes for the year 2030. The parameters are strongly dependent on external factors such as temperature (strong winters increase load and would require more installed capacity for generation) or meteorology. The goal of this data set is to take into account several alternatives for each parameter that represent several possibilities for strong/soft winter, solar activity, wind activity, unforeseen technical problems in a power plant etc.

Implementing a selection method will automatically reduce the precision of the computations. The full data set representing 100 possible outcomes is already a small sample (and thus an approximation) of the realm of possibilities.

As it is not feasible to compute the results for all 100 years, it does not seem reasonable as well to compute the results for one of the hundred years only. Indeed, a year of the data set cannot represent the set in its whole.

The week selection method, that is used in this study, provides a set of 52 weeks which are not related to each other.

In Figure 3.1 the chosen approach for this reduction is represented in an illustration:

![Figure 3.1: Illustration of the pure random week selection approach](image)
This selection is made according to a criterion that is exposed further ahead in this chapter.

The aim of this technique is to keep a good representation of all possibilities for load peaks, RES activity etc. But it is also important to keep coherence in the organization of the set. The frequency of the sampling cannot be too high as the junctions between samples would no longer be coherent. This selection technique enables to keep coherence between two following load values for instance (i.e. energy gradient between two consecutive hours). Moreover, it enables to perform a medium-term storage hydro dispatch along weeks, which is one of the approaches commonly performed at RTE.

In a nutshell, the ultimate goal is to select a set of weeks for which the solution of the optimization problem is close to the one we would have found by solving the problem for the complete data set (knowing that a data set is already a sample of the entire set of possibilities).

N.B.: One can notice that 52 weeks in a year makes 364 days. For practical reasons, it has been decided to ignore one day in every data sets in order to obtain an even number of weeks in every year. This means that one year is represented by 8,736 values of hourly load.

### 3.1.1 Week selection’s heuristic

#### 3.1.1.1 Systematic approach

The week selection can be done with different approaches. One possible technique is the "systematic approach". The idea is to find the best selection of 52 weeks among the 5,200 available - according to a given criterion - by testing all possible combinations of 52 weeks.

This approach has been implemented by the Massachusetts Institute of Technology in 2013 with a selection of 4 weeks among 52 [4]. In this publication, it is shown that it is possible to represent the net load duration curve of the full data set of 52 weeks with an optimal selection of 4 weeks with a very good precision.

However, the selection of 4 elements from an 52-element set represents 270,725 combinations and it takes around an hour to test them all. In the problem exposed earlier in
this report, it is necessary to select 52 weeks among 5,200. One must consider that a
selection of 52 elements among a 5,200-element set represents around \(3 \cdot 10^{125}\) combina-
tions. With a simple cross product, one can notice that this computation would be far
from finished by 2030. This rules out this alternative.

3.1.1.2 Statistical approach

Another conceivable approach is the statistical one. Instead of trying out all combina-
tions of weeks, which include a great number of unconceivable selections, it is possible
to test a great number of randomly selected weeks and retain the one that fits best a
chosen criterion.

The statistical approach has been chosen for this study and is explained in the following
section.

3.1.2 Criterion of selection

Before explaining the selection method, it becomes necessary to define a criterion in
order to judge the quality of a given week selection. As explained in chapter 1, it is
possible to find an optimal energy mix by using the screening curves method. This
method is based on the net load duration curve and characterizes the energy mix of
least cost by finding the best repartition of each electricity generation technology. This
repartition is made by equaling - for a given power plant - the investments costs on
installed capacity (installed capacity times fixed costs in €/MW/year) with producer
surplus of this power plant.

Thus, the optimal installed capacity of each power plant, using the screening curves
approach, is obtained by using the load duration curve. As the aim of the optimization
problem defined in chapter 2 is close to the one of the screening curve method, it seems
appropriate to define the selection’s criterion on the net load duration curve.

In order to compare the resulting net load duration curve of the aggregated set (i.e. the
selected weeks) and the net load duration curve of the entire data set, it is necessary to
define a criterion based on the distance between the two load duration curves. In Figure
3.2, the distance at a given hour is depicted.
Figure 3.2: Illustration of the distance between the reference and approximated net load duration curves at a given hour \( t \)

As can be seen in Figure 3.2, the distance is defined at every hour and represents the difference (in MWh) between the value at hour \( t \) of the approximated net load duration curve and the value at the same hour for the overall net load duration curve.

The mathematical formulation of the selected criterion is given in equation 3.1. It is based on the Root Mean Square Error.

\[
Error = \sqrt{\frac{\sum_{t=1}^{8760} (NLDC_t - \widehat{NLDC}_t)^2}{\sum_{t=1}^{8760} \widehat{NLDC}_t}} \text{ in } \% 
\] (3.1)

With:

- \( NLDC_t \) Net load duration curve value of the whole data set at hour \( t \) (in MWh)
- \( \widehat{NLDC}_t \) Net load duration curve value of an approximated subset at hour \( t \) (in MWh)
Chapter 3. Reducing the size of the data set

$NLDC_t - \hat{NLDC}_t$ is referred as the distance between the two load duration curves at hour $t$.

Among all the randomly selected sets of 52 weeks, the one with the least $Error$ is kept. This enables to obtain a selection of weeks which characterize the overall net load duration curve of the data set.

N.B.: The NLDC is obtained by sorting all load values of the 100 load subsets that are forming the data set. Hence, the NLDC is made of $8,736 \times 100 = 876,000$ hours. Nevertheless, the approximated NLDC is made of 8,736 hours only. In order to be able to compare the NLDC with the approximated one, it is necessary to sample the NLDC. This can be done by using a constant sampling step of 100 hours on the NLDC. The first point of the NLDC used is set to 51.

3.2 Results of the week selection by statistical approach

A special tool for week selection has been developed on the software environment for statistical computing $R$. This tool enables to perform different type of week selection with different input parameters:

- Week sampling method
- Number of draws
- Countries on which the selection is applied

In the following subsections, several selection methods are depicted. Their results and accuracy are then compared in order to define which method is the most appropriate. The selection can also be time consuming. That is why an improvement method on the computing time is also performed. Finally, some post-selection verifications are performed in order to check the coherence of the resulting aggregated subset.

3.2.1 Week sampling methods

Different week sampling methods can be used in order to find an approximation of the NLDC of the whole data set. Several are presented in the following subsections. Of
course, these methods are not representing an exhaustive list and one can think of other approaches in order to perform this approximation.

All following figures are given as examples and their purpose is to clarify the different approaches developed hereafter. They have all been obtained with the data set of France in the data set \textit{New Mix} (cf. chapter 2).

From the data set, it is possible to extract the yearly load. In order to obtain the yearly \textit{net} load, one must withdraw all must-run RES generations to the yearly load.

The must-run RES generations considered for this week selections and in the case studies of chapters 4 and 5 are:

- Solar power
- Wind power
- Run-of-the-river hydro

The net load is obtained by withdrawing these three must-run generations to the load. From this matrix made of 8,736 hours (rows) and 100 scenarios (columns), it becomes possible to perform the selection of aggregated sets of 52 weeks among all of the 100 scenarios.

### 3.2.1.1 Pure random sampling

This selection method is the simplest and the most basic selection method. It is based on the \textit{error} indicator.

Weeks are selected randomly among all 5,200 available weeks without replacement. At each draw, 52 weeks are selected completely randomly and a yearly net load set is formed by aggregating the net load set of each selected week (each set is made of 168 hours). For each draw, one can compute the \textit{error} criterion by comparing the net load duration of the aggregated set to the overall NLDC. One can refer to equation 3.1 for more details on the criterion.

Several draws can be made and the one of least \textit{error} is kept. One can easily foresee that, by minimizing the \textit{error}, the approximated net load duration curve obtained from the week selection will get closer to the reference NLDC.
One can notice this trend by drawing one’s attention to Figure 3.3. It represents the reference net load duration curve with two approximations obtained with the pure random week selection method. One of the approximated sets has been obtained with only one draw, the other one with 50 draws.

![Figure 3.3: Aggregated and reference NLDC for 1 and 50 draws](image)

The overall precision obtained after a few draws is significantly increased. The approximated NLDC tends to go closer to the reference one. A zoomed version of Figure 3.3 is represented in Figure 3.4 in order to reveal this trend more clearly.

When the number of draws increases, it becomes harder to notice this improvement by looking at the net load duration curves. However, the error criterion is useful to analyze the increase in precision of the number of draws. In Figure 3.5, the evolution of the error criterion with the number of draws is shown.

The error decreases significantly with the number of draws. However when the sampling is made in a purely random way, a lot of the aggregated sets could have been eliminated even before computing their error. There is a rather low probability that the random week selection, made with the earlier mentioned technique, produces a precise result according to the selection criterion. Indeed, for each aggregated set it is necessary to:
Figure 3.4: Zoom in: aggregated and reference NLDC for 1 and 50 draws

Figure 3.5: Evolution of the error criterion with the number of draws for pure random selection (semi-log)
• Sort the 8,736 (i.e. 4 seasons × 13 weeks × 7 days · 24 hours = 8,736) values of net load of the set in order to obtain the NLDC

• Evaluate the distances for all the values of NLDC

• Compute the error

In order to improve the week selection method, other approaches can be implemented. It is possible to find other techniques for ruling out unreasonable solutions which are less time consuming than the computations enumerated above. The two methods exposed in the following subsections characterize two suitable techniques for this purpose.

### 3.2.1.2 Seasonal random sampling

This week selection method is not far from the pure random sample method. Figure 3.6 shows an illustration of the seasonal random week selection.

![Illustration of the seasonal random week selection approach](image)

Figure 3.6: Illustration of the seasonal random week selection approach

The only difference with the pure random selection is that weeks are no longer selected in a complete random manner among all 5,200 available ones, but they are selected randomly within their season. A number of 13 weeks is selected in every season. By selecting weeks among the seasons, it increases significantly the probability of having an aggregated set which has its net load duration curve close to the reference one. In other words, this selection technique creates samples that are more coherent.

The repartition of seasons has been chosen as follows:
• Winter: December, January, February
• Spring: March, April, May
• Summer: June, July, August
• Autumn: September, October, November

Each of these seasons is made of 13 weeks. They are still selected randomly, but the random sampling is made within each season. As a result, there are $13 \times 100 = 1,300$ possible weeks within each season.

For each week selection, 13 weeks among all 1,300 weeks available are drawn per season. This results in an aggregated set made of $13 \times 4 = 52$ weeks. The obtained set is used for comparison between net load duration curves.

The evolution of the error is shown in Figure 3.7 for both pure random and seasonal random selection techniques.

![Figure 3.7: Evolution of the error criterion with the number of draws for pure and seasonal random selection (semi-log)](image)

Figure 3.7 shows that seasonal selection tends to produce an increased precision compared to pure random selections and with the same number of draws. This can be seen
from an other perspective, depending on the need of the user. Seasonal sampling tends to require less computing time than pure random sampling for a same precision of the results.

### 3.2.1.3 Adding a pre-selection criterion

Other techniques can be used in order to improve the random selection. A convenient technique would be to rule out imprecise aggregated sets before sorting the yearly net load and calculating the *error*. Indeed these two computations are the most time-consuming part of the selection method.

The improvement technique is carried out by a pre-selection criterion. The one used in this study is based on the mean annual net load. This criterion can be applied for both pure random and seasonal random approaches and tends to increase the efficiency of the selection.

As for the previous selections, a week selection process is completed and it results in an aggregated set of 8,736 values of net load. This aggregated set is kept for *error* computation only if condition 3.2 is fulfilled. In this report, this condition is based on the mean annual net load (NL) of the aggregated set. The latter must be close enough (set by the margin of error) to the mean annual net load of the entire data set.

This pre-selection criterion can be written as follow:

\[
NL_z^{\text{mean}} \cdot (1 - \varepsilon) \leq \hat{NL}_z^{\text{mean}} \leq NL_z^{\text{mean}} \cdot (1 + \varepsilon)
\]  

(3.2)

With:

- \(NL_z^{\text{mean}}\): Mean annual net load for the entire data set in zone \(z\) (in MWh)
- \(\hat{NL}_z^{\text{mean}}\): Mean annual net load for the aggregated set in zone \(z\) (in MWh)
- \(\varepsilon\): Margin of error on the pre-selection (in %)

An aggregated set is kept only if it fits the requirement of 3.2. Otherwise, another week selection is performed directly, without computing the *error*. A margin of error \(\varepsilon\) is admitted on the mean annual net load of the aggregated set. This margin is given in
percent and can be adjusted between selections. Typical values for $\varepsilon$ are between 0.5% and 3%. The selection for the following studies are obtained with a 0.5% margin of error.

By adding this new criterion to the previously presented sampling methods, it is possible to draw much more aggregated sets than before in an equivalent time period. The sets that are compared to the reference NLDC are more likely to have a reasonable error in comparison with the above mentioned methods.

In Figure 3.8, the evolution of the error with the number draws is shown for all four cases presented so far in this report.

![Figure 3.8: Evolution of the error criterion with the number of draws for pure and seasonal random selection with and without a pre-selection criterion (semi-log)](image)

The improvement coming from this pre-selection criterion is in some cases subtle (cf. Figure 3.8). In this section, two techniques have been implemented in order to increase the efficiency of the week selection methods. These two acceleration processes, seasonal sampling & pre-selection criterion, are both useful. However one can notice that the pre-selection criterion is less effective on the seasonal week samplings than on the pure random one. This is due to the fact that these two methods are partly redundant. Indeed, the pre-selection criterion is more likely to be fulfilled as the pre-selection is made on a seasonal sampled set instead of a pure sampled one.
3.2.1.4 Preliminary conclusion on the week selection method

The aim of the week selection method is to create a set of 52 weeks (made of hourly values of load) that has a net load duration curve which is as close as possible to the net load duration curve of the entire data set. The latter is formed of 100 scenarios of 52 weeks.

The approach used for this week selection is based on random draws. The one minimizing an error criterion is kept for the studies. With a significant amount of draws, it is possible to approach the NLDC with a good precision.

The more precise selection seems to be the seasonal week selection coupled with a pre-selection criterion, thus it the one that is kept for the studies detailed in this report.

3.2.2 Precision limits of the selections

After a significant number of draws, the final aggregated set kept seems to represent the reference NLDC with a rather good accuracy. However, the two main drawbacks of this approach are analyzed in the following subsections because of their possible impact on the case studies detailed in chapters 4 and 5:

- The \textit{error} criterion does not transpose the origin of the error within the NLDC. Depending on where the error comes from, it can have a significant impact on the results of the model detailed in chapter 2.

- There is no criterion based on the gradient of energy between two consecutive hours. This can have an impact on the modeling of dispatchable hydro storage and demand response for instance.

3.2.2.1 Precision on LDC’s ends

The \textit{error} criterion, on which the week selection method is performed, is based on the distance between the NLDC of the aggregated set and the reference NLDC. The selection of 52 weeks kept is the one with the minimal \textit{error}. However, this criterion does not take into account the repartition of the error (i.e. repartition of high distances) within
Chapter 3. Reducing the size of the data set

the net load duration curve. One can refer to Figure 3.2 and equation 3.1 in order to have more information on the distance at a given hour and the error criterion.

In the screening curves method, the shape of the NLDC plays a key role in the results obtained for the optimal deployment of each power plant. Thus is important that the approximated NLDC is close to the reference NLDC at every hour.

However, for most of the NLDCs obtained by using the week selection approach, the largest distances are observed at both ends of the load duration curves. This phenomenon can be observed by looking at the left-end side of the NLDC, that corresponds to the highest values of load. This part of the NLDC in shown in Figure 3.9.

![Net Load Duration Curve](image)

Figure 3.9: Zoom on the net load duration curves for both pure and seasonal samplings

The distance for both pure and seasonal samplings seems to get higher while the value of load increases. It is easier to note this trend by having a look at the distances between the reference NLDC and the NLDC obtained with pure and seasonal samplings. The result is shown in Figure 3.10 for both sampling techniques and for 10,000 draws.

This phenomenon is accentuated for the pure random selection, which explain, for the most part, its higher value of error.

The fact that the highest values of distance are located at the end of the distribution can be an issue. It is especially the case for the left end of the NLDC (i.e. large values of
load). These values are the most expensive MWh and correspond to a significant part of the overall cost even though they represent a few hours of the year only. This part of the plot is directly related to the deployment of the load shedding and technologies having a high variable costs. These technologies are deployed only during a few hours a year (i.e. the first dozens of hours of the load duration curve). If a significant error is concentrated in this part of the NLDC, it could change the arrangement of each technology and could deteriorate the validity of the model.

This error is more likely to be reduced if the number of draws is high. However one must understand that, as the approach is based on statistical draws, two aggregated sets obtained with the same input parameters can present significantly different repartition of the error.

On the other hand, high distances on the right end of the NLDC do not have a significant impact on the deployment of each technology.
3.2.2.2 Selection of the week of maximal load

In order to improve the representation of the left end of the NLDC, one can think of other selection techniques to implement. A technique tested for this report consists in forcing the selection of the week containing the hour of maximal electricity consumption. The aim is to force the selection of high load values.

The NLDC of such a selection is shown in Figure 3.11.

![NLDC including the week of maximal load for pure and seasonal sampling methods](image)

**Figure 3.11:** NLDC including the week of maximal load for pure and seasonal sampling methods

The approximated NLDC is above the reference NLDC at the left end of the duration curves (cf. Figure 3.11). A zoomed version of the NLDC is shown in Figure 3.12 for clarification purposes.

These high values of load correspond to the week of maximum load. One can notice that both pure and seasonal methods are impacted in the same way.

The direct consequences of selecting the week of maximum load are:

- The first hour of the NLDC is always selected in the aggregated set. Thus, the distance is equal to zero for the first load value of the duration curve.
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Figure 3.12: NLDC including the week of maximal load for pure and seasonal sampling methods

- The maximum load value has strong probabilities to be part of a week of high electricity consumption. This means that a significant amount of high load values come with the maximal one. This explains why the approximated NLDC is situated above the reference NLDC.

Thus the NLDC of the aggregated set is always situated over the reference NLDC. This is confirmed by Figure 3.13 that shows the distances for these new selections.

As one could have predicted, the values of distances have increased significantly. If one computes the error criterion of such a selection, it will automatically rise significantly.

The conclusion of this new selection method is that forcing the introduction of the week of maximal load add too many high values of load. Thus it creates more imprecisions on the left end side of the duration curve than before. That is why this approach has been ruled out.

However, the error at the left end side of the NLDC is at stake as its impact on the optimal electricity mix can be non-negligible.
Figure 3.13: Distances for pure and seasonal sampling methods including the week of maximal load

3.2.2.3 Energy gradient duration curve

The energy gradient is defined as the difference of energy between two consecutive hours.

\[
\text{Gradient}_t = \text{NetLoad}_{t+1} - \text{NetLoad}_t \quad \text{with } t \in 1..8735
\]  

(3.3)

Even though no criterion has been implemented in order to influence the energy gradient duration curve, it seems interesting to analyze the influence of the sampling method on this duration curve. Indeed, the energy gradient duration curve has great importance in order to ensure the coherence of flexibility indicators in the case studies.

Flexibility factors that are used for this study are:

- Hydro storage
- Demand Response

Both flexibilities are considering optimal dispatching of their availability within a time period. In the case of Demand Response, adjournments can be performed on the hours

...
following the activation. Thus, energy gradient takes an important role in the dispatch of these resources.

In Figure 3.14, one can observe the distance of two energy duration curves (pure random and seasonal random) from the reference energy duration curve.

![Figure 3.14: Distances from the gradient duration curve to the reference one, for pure and seasonal samplings](image)

The distances between the gradient duration curves of the aggregated sets and the one of the reference set are really close to zero. This means that the energy gradient duration curve is close to the reference one. Nevertheless, some high gradients of energy (up to 20,000 MWh) are observed at both ends.

The extreme distances are very likely due to the week junctions. Indeed, the random sampling method implements week junctions without considering the fact that it can create deep discontinuities at the load between the two hours joining two weeks.

It is possible to confirm this analysis by excluding the junctions’ energy gradients of Figure 3.14. The result is given on figure 3.15.
3.2.3 Extension of the method for several countries

The week selection technique has been presented for one country. However, in order to be able to model the electricity market in several countries, it is necessary to extend this week selection method.

Some correlations between each countries of the data set must be taken into account. That is why weeks are selected jointly between all countries. This means that the net load of the same drawn week is selected in each country. Thus, in the final selection, all load and RES availabilities of each country correspond to the same selection of 52 weeks.
For each sampled set, an error is computed for every country (i.e. obtained by comparison the the respective reference NLDC of each country). Then a general criterion needs to be settled in order to compare the sampled sets. The one used for the further studies has been taken as the product of the error in each country, in order to favor homogeneously spread errors between the countries.

The error criterion is shown in equation 3.4.

\[ Error_{all} = \prod_{z \in Zones} Error_z \]  \hspace{1cm} (3.4)

N.B.: In prior version of the sampling method, the general criterion made as the sum of the error in each country had been implemented. It resulted - in some cases - to a good precision is some countries made to the detriment of some others. The product approach tends to spread the error.

### 3.3 Conclusions on the week selection by statistical approach

#### 3.3.1 Overview of the outputs

From the sampling methods exposed in this chapter, it is possible to find a suitable selection of 52 weeks according to a defined criterion. The one chosen for this study is based on the distance between the approximated NLDC and the reference NLDC.

For the case studies that are going to be studied in the next chapters, the data set *New Mix* has been contracted into a single year made of aggregated weeks. The input parameters of the week selection method are chosen depending on the case study and the selected countries for it.

The selection of the aggregated set has been implemented on the NLDC. But in order to model the electricity system, it is necessary to export the aggregated set of:

- The *(gross)* load
- The must-run generation of all RES
• The available capacity (in MW) of each thermal power plant

• The equivalent energy of dispatchable hydro stored water available within each week

All these values are exported according to the week selection obtained with the least error method. This means that all parameters correspond to the same time period from the raw data set. Thus it still characterizes the possible correlation between all parameters.

### 3.3.2 Limits of this approach and possible further studies

The week selection method is performed in order to reduce the size of the raw data set. Of course this selection is made to the detriment of precision and even coherence of the data set. One must put all results into perspectives while using results obtained from this approximated data set.

The week selection method seems a reasonable approach in order to characterize a whole data set. However, the accuracy of the results depends on the use of this approximated data set and how it has been obtained. In this report, the selection is performed with a single criterion based on the net load duration curve. As one saw with the screening curves method, the NLDC is considered as a key parameter for the definition of an optimal energy mix. However, the remaining parameters are of no influence on the selection’s criterion. Thus their coherence within the approximated data set is not ensured.

The week selection method does not ensure the overall coherence of the data set and depending on its use, one must adapt the criterion. The selection should certainly be adapted to the model in which it is used. Moreover, the week junctions can represent an issue for the model. One must take it into account while building it up.

One could improve this selection by using multiple criteria instead of one and by adapting the selection to its future usage. Moreover, it could also be possible to evaluate the accuracy of the approximated data set by using indicators based on the outputs of the model where the data set is used.
Chapter 4

Case study: impact of interconnections on the cost of integrating RES

4.1 Scope of this study

An example of a possible application for the model detailed in chapter 2 is the impact of interconnections on the intermittency cost. Indeed, interconnections represent an important flexibility factor to the system. The volatility created by RES power plants can be shared between the countries and then a smoothing (or balancing) effect is to expect compared to a situation with isolated countries.

4.1.1 Context & Issues

Regardless of their costs, the share of RES will surely increase in the following decades, due to environmental reasons and thanks to political incentives. It will happen even if their integration does not represent the best investment policy, seen from the least cost optimization perspective. This transition will result in a additional cost to the system. Must-run electricity generation increases the volatility of the net load values and thus creates a need in back-up capacities. The real-time electricity price will also endure
strong modifications [5, 6]. The model detailed in chapter 2 can be used to quantify the influence of the interconnections on this additional cost.

The idea of this study is to solve the optimization problem with different hypotheses for the RES integration while maintaining the installed capacities of all other power plants as free variables. By comparing the overall cost of an energy mix for different scenarios together, it becomes possible to evaluate the cost of integrating renewables energies in the system. However, such cost strongly depends on the technology costs. Determining the projected fixed and variable costs for each technology with strong accuracy requires a complete study on its own and it is considered out of the scope of this study. Thus, in this case study, it seems more relevant and interesting to focus on the increase in the overall cost due to the modification of the thermal generation portfolio.

4.1.2 Approach

The variation in the overall cost of the system due to forced RES integration is mostly due to two factors:

- The non-competitiveness of must-run RES technologies
- The changes required in the thermal energy mix due to must-run RES integration

It is possible to split the overall costs between two sub-costs characterizing these two factors:

- The non-competitiveness cost comes from the fact that the mean cost of producing electricity from RES technologies becomes higher than the one from thermal power plants. Thus it can be defined as the difference between the mean cost of RES generation and the mean cost of thermal generation.

- The intermittency cost is related to the structural modifications made to the electricity system. The intermittency will impact the thermal generation portfolio. It tends to transfer capacities from base-load technologies to peak-load ones. As a direct consequence, the average cost thermal thermal generation, $\overline{MC_{thermal}}$, increases when RES are forced into the energy mix. The intermittency cost can
then be defined as:

\[
Cost_{intermittency} = AC_{thermal}^{RES\ constrained} - AC_{thermal}^{Reference} \ (€/MWh_{thermal}) \quad (4.1)
\]

## 4.2 Hypotheses

### 4.2.1 General hypotheses

This case study has been performed considering the set of the six following countries:

- France
- Germany
- The Netherlands
- Belgium
- Spain
- Portugal

A week selection is performed for this selection of countries and all the required parameters for the model are extracted for the given selection (cf. chapter 3).

Figure 4.1 shows all considered interconnections between each countries.

**Figure 4.1:** Interconnection map between the six considered countries
The hourly values of transfer capacity between each country are taken from the New Mix scenario.

### 4.2.2 Input parameters for technologies

This case study is conducted without considering DR. Thus the characteristic parameters, variables and constraints for DR, detailed in chapter 2, are omitted for this case study.

The technologies considered in this case study are listed in table 2.1. Moreover, this case study is performed according to the chosen set of cost parameters detailed in appendix A. These parameters are considered to be independent of the country.

As explained in subsection 2.1.3.2, load shedding is modeled by an extra technology having the highest variable cost and no fixed costs. For this case study, the variable cost of load shedding $V_{C_{\text{LoadShedding}}}$ is equal to $20,000 \, €/MWh$.

Some additional constraints on the installed capacity of each technology depend on the considered country. The one chosen for this case study are shown in table 4.1.

<table>
<thead>
<tr>
<th>Technology</th>
<th>France (MW)</th>
<th>Germany (MW)</th>
<th>Belgium (MW)</th>
<th>Netherlands (MW)</th>
<th>Spain (MW)</th>
<th>Portugal (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solar</td>
<td>= 24,100</td>
<td>= 67,000</td>
<td>= 6,000</td>
<td>= 5,500</td>
<td>= 17,500</td>
<td>= 1,500</td>
</tr>
<tr>
<td>Wind</td>
<td>= 36,600</td>
<td>= 89,000</td>
<td>= 9,000</td>
<td>= 10,500</td>
<td>= 38,000</td>
<td>= 6,500</td>
</tr>
<tr>
<td>Run-of-the-river</td>
<td>= 9,142</td>
<td>= 2,408</td>
<td>= 62</td>
<td>= 0</td>
<td>= 5,926</td>
<td>= 2,808</td>
</tr>
<tr>
<td>Nuclear</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hard Coal</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lignite</td>
<td>= 0</td>
<td>= 0</td>
<td>= 0</td>
<td>= 0</td>
<td>= 0</td>
<td>= 0</td>
</tr>
<tr>
<td>CCG</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OCGT</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Combustion</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Turbines</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hydro storage</td>
<td>= 8,000</td>
<td>= 900</td>
<td>= 1,000</td>
<td>= 0</td>
<td>= 5,500</td>
<td>= 8,200</td>
</tr>
</tbody>
</table>

**Table 4.1:** Additional constraints on the installed capacity of each technology in each country in 2030.
These additional constraints on the installed capacities come from the Generation Adequacy Report [1] and they are applied for all this case study. A certain number of technologies must not be developed in some countries due to the country configuration or its long-term political decisions for instance. Both installed capacities for run-of-the-river and hydro storage are considered as fixed in the system. One must understand that these type of facilities are really convenient sources of generation (emission-free, fuel-free etc.) and have a high lifetime, however it is considered that the hydro potential is limited and will systematically be fully used. Thus, the installed capacity of these power plants are given as parameters.

### 4.3 Sensitivity analysis for interconnections

Several scenarios can be imagined in order to evaluate the impact of interconnections on the intermittency cost. A illustrative representation of the chosen scenarios are shown in Figure 4.2.

![Figure 4.2: Illustrative representation of the scenarios of the intermittency cost’s case study](image)

This study is performed considering three different scenarios. Each of them is divided into two sub-scenarios having the exact same parameters except from border capacity transfers. One is considering all countries isolated from the others while the other one
is considering the all countries interconnected according to Figure 4.1. The 2030 level for RES technologies a given in table 4.1. The idea is to compare the long-term optimal energy mixes with two reference scenarios:

- One considering the installed capacity of solar and wind free and named reference
- One considering the installed capacity of solar and wind to be at 85% of their value in 2030 (according the New Mix scenario) and named reference 85%

For the reference scenario, the installed capacities of solar and wind are free. The results found for these technologies are shown in table 4.2.

<table>
<thead>
<tr>
<th>in MW</th>
<th>France</th>
<th>Germany</th>
<th>Belgium</th>
<th>Netherlands</th>
<th>Spain</th>
<th>Portugal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Isolated</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Solar</td>
<td>0</td>
<td>3,436</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Wind</td>
<td>1,608</td>
<td>90,619</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Interconnected</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Solar</td>
<td>0</td>
<td>8,165</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Wind</td>
<td>0</td>
<td>84,245</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 4.2: Installed capacities for RES technologies for the two reference scenarios

The zero-nuclear policy in Germany has a significant impact on the profitability of RES technologies and especially wind power. The deployment of nuclear in this model configuration is favored in general. This is due to the fact that it is not dynamically constrained and that, on the contrary to other thermal technologies, its variable cost is not impacted by the hypothesis of high CO\(_2\) price (set to 95 €/ton). According to the considered set of parameters, the deployment of solar power seem significantly less profitable than wind power. This is due to its typical availability profile where generation is peaking at noon, which does not necessarily match with the load peak hours.

In order to be able to compare the mean and marginal intermittency costs, one must compute its value in comparison to the additional RES production between the long-term and the reference scenarios.
\[ \text{OverallCost}_{\text{intermitt.}}(\text{M€}) = \text{Cost}_{\text{intermitt.}}(\text{€/MWh}_{\text{ther.}}) \times \text{Prod}_{\text{Thermal, yearly}}(\text{TWh}_{\text{ther.}}) \] (4.2)

\[ \text{Cost}_{\text{intermitt.}}(\text{€/MWh}_{\text{RES}}) = \frac{\text{OverallCost}_{\text{intermitt.}}(\text{M€})}{\text{Prod}_{\text{RES, Long-term}} - \text{Prod}_{\text{RES, Reference}}(\text{TWh}_{\text{RES}})} \] (4.3)

Figure 4.3 shows the evolution of the intermittency cost with and without interconnections between the 6 selected countries. It includes intermittency related to the comparison of the long-term scenario with the reference scenario (mean intermittency cost) and the reference 85% scenario (marginal intermittency cost\(^1\)).

One can notice that the intermittency cost is approximately situated between 15 and 20 €/MWh. The same range is obtained in comparable studies on that matter [7–9]. These results mean that due to the variability of must-run power plants, the energy mix becomes de-optimized. In comparison to the reference scenario, the production of one

\(^1\)In this context, “marginal” must be understood in the sense of the intermittency cost of the generation of an additional GW around the 2030 situation
MWh of renewable energy an increase in cost of around $15\,€$. Thus, the intermittent behavior of RES leads to an increase in the electricity price.

As expected, the introduction of interconnections between countries tends to reduce the intermittency cost due to RES integration. This reduction is due to the smoothing effect of RES technologies among all countries. Thus this balancing effect is saving around $5\,€$ per MWh generated by RES power plants. Moreover, it seems that an inversion of the concavity of the intermittency cost close to the level of 2030 since the marginal intermittency cost becomes higher than the mean one.

### 4.4 Limits of the study

This case study presents an example of application for the model developed in chapter 2. However, one can think of several limits for this study:

- The results are highly dependent of the sets of parameters.
  - The costs hypotheses
  - The week selection method and results

- The scenarios are simple. A consequence is that no strong limitations are given to technologies. This is made in order to find the optimal repartition of each technology. However some results can seem unfeasible in the current context and trend for the future years (e.g. strong incentives to reduce the share of nuclear power plants in Europe).

- The optimization made with several interconnected countries can report capacities from some countries to others. The result is that small countries can obtain an unrealistic energy mix with an excess of installed capacity for one technology.

- The modeling of the load shedding is basic and makes it uneasy to control the loss of load duration. The security of supply criterion is not always exactly fulfilled due to additional flexibilities such as interconnection or hydro storage. It is not necessarily possible to spread the total amount of hours of load shedding equally in each country. Big countries tend to monopolize these hours while small countries present usually too few hours of load shedding.
• There are other definitions of the intermittency cost.

• etc.

The model and the scenarios used in this case study are the result of strong simplifications. Thus, one must put each result into perspective.
Chapter 5

Case study: impact of RES on DR’s deployment

5.1 Scope of this study

In this case study, four scenarios are compared which all have different developments of RES and DR. Then, the scenarios are compared and enable to evaluate the impact of RES integration on the deployment of DR on a mid and long-term basis.

5.1.1 Context

DR consists in creating incentives for the end user to adapt its electricity consumption. This can be used in order to avoid load peaks, and thus reduce the amount of peaking generation capacity required to fulfill a given criterion of security of supply. The use of demand response aims at reducing the volatility of the load.

By actively supporting several renewable technologies (especially solar power and wind power), public authorities are making choices on the energy mix that have an influence on the economic area of other power technologies. On a short-term basis, demand response development could be restrained by too low prices while on a long-term basis, massive RES integration in the energy mix would create a need in flexible and high variable cost power technologies. DR have characteristics close to this type of technology and could usefully fulfill a part of this need.
Some of the DR may involve adjournments on the following hours. For instance, residential DR is mostly related to the electrical heating. It is possible to adjourn the start-up of the some heating systems when it matches with a peak load hour. But the end user can only accept to perform DR if it has no (or a limited) impact on his personal comfort. Because the time constant of the drop in temperature is high, it is possible to adjourn the start-up of the electrical heating systems for a time, but this drop needs to be compensated by an over-heating, spread out during the next hours.

5.1.2 Issues

DR represents a significant flexibility in the electrical system and its impact on the overall system cost on a long-term basis is of interest. However, the RES benefit from significantly more political support than DR for now. Their introduction is thus easier and on a larger scale. One can wonder to what extent:

- Subsidies to renewable energy sources limit the profitability of Demand Response (on a short/mid term basis)
- This phenomenon goes against the overall cost minimization objective on a long-term basis.

5.2 Hypotheses

5.2.1 General hypotheses

The objective is to evaluate the optimal deployment of DR in several levels of RES integration.

The scope of this study is reduced to France only. Thus France is considered as isolated from all other European countries. Macroeconomic hypotheses (such as fuel prices, CO\textsubscript{2} price, load, etc.) and technologies are taken from the New Mix data set of the Generation Adequacy Report of 2014 [1]. A new week selection (cf chapter 3), concerning France only, needs to be computed for this case study.
The availability of each power technology is obtained with the week selection and are supposed to be independent from the installed capacity.

Concerning the investments, the discount rate is set to 5.5%. It corresponds to a hypothesis which reflects the practices of French companies in the electricity sector (e.g. EDF, RTE). Hypotheses for fixed and variable costs are kept the same as in the study case of chapter 4. They are detailed in appendix A.

5.2.2 Input parameters for DR modeling

An hourly availability is used for all types of DR. Moreover, both residential and tertiary DR are considered having a 100% adjourned energy on all their activations.

Cost hypotheses come from a report about the socio-economic value-creation of smart electric grids in France (Valorisation socio-économique des réseaux électriques intelligents) published by RTE in July 2015 [10].

5.2.2.1 Industrial DR

The industrial DR deposit is considered non-homogeneous in the ways that all installed MW of DR do not cost the same amount of money. In this case study, industrial DR is modeled as eight technologies each of maximum 1GW of installed capacity each and with different fixed costs in order to represent with a reasonable approximation the targeted market. This repartition into stepwise increasing fixed costs is shown in Figure 5.1.

The features of the industrial DR modeling characterize the fact that the first MW of the potential are cheaper to dispatch than the last ones. Even though these eight power plants can be distinguished according to their fixed costs, the model considers all other parameters equivalent for the eight plants. This includes the following features:

- Their variable cost is of 300 €/MWh. In practice the costs are incremented with a step of $10^{-4}$ €/MWh in order ensure the unicity of the solution and thus reduce the computing time. Furthermore, there is no consideration of possible CO₂ emissions linked to auto-consumption.

- They are available on business days and work hours only
5.2.2.2 Residential & Tertiary DR

Residential and tertiary DR are modeled as one technology each. Their main features are listed in table 5.1.

<table>
<thead>
<tr>
<th>Maximum installed capacity</th>
<th>Fixed Cost</th>
<th>Variable Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residential DR</td>
<td>10 GW</td>
<td>29 k€/MW/year</td>
</tr>
<tr>
<td>Tertiary DR</td>
<td>3 GW</td>
<td>18 k€/MW/year</td>
</tr>
</tbody>
</table>

Table 5.1: DR specific parameters

Moreover, both DR types are characterized with the following additional features:

- A 100% adjournment of the activated energy (it results in a money transfer between the DR operator and the supplier, nevertheless this transfer has no influence on the optimization because it is fully refunded thanks to the adjournment)
• The availability represents the heating power that can be shed by standard users. Its computation is made by taking into account meteorological scenarios with the corresponding load and is not in the scope of this study.

The adjournment of both DR types are considered to be performed within the next six hours after activation. The profile used in this case study is the one shown in Figure 2.8 (cf. chapter 2).

5.3 Methodology

The optimal energy mix is computed for four scenarios with the model detailed in chapter 2 (according to the least overall cost objective function). Thus, it corresponds to both the composition of the mix (RES, thermal and DR power plants) and the use of these capacities throughout the year. These four scenarios correspond to different constraints on RES, thermal and/or DR deployments. Then the results of these scenarios are compared.

A illustrative representation of the four scenarios is given in Figure 5.2.

![Figure 5.2: Illustrative representation of the case study’s four scenarios](image-url)

The four scenarios can be detailed as follows:
• **Reference scenario:** computation of the optimal energy mix without any constraints on the installed capacities for RES and thermal power plants (except for both storage and run-of-the-river hydro). It represents a scenario without any support from public authorities.

• **Mid-term 1 scenario (with excess of capacity):** computation of the use of each installed capacity throughout the year with a cumulated level of 15 GW for solar and wind power (i.e. the current deployment of RES in France) and all other installed capacities fixed to the level obtained in the reference scenario. This means that this scenario is in excess of installed capacity (all installed capacity are fixed by additional constraints to the model). It represents the short/mid-term effect of a RES support policy according to the fact that this RES deployment has not been anticipated by the actors in the electricity market (i.e. the installed capacities have not been adapted. The comparison between the mid-term 1 scenario with excess of capacity and the reference scenario enables to evaluate the short/mid-term impact of RES deployment on the profitability of DR technologies (cf. subsection 5.4.1).

• **Mid-term 2 scenario (with adaptation of DR capacities):** the thermal energy mix is the one obtained in the reference scenario whereas RES deployment is set to 15 GW. DR’s installed capacities are no more set and are optimized according to the given energy mix. Thus, this scenario represents another example of excess of capacity except that DR’s installed capacity had time to adapt to this RES deployment, contrary to thermal technologies. The comparison between the mid-term 2 scenario with adaptation of DR capacities and the reference scenario enables to evaluate the short/mid-term impact of RES deployment on DR deployment (cf. subsection 5.4.1).

• **Long-term scenario:** computation of the optimal energy mix with a imposed cumulated level of 61GW for solar and wind power. This scenario represents the long-term adaptation of the whole energy mix (thermal and DR) with the installation of the targeted RES installed capacity in 2030 (cf. subsection 5.4.2).

Because *MICadO* optimizes the installed capacities, one must understand that, if no additional constraints are limiting the installed capacities, all technologies will be exactly profitable. This means that the surplus of each technology will be equal to its fixed costs (i.e. corresponding to its return on investments).
5.4 Results

5.4.1 Short/Mid-term impact of RES integration on profitability and upholding of DR

With all the above mentioned hypotheses and in the reference scenario, *MICadO* gives a deployment of 0 GW for both solar and wind power. This means that RES technologies are judged as non-profitable compared to the other power sources (given the chosen set of parameters). However, Demand Response is profitable up to around 6 GW of installed capacity (4.6 GW of industrial DR, 1.4 GW of tertiary DR and no residential DR). The mean profitability of these installed capacities are of 11 k€/MW/year for industrial DR and 9 k€/MW/year for tertiary DR.

The profitability results for each DR technology are shown in Figure 5.3.

![Figure 5.3: Comparison of DR profitabilities between reference and mid-term scenarios](image)

In the mid-term 1 scenario (with excess of capacity), the additional 15 GW of RES reduces the profitability of the industrial DR by 30 k€/MW/year and of around 15 k€/MW/year for tertiary DR. Thus, their profitability becomes negative. This makes the mean profitability of industrial DR at -19 k€/MW/year and -7 k€/MW/year for
tertiary DR. This strong drop in the profitability is for a part caused by the reduction of the number of load shedding hours (from 3 to 0 hours).

Thus, this loss in profitability results in an adaptation of the installed capacity of DR technologies in the mid-term 2 scenario. The installed capacity is significantly reduced. Results for both reference and mid-term scenarios are shown in Figure 5.4.

One must notice disappearance of distributed DR technologies in the energy mix and a drop to 2 GW of installed capacity for industrial DR. Compared to the mid-term scenario 1 (with excess of capacity), the loss of 4 GW of DR capacity restore the profitability of the first 2 GW which are kept.

From this analysis, one can understand that a support from public authorities that leads to a quicker RES deployment (than expected by the market’s actors) will most certainly degrade the profitability of Demand Response on a mid-term basis. It could also lead to a disappearance of the less profitable ones.
5.4.2 Long-term impact of RES integration

In the long-term scenario, both thermal and DR technologies are adapting their installed capacities while facing an introduction of 61 GW of RES (corresponding to the amount of RES planed in the New Mix scenario of the Generation Adequacy Report, i.e. 36,600 MW of wind power and 24,100 MW of solar power).

The optimized installed capacities for DR for both the reference and the long-term scenarios are shown in Figure 5.5.

The share of DR which is profitable thus rises slightly between the reference and the long-term scenario (reaching 6.7 GW instead of 6 GW). In particular, one must notice that industrial DR deployment is more or less kept constant between both scenarios, residential DR still seems non-profitable, however tertiary DR installed capacity rises from 1.4 GW to 2.1 GW. This means that when a large deployment of RES technologies is well anticipated:

![Diagram of DR installed capacities between reference and long-term scenarios]
Thermal technologies can adapt their share in the energy mix

The deployment level and the profitability of DR technologies tend to increase

According to this study, one can conclude that active support from public authorities to renewable energies do not have, on a long-term basis, a negative impact on the profitability of Demand Response, but it could, on the contrary, favor its deployment.

Figure 5.6 details the evolution between all installed capacities is the reference and long-term scenarios.

![Comparison of DR installed capacities between reference and long-term scenarios](image)

One can notice that the large deployment of RES have an impact on the optimal thermal energy mix. A capacity transfer is performed from base production such as nuclear to peak production such as combustion turbines. It characterizes a need of peak production power plants (with low fixed costs and high variable costs) due to RES production.

### 5.5 Conclusion of the case study

If, because of a strong political support, RES deployment is performed faster than what market’s actors expect, then this deployment could have a negative impact on
the profitability of demand response. In theory, this would result in their diminishing or even their disappearance. However, if this deployment is well anticipated, or if the adjustment is performed after a period with excess of capacity, then the room and the profitability of demand response will not be affected negatively by this large deployment of RES.

5.6 Limits of the study

This case study presents an example of application for the model developed in chapter 2. However, one can think of several limits for this study:

- The results are highly dependent of the sets of parameters.
  - The costs hypotheses
  - The week selection method and results
- The scenarios are simple. A consequence is that no strong limitations are given to technologies. This is made in order to find the optimal repartition of each technology. However some results can seem unfeasible in the current context and trend for the future years (e.g. strong incentives to reduce the share of nuclear power plants in Europe).
- The modeling of the load shedding is basic and difficult to control. The three hour criterion is not always fulfilled due to additional flexibilities such as interconnection or hydro storage.
- The modeling of Demand Response is also basic and does not represent it with all its constraints. Moreover, some hypotheses are made on the adjournment profile which are not realistic and homogeneous. As a matter of fact, Demand Response is not developed in a large scale so far and it is rather difficult to model its behavior with certainty.
- etc.

The model and the scenarios used in this case study are the result of strong simplifications. Thus, one must put each result into perspective.
Chapter 6

Conclusion

6.1 Summary & General conclusions

The electricity markets sector is facing several transitions since the recent liberalization of this sector. The increasing number of policies in the matter of energy and climate creates new issues that must be taken seriously. It is clear that the renewable energies are going to extend their deployment in the future years. They represent a must-run (intermittent) and decentralized source of energy that cannot be handled as other power sources.

This type of transition must be prepared because the energy portfolio must be adapted to these changes. The lifetime of power plants is long and each modification in the share of each technology in the energy mix must be prepared in advance. In this report, it is assumed that the best transition to a world with a important share of green energy would be the one that still supply the electricity demand (without more curtailments than before) while minimizing the overall costs that is shared between actors. Thermal power plants are used to fulfill the remaining supply required in order to do so.

One can be interested in characterizing an optimal repartition of each technology that fulfill the requirement of supply for the modeled area. This can be done by modeling the electricity markets. As for every model, several simplifications must be performed while keeping it reasonably accurate modeling. This report presents a model aiming at optimizing the installed capacity of each generating technology. It is based on a sets of data produced by RTE.
This model is subjected to strong simplifications but the trend obtained in the results can be seen as coherent. It enables to study more complicated problems than with the screening curves methodology. Moreover, it can be tuned easily in order to fulfill new requirements or to take into account new facilities, modeling features. Nevertheless, the optimization problem rapidly becomes of a significant size and can take time to be solved.

6.2 Conclusions from case studies

Two case studies are performed in this report in order to illustrate two possible applications of the model built at the beginning of the report. One is focused on the additional cost of energy generation that comes from the intermittency of renewable energy sources and the impact of interconnections on this additional cost. The other case study tends to characterize the impact of green energy’s integration on the deployment of Demand Response.

From the case study developed in chapter 4, one can conclude that the integration of renewable energy sources has a significant impact on the remaining installed capacity, mostly made of thermal technologies. Due to the intermittency of their generation, the need of thermal power plants evolves. The formerly required part of base-load generation (i.e. that generates electricity during almost all hours of the year) is reduced in favor of the peak-load types of technology, that are used only a few hours a year. This will results in a rise in the cost of generation electricity. This increase is directly related to the intermittency generation of renewable means of electricity production. As one can imagine, the intermittency cost of RES is strongly dependent on several problem characteristics. One of these is the interconnections between multiple countries and is studied in chapter 4. The development of an extended electricity grid that connects several countries tends to reduce the intermittency cost. This phenomenon is due to the smoothing effect by the increase in scale of the impacted area.

Another case study is developed in chapter 5. It aims at characterizing the impact of RES integration onto the deployment of Demand Response. This study comes in a context of strong political support for RES. It tends to evaluate the impact of strong and active support to RES on the deployment of Demand Response. The major conclusion
of it is that RES integration seem to not have a significant impact on DR deployment on a long-term basis.
Chapter 7

Future studies

The future work on this subject can be separated into two main categories. First, one could improve the model in order to make it more accurate. Furthermore, one could imagine several application studies based on results produced by the model.

Several improvements can be performed on the model. The week selection method is performed to a unique criterion based on the net load duration curve and does not take into account the possible resulting incoherence of other parameters (availability of power plants, hydro storage’s dispatch, etc.). Thus a more precise week selection (or new considerations on the pre-processing of the raw data set) could be a track for improvements. Another approach could be aimed at simplifying the optimization model in order to make it faster to be solved. One could use a data set with several input subsets (i.e. years) so that it becomes possible to perform a Monte-Carlo approach on the study results. Furthermore, one could increase the complexity and accurateness of the model by modeling more precisely each technology (and especially thermal power plants). Indeed, one could add constraints on the use of thermal power plants (minimum up and down time, start-up costs etc.). Another improvement could be the integration of reserve considerations (spinning, non-spinning and replacement reserves).

Using such a model that optimizes the installed capacity of each technology. One can imagine a great number of studies about technology integration and the respective impact of parameters on those integrations. Studies can be performed within both short and long-term timeframes. Besides interconnections, the impact of hydro storage and demand response, that both represent flexibility in the system, could be of importance.
Moreover, one could also develop interest on the the impact of additional constraints on the energy mixes of each considered country. Finally, after the case study of 5, one could imagine a study aiming at characterizing the impact of DR deployment on the integration of RES.
## Appendix A

### Cost hypotheses

<table>
<thead>
<tr>
<th>Technology</th>
<th>Overnight cost (k€/MW)</th>
<th>Fuel-less OpEx (k€/MW/y)</th>
<th>Lifetime (year)</th>
<th>Yearly FC (k€/MW/y)</th>
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<tbody>
<tr>
<td><strong>RES</strong></td>
<td></td>
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</tr>
<tr>
<td>Solar</td>
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<td>21</td>
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<td>107</td>
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<td>Wind</td>
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<td>45</td>
<td>25</td>
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<td>Run-of-the-river</td>
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<td>80</td>
<td>266</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Nuclear</td>
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<td>285</td>
</tr>
<tr>
<td>Hard Coal</td>
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<td>40</td>
<td>140</td>
</tr>
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<td>Lignite</td>
<td>1,811</td>
<td>28</td>
<td>40</td>
<td>140</td>
</tr>
<tr>
<td>CCG</td>
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<td>24</td>
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<td>79</td>
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<tr>
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<td>24</td>
<td>25</td>
<td>65</td>
</tr>
<tr>
<td>Combustion Turb.</td>
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<td>25</td>
<td>65</td>
</tr>
<tr>
<td><strong>Hydro storage</strong></td>
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<td><strong>Demand Response</strong></td>
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</tr>
<tr>
<td>InduDR 1</td>
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<td>3</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>InduDR 2</td>
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<td>3</td>
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<tr>
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<td>20</td>
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</tr>
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<td>10</td>
<td>55</td>
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<tr>
<td>TertiaryDR</td>
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<td>1</td>
<td>20</td>
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<tr>
<td>ResidentialDR</td>
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<td>10</td>
<td>10</td>
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</table>

*Table A.1: Fixed cost hypotheses for technologies in 2030*
### Table A.2: Variable cost hypotheses for technologies in 2030

<table>
<thead>
<tr>
<th>Technology</th>
<th>VC without CO₂ ($/MWh)</th>
<th>Emission factor (tons/MWh)</th>
<th>VC incl. CO₂ ($/MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RES</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Solar</td>
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<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Wind</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Run-of-the-river</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Nuclear</td>
<td>10.23</td>
<td>0</td>
<td>10.23</td>
</tr>
<tr>
<td>Hard Coal</td>
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<td>0.956</td>
<td>118.82</td>
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<tr>
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<td></td>
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<td>Hydro storage</td>
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<td>-</td>
<td>-</td>
</tr>
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<td>InduDR 1</td>
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<td>0</td>
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<td>TertiaryDR</td>
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<td>50</td>
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</tbody>
</table>

Tables A.1 and A.2 details the cost hypotheses for all technologies used in the case studies presented in chapters 4 and 5. All cost hypotheses are taken from the *Generation Adequacy Report*, the International Energy Agency report about the *Projected Costs of Generating Electricity* and the report published by RTE about the socio-economic value-creation of smart electric grids in France [1, 10, 11].

The discount rate used for all technologies is set to 5.5% and the CO₂ cost is set to 95 €/ton (according to the *New Mix* scenario [1]). Moreover, the energy spillage cost is
supposed to be equal to zero in the two case studies of chapter 4 and 5.

Load shedding is represented by a technology with no fixed cost and a variable cost that leads to a 3 hours curtailment per country during the year.
Bibliography


