

École polytechnique de Louvain

Optimization of our future energy system

Near optimal solutions space analysis of an energy system model

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Abstract

Energy System Optimization Models (ESOMs) have emerged as a very useful tool for the analysis of energy and climate policy at national scale. Given the many different engineering knowledge, decision makers and timescales involved in such models, address their uncertainties is critical.

This work tries to address all uncertainties by using the ESOM in an interactive way by searching for near cost optimal solutions. In this context, three methods to find near optimal solutions have been developed. The analysis of these new solutions leads to new insights that are unattainable by only analyzing the optimal solution. Moreover, new alternative energy systems, that decision makers might prefer over the optimal one, can emerge.

This work applies this analysis on EnergyScopeTD for the Belgian energy system. Three scenarios corresponding to three CO_2 emissions reduction policy are analyzed and interesting conclusions are made based on the optimal scenario and its surrounding.

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1 Introduction

In 2015, an international political agreement made at COP21 in Paris has set a goal of limiting the global mean surface temperature rise to well below 2°C above pre-industrial levels [1]. Today, it becomes clear in the scientific community that the impact of our human society, with greenhouse gas (GHG) emissions, is a real threat not only for us, but for every living species on Earth [2] [3].

The GHG emissions mainly (but not only) come from the human activity through its energy consumption. To face this huge challenge, a deep transformation of our energy systems is needed. This transformation should take place in the primary energy resources used (natural gas, wind, coal, etc.), but also in the conversion technologies that transform those primary resources to end-use demands of consumers (i.e. electricity, heat and mobility).

Numerous new low-carbon technologies are emerging and the research on new technologies evolves at full speed. These technologies sometimes interact between different sectors of energy and make energy systems more complex. Furthermore, renewable energies grow quickly but are sometimes intermittent and add even more complexity to the energy system.

In this context, nowadays, there is a growing interest for Energy System Optimisation Models (ESOMs). These kind of models usually optimize the investment and operation costs of an energy system at a regional or national scale, while ensuring that the energy end-use demand is satisfied. ESOMs can have a lot of technologies represented with a great level of details. Furthermore, ESOMs can have a low time resolution (about an hour) and allow to correctly take into account the intermittence of renewable technologies.

The great interest for ESOMs is thus explained easily by the increasing complexity of energy systems and, as energy infrastructures are expensive and long-lived, the need of long term planning for the energy transition required to face climate change. ESOMs allow to optimize long term energy systems with many resources and technologies and is thus an important tool to develop planning and investment strategies and consider the different options that decision makers might have [6].

However, one of the biggest limitation of ESOMs is that they are often deterministic, although the fact that they are subject to great uncertainties. In 2017, a review of 134 ESOMs classified the different approaches for uncertainties assessment [15]. The conclusion is that 100 of them does not apply a systematic formal approach to deal with uncertainties. They use small ensemble scenario analysis and simple sensitivity analysis to handle them. This kind of analysis is not sufficient to fully understand the impact of uncertainties in the model. Indeed, the scenarios are often highly detailed, owing to the wide range of model input assumptions that can be affected. However, these small sets of scenarios, each with a high degree of detail, can actually have the opposite effect by creating cognitively compelling storylines that obscure other equally plausible alternatives and betray the true underlying uncertainty [9].

Some studies already pointed the major differences that can occur between the model

results and reality, and the importance to address uncertainties in a more rigorous way [12, 13, 14].

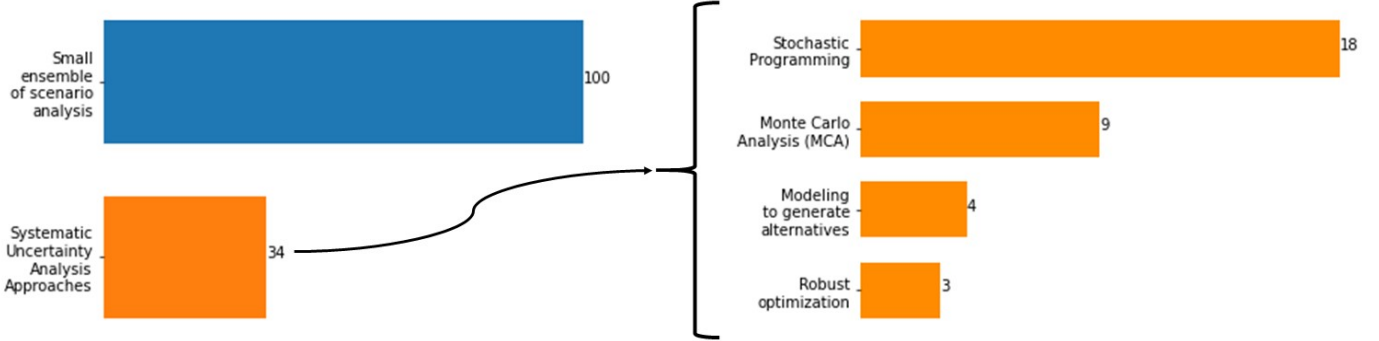


Figure 1.1: Number of ESOMs that address uncertainties (source : [15])

In energy systems, uncertainties are generally classified into two parts [26] :

1. **Parametric uncertainties** come from lack of knowledge on empirical values for the model parameters (e.g. the uncertainty on the investment cost of photovoltaic (PV) panels in 10 years) or parameters that vary stochastically over time (e.g wind speed). They are usually reducible by having more informations and their impact on the system output can be quantified with different methods such as global sensitivity analysis. For example, in [17], Limpens et al. quantified some parameters uncertainties impacts on the system total cost and found that the hydrocarbons price uncertainty drives 64% of the total cost variation of the energy system studied.
2. **Structural uncertainties** refer to the imperfect and incomplete nature of the equations describing the system. They are hardly reducible. Conventional ways to deal with these uncertainties consist in making the model more complex to account for additional dynamic processes, or compare different models [23]. For example, a structural uncertainty could be the ignorance of the heterogeneity among decision makers in the energy system, the manner in which non-economic considerations factor into energy purchasing decisions, or the role that politics, social norms, and culture play in shaping public policy [15].

Most studies [17, 18, 19] only address parametric uncertainties with Monte-Carlo (MC) analysis or stochastic programming (SP). However, these methods, as well as robust optimization or sensitivity analysis, do not take into account structural uncertainties, and often suffer from computational complexity. Furthermore, the values or distributions of key uncertain parameters are often themselves subject to great uncertainties.

Since ESOMs try to represent complex real systems involving many different engineering knowledge and decision makers, the structural uncertainties will always be strong

[26]. As they are hardly reducible, not taking them into account could result in a lack of insights or robustness and thus mislead the decision makers. Some studies already have pointed this lack of focus on structural uncertainties [20, 21, 22]. Furthermore, Casman et al. pointed in 1999 that even if all parametric uncertainties could be eliminated in an energy system model, it would still be a poor predictor of future outcomes because the set of mathematical equations that describe the system will always be imperfect and incomplete [10].

In this context, this work tries to address this problem in an innovative way : instead of considering only the optimized solution given by the ESOM, this work considers every near-optimal solutions that could represent an alternative to the optimal solution. These alternative solutions may be preferable to the optimal one for decision makers, as they usually are concerned with factors outside the modelling scope (e.g. political feasibility, permitting and regulation, timing of action). Furthermore, these new solutions can give more insights into the complexity of the energy system to the analysts.

This kind of analysis uses the ESOM interactively in order to find knife-edge¹ solutions, explores alternative system configurations and suggest different ways to achieve policy objectives under conditions of big uncertainty. The ESOM is not used to find detailed scenarios that could mislead the decision makers, but more in an iterative way to give insights that account for all uncertainties.

Moreover, as the alternative solutions are computer-generated, this method avoids cognitive biases associated with the analysis of detailed scenarios [9].

Based on the optimal cost energy system for Belgium in 2035² [5], the near cost optimal solutions space will be explored.

Two more scenarios will be analyzed in the same way : one mitigate CO_2 emissions reduction policy and one aggressive CO_2 emissions reduction policy. The mitigate policy corresponds to a reduction of CO_2 emissions of approximately 50% while the aggressive one is more about 90%, compared to the emissions of the optimal cost energy system for Belgium in 2035.

This analysis aims at answering the following questions :

- Are there cost competitive alternatives to the optimum given by the ESOM ?
- Are there essential conversion technologies, or some technologies to avoid ? Which are they ?
- Can we get relevant insights on the energy system by analyzing the near cost optimal solutions space ?
- What is the impact of decarbonization ?

This work is structured into 4 different sections :

¹A solution is considered to be a knife-edge solution when small perturbations to input assumptions result in a big difference in the solution

²Nuclear technology will not be taken into account as the actual energy policy seems to get out of nuclear for 2025

- **Section 2 :** The ESOM EnergyScopeTD (ESTD) used for this work will be presented. The three cost-optimal scenarios, corresponding to the three CO_2 policies will then be given
- **Section 3 :** The three different methods developed in order to find near-optimal solutions will be explained.
- **Section 4 :** The results will be given and analyzed. For each CO_2 policy scenario, a statistic analysis, based on large sample of alternative energy systems, will first be given. After that, a second analysis based on the third method will be given. This analysis consider less alternative energy systems and is more suitable for a hand analysis
- **Section 5 & Section 6 :** Finally, the results will be discussed. Results between the statistic approach (with large sample of energy systems) and the second approach (with low sample of energy systems) will be compared and conclusions from both analysis will be given

2 The ESOM : EnergyScopeTD and the three cost optimal scenarios

2.1 The ESOM : EnergyScope Typical Days

ESTD [24] is an open source energy system model that optimizes, with a hourly resolution, both the investment and the operation costs over a geographical region, typically a country. Unlike many other energy models, EnergyScope TD does not specifically focus on the electricity sector, but models an entire energy system (electricity, heat and mobility).

This model is based on 2 steps : the selection of the typical days, which is a Mixed-Integer Linear Programming (MILP) problem and the optimization on these typical days of the investment and operation costs, which is a Linear Programming (LP) problem. Its functioning is resumed in fig.2.1

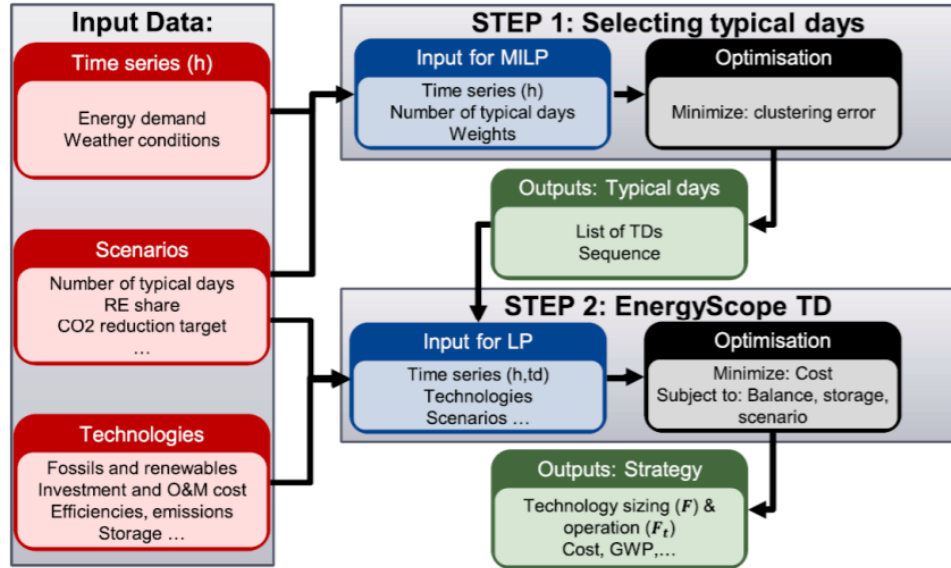


Figure 2.1: The 2 steps of EnergyScope TD. First, the selection of the typical days in order to reduce the computational cost. Second, the energy system modelling and its optimization

Step 1 : selection of typical days

Due to computational restrictions, EnergyScope TD does not optimize the energy system over the 8760 hours of the year. 12 typical days are selected in order to represent well the profile of the different days of the year. This is a trade-off between

computational cost and introducing an error in the representation of the energy system. The different figures of this work that will show hourly data will be presented over these 12 typical days³, but the reader should keep in mind that these 12 days represents well the whole year.

Step 2 : EnergyScope TD

This second step is the core of the energy model. It will be presented in 2 parts : the framework of the model with a simple example, and the model formulation done with linear programming.

1. Framework of the model

The first goal of this step is to balance the energy demand (which is an input data) with the supply. There are 3 main categories to consider : the resources (e.g. Natural Gas (NG), sun, wind, etc), the energy conversion and the End-Use Demand (EUD). An illustrative example of ESTD is shown in figure 2.2.

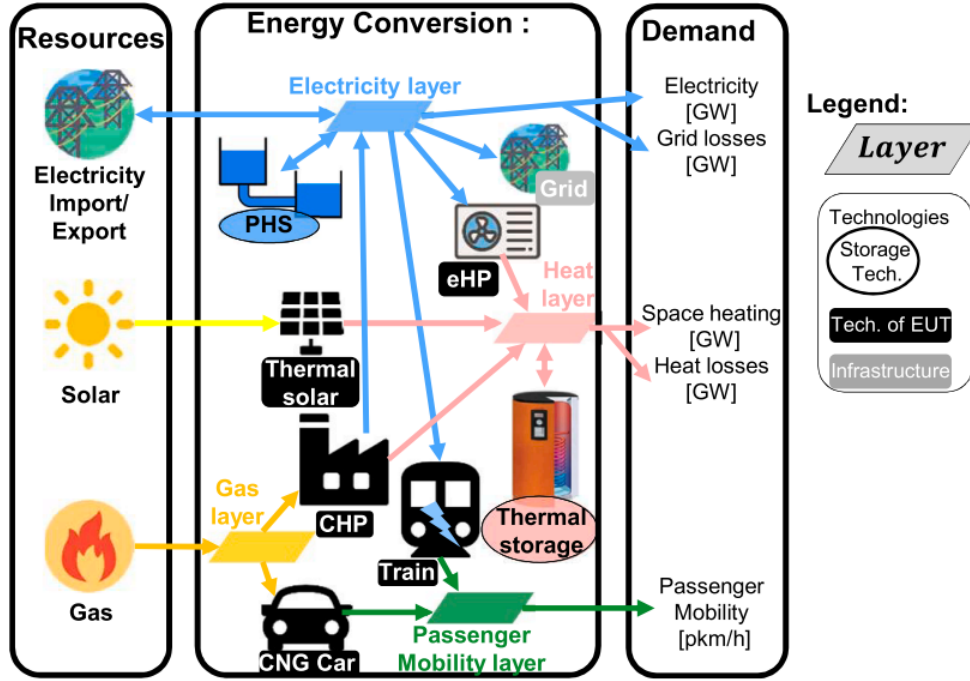


Figure 2.2: Illustrative example of EnergyScopeTD model [24]. There are 3 resources, 8 technologies for energy conversion (with 2 storages and 1 infrastructure) and 5 end-use demands (with 2 losses : electricity and heat)

³Except for energy storage figures, which is computed for the whole year in ESTD

The energy conversion encompasses all technologies needed to transform resources in EUDs. For example, gas can't directly provide heat or mobility. Combined Heat Power (CHP) and Compressed Natural Gas (CNG) car are needed to fulfill the EUDs. It is also important to notice that, in the example of figure 2.2, there are 4 layers (electricity, heat, gas and passenger mobility). These layers are defined as all the elements in the model that need to be balanced at each time period. In this sense, technologies allow to go from one layer to another.

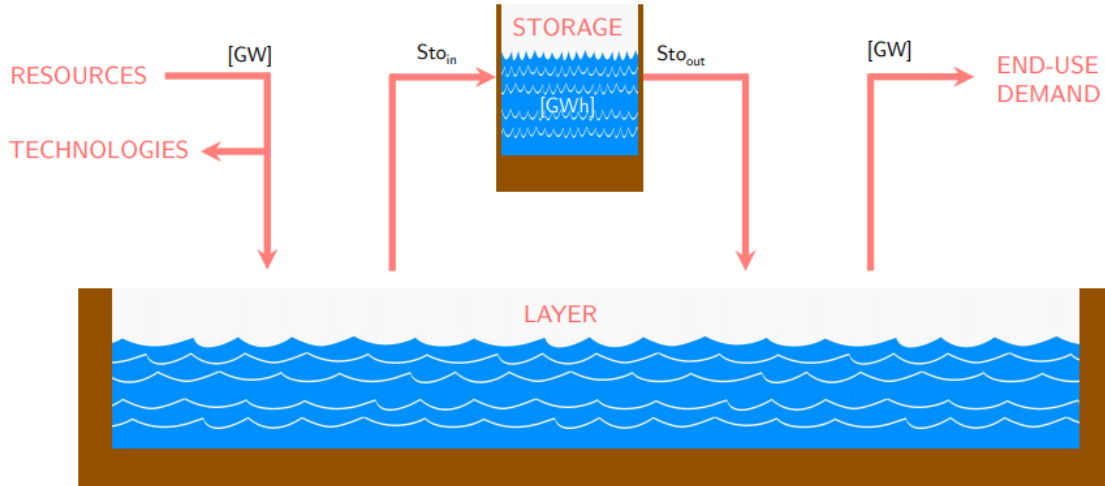


Figure 2.3: Illustration of EnergyScope TD layers. Layers are always balanced (which means that their input is equal to their output).

There are 3 different types of technologies :

1. **End-Use Type (EUT) technologies** transform energy from one layer to an end-use type layer. For example, CHP transforms gas into heat and electricity,
2. **Storage technologies** convert energy from one layer to the same one (e.g. PHS stores and produces electricity),
3. **Infrastructure technologies** are the other technologies such as the power grid or the district heating network (DHN), but also technologies linking non-end use layers.

You will find more information about the different resources, technologies and demands that are implemented in ESTD in figure A.1 in the Annex section.

2. Linear programming model formulation

The model is expressed as a LP problem. It meets the energy demand and minimizes

the annual total cost of the system.

A LP problem is made up of 3 different parts : the linear objective function, the variables and the linear constraints.

1. An objective linear function to minimize

This minimization problem is expressed as :

$$\min \mathbf{C}_{tot} = \sum_{j \in TECH} (\tau(j) \mathbf{C}_{inv}(j) + \mathbf{C}_{maint}(j)) + \sum_{i \in RES} \mathbf{C}_{op}(i) \quad (2.1)$$

$$\text{s.t. } \tau(j) = \frac{i_{rate} (i_{rate} + 1)^{lifetime(j)}}{(i_{rate} + 1)^{lifetime(j)} - 1} \quad \forall j \in TECH \quad (2.2)$$

$$\mathbf{C}_{inv}(j) = c_{inv}(j) \mathbf{F}(j) \quad \forall j \in TECH \quad (2.3)$$

$$\mathbf{C}_{maint}(j) = c_{maint}(j) \mathbf{F}(j) \quad \forall j \in TECH \quad (2.4)$$

$$\mathbf{C}_{op}(i) = \sum_{t \in T | \{h, td\} \in T_H_TD(t)} c_{op}(i) \mathbf{F}_t(i, h, td) t_{op}(h, td) \quad \forall i \in RES \quad (2.5)$$

Equation 2.1 states that the annual total cost of the system is the sum of the annualized total investment cost of technologies ($\tau \mathbf{C}_{inv}$), the annual total maintenance cost of technologies ($\mathbf{C}_{maint}$) and the annual total operational cost of resources ($\mathbf{C}_{op}$).

$\mathbf{C}_{inv}$ is annualized with the factor τ , which takes into account the interest rate (i_{rate}) and the technology lifetime ($lifetime$) (see equation 2.2).

$\mathbf{C}_{inv}$ and $\mathbf{C}_{maint}$ are defined for each technology as the product between the specific investment and maintenance cost (c_{inv} and c_{maint}) of the technology and its installed capacity ($\mathbf{F}$) (see equations 2.3 & 2.4).

Finally, $\mathbf{C}_{op}$ is the sum for each typical day of the product between the specific operational cost of the resource, the end-use over different periods ($\mathbf{F}_t$) and the periods duration (t_{op}) (see equation 2.5).

Notice that all these equations are constraints in the model and $\mathbf{C}_{tot}$ defines the objective function.

2. Variables

The variables represent all the decisions ESTD have to make to solve the LP problem. There are 25 type of variables in ESTD, given in table A.1.

The important variables that we are going to use in this work are the installed capacity $\mathbf{F}[GW]$ for each technology and their hourly operations $\mathbf{F}_t[GW]$.

3. Constraints

The constraints define the model and they can be of different nature. For example, the installed capacity of each technology has an upper bound (f_{max}) and a

lower bound $(f_{min})^4$:

$$f_{min}(j) \leq \mathbf{F}(j) \leq f_{max}(j) \quad \forall j \in TECH \quad (2.6)$$

Or the total use of resources is limited by their availability :

$$\sum_{t \in T | \{h, td\} \in T-H-TD(t)} \mathbf{F}_t(i, h, td) t_{op}(h, td) \leq \text{avail}(i) \quad \forall i \in RES \quad (2.7)$$

The computation of the total GWP of the system is also a constraint in the model :

$$\mathbf{GWP}_{tot} = \sum_{j \in TECH} \frac{\mathbf{GWP}_{constr}(j)}{\text{lifetime}(j)} + \sum_{i \in RES} \mathbf{GWP}_{op}(i) \quad (2.8)$$

$$\mathbf{GWP}_{constr}(j) = gwp_{constr}(j) \mathbf{F}(j) \quad \forall j \in TECH \quad (2.9)$$

$$\mathbf{GWP}_{op}(i) = \sum_{t \in T | \{h, td\} \in T-H-TD(t)} gwp_{op}(i) \mathbf{F}_t(i, h, td) t_{op}(h, td) \quad \forall i \in RES \quad (2.10)$$

Equation 2.8 states that the total yearly emissions of the system ($\mathbf{GWP}_{tot}$ ⁵) are defined as the sum of the emissions related to the construction and end-of-life of the energy conversion technologies ($\mathbf{GWP}_{constr}$), allocated to one year based on the technology lifetime (lifetime), and the emissions related to resources ($\mathbf{GWP}_{op}$) [24].

There are many other constraints in ESTD, all useful to correctly represent the energy system.

All these constraints form the feasible domain. The feasible domain represents all the energy systems that respect all the constraints, and thus could be the optimal solution.

2.2 Optimal cost energy system for Belgium in 2035

The optimal cost energy system given by ESTD is presented below. No additional constraint (on GWP or technology sizings) has been implemented and thus the system is totally free to choose the resources and technologies it needs to fulfill the objective. The different parameters for the resources and the technologies describe the situation of Belgium in 2035. They are given in the tables A.3, A.4 & A.5 in the Annex section. It is interesting to note that, even if this scenario has no constraints on its CO_2 emissions, it actually reduces the CO_2 emissions compared to the actual Belgian energy system. Indeed, this scenario has a GWP of around 73 [$MtCO_{2,eq}$] while the actual Belgian energy system has a GWP of 96.68 [$MtCO_{2,eq}$] [5]. Finally, you will find the Sankey Diagram in the Annex section in figure A.8.

⁴These 2 bounds are useful to take into account already existing infrastructures and potential limits for some technologies.

⁵GWP stands for Global Warming Potential and is expressed in $MtCO_{2eq}$

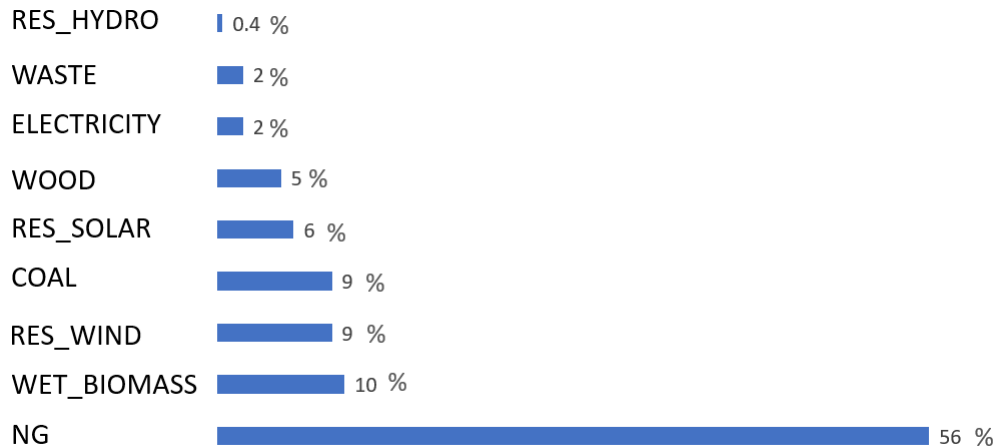


Figure 2.4: Optimum energy system resources repartition for Belgium in 2035. NG is the main resource used as it is the only resource in private and public mobility, the main resource for electricity and low temperature heat production.

Electricity

The electricity demand is satisfied with 4 resources : Natural Gas (NG), wind, sun and imported electricity. The main resource is the NG, which accounts for half of the electricity production with the Combined Cycle Gas Turbine (CCGT) technology. The other half is mainly provided by photovoltaic (PV) panels and wind turbines, while around 6% of the electricity is imported. This importation is expensive (imported electricity costs twice the price of NG), but necessary to satisfy the peak demand, without over-sizing the CCGT (without imported electricity, CCGT capacity increases of 45% but its capacity factor decreases of 15%, resulting in a greater cost). Finally, around 1% of the production comes from hydraulic production from rivers.

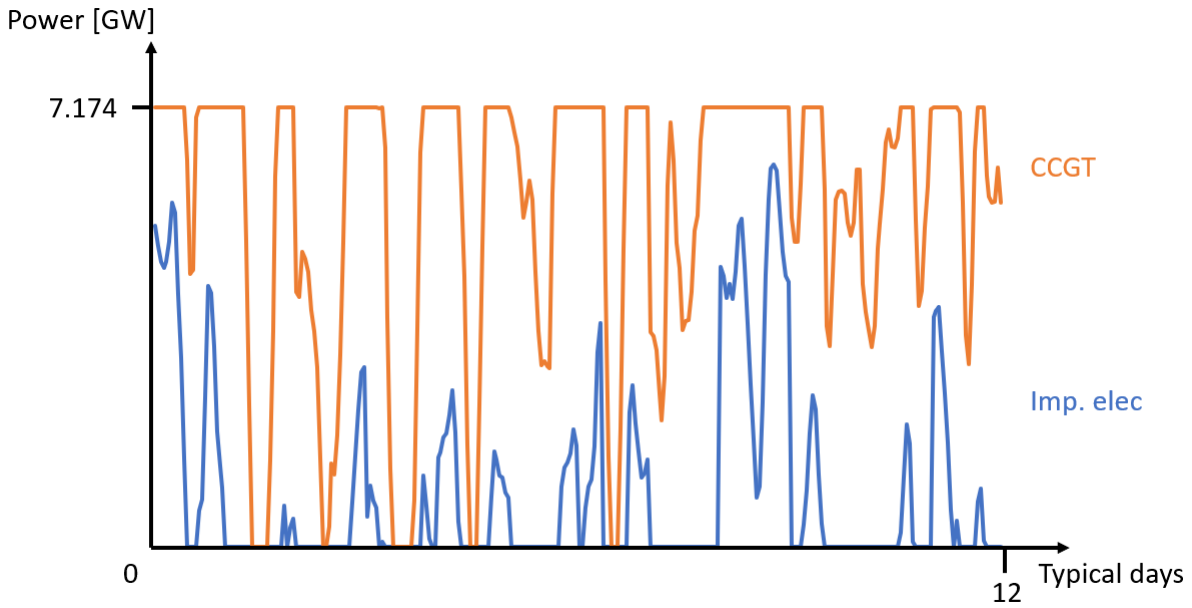


Figure 2.5: CCGT production (in orange) and imported electricity (in blue). Imported electricity peaks occur when CCGT is already at maximum capacity (7.174 GW). Imported electricity is thus necessary to satisfy the demand peaks.

It is interesting to notice that ESTD has installed the maximum capacity of wind turbines (13.5 GW) and huge amount of PV (21 GW), despite the fact that they are intermittent technologies. This intermittency is compensated with the CCGT. On figure 2.6, we can clearly see the complementarity of these 2 technologies. ESTD sets the priority to PV production and CCGT supports it.

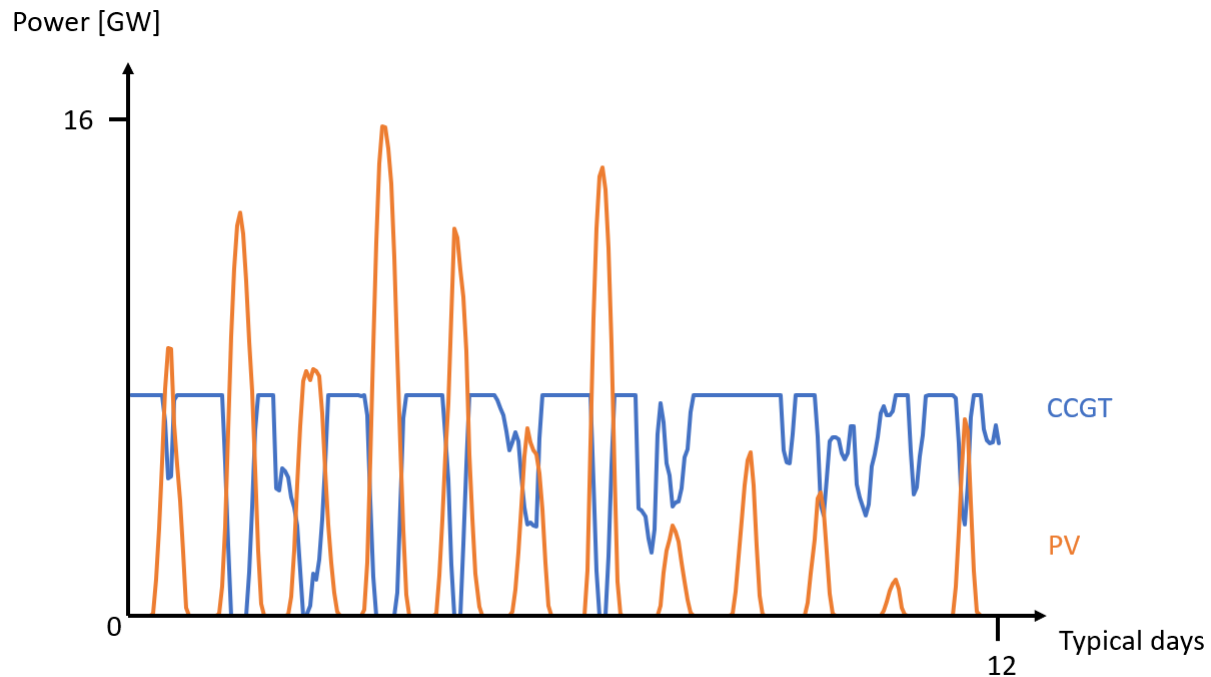


Figure 2.6: CCGT and PV productions. When PV production peaks occur, CCGT production goes down and even stops for big PV peaks.

Low temperature heat

The low temperature heat demand is divided into 2 different parts : centralized demand with the district heat network (DHN) and decentralized demand.

Both are entirely satisfied with heat pumps. The centralized demand is fulfilled with electric heat pumps, while decentralized demand is fulfilled with gas heat pumps. Electric and gas heat pumps respectively produce 40% and 60% of the LT heat demand. Seasonal thermal storage also plays a crucial role in the DHN. Around 35% of the heat produced by the heat pumps goes to storage.

Freight

The freight is mainly provided with NG (boats and trucks). A little part of freight (around 5%) is provided with electric trains.

Public mobility

Public mobility is mainly provided with NG (compressed natural gas buses). A little part of it (around 9%) is provided with electricity (with tramways).

Private mobility

Private mobility is entirely provided with NG. NG is transformed into hydrogen (H_2) and then used in fuel cell cars. It is interesting to note that ESTD does not install NG cars, even if their investment cost is lower than fuel cell cars. Indeed, fuel cell cars have a lower maintenance cost (around 6 times cheaper), and a better yield. ESTD thus prefers to install natural gas reformer to transform NG to H_2 .

High temperature heat

All the HT heat demand is fulfilled with boilers. These boilers are powered by coal, wood and waste. It is interesting to notice that 100% of coal and waste availability are used in the boilers, and around 86% of wood is used in the boilers.

2.3 Optimal cost energy system for Belgium in 2035 with a mitigate CO2 policy scenario

In this subsection, we are going to present you the cost optimal energy system given by ESTD with a constraint on the emission limit set to 40Mt of equivalent CO_2 .

You will find the Sankey Diagram in the Annex section in figure A.9

Electricity

In this scenario, the electricity demand is satisfied by the 3 basic renewable technologies (hydro, wind turbines and PV panels) at their maximum capacity, the imported electricity (also used at full potential), gas turbine (CCGT) and electricity generated by the combined heat and power generator, which was not present without the GWP constraint.

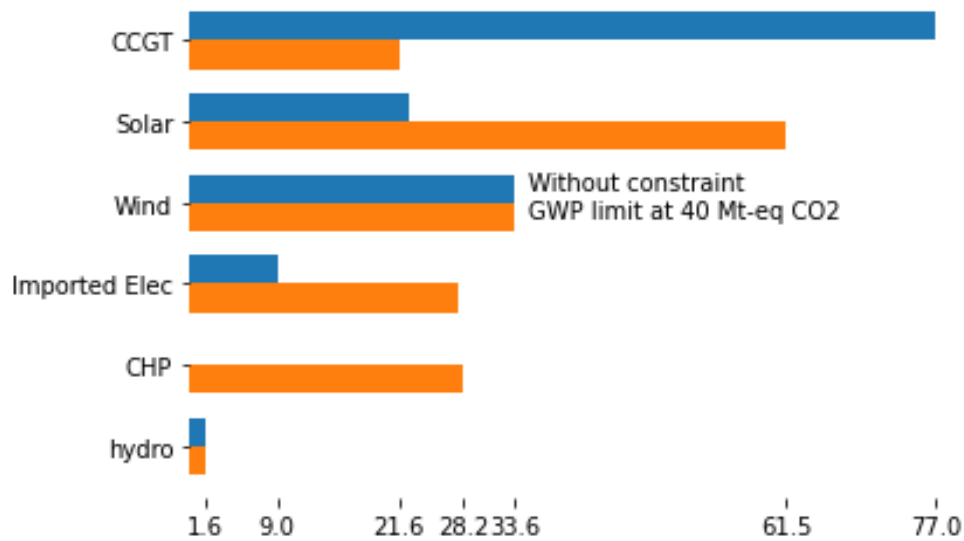


Figure 2.7: Comparison of electricity produced in TWh by sources with and without constraint on GWP. The CCGT production has decreased in favour of the PV production. Imported electricity has increased and CHP starts producing.

We can observe an increase of the electricity demand which is linked to the modification of the low temperature heat production. Indeed in this scenario, more than 91% of the low temperature heat is provided by electric heat pumps.

Low temperature heat

On the low temperature heat sector, we observe that the totality of the gas heat pumps used in decentralized heating were replaced by electric heat pumps as observed before and some of the electric heat pumps used in the DHN are replaced by bio-hydrolysis cogeneration units (Around 22% of the DHN heat production comes from CHP units).

High temperature heat

For the high temperature heat sector, we observe that the demand is satisfied by boilers of waste and wood as in the solution without GWP constraint and by CHP units using natural gas. 37% of the HT heat is now provided by CHP units. We can notice that it uses the entire capacity of wood contrarily to the case without constraint and installs a higher capacity of waste boiler. This higher capacity leads to a decrease in the capacity factor from 90% to 57% as all availability of waste is used in both scenarios. Also the use of coal has totally disappeared and has been replaced by gas CHP units and some direct electricity heating system.

We can also observe that the heat production by electric heater is linked to the PV electricity production. When the PV panels are producing a lot of electricity to the network, we can observe on figures 2.8 and 2.9 that the electric heat production is launched as well as the battery storage and a diminution of all the other means of electricity production. Consequently, we can observe on figures 2.10 and 2.11 that the other means of heat production are also decreasing due to the increase of electric heat production.

This electric heat production occurs only when PV is producing enough electricity. Indeed, its capacity factor is actually quite low (8%).

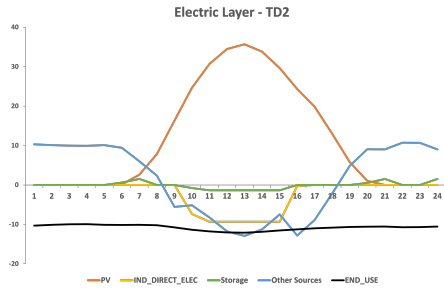


Figure 2.8: Electricity produced and consumed in GWh during TD 2

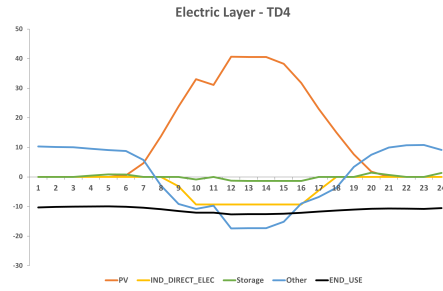


Figure 2.9: Electricity produced and consumed in GWh during TD 4

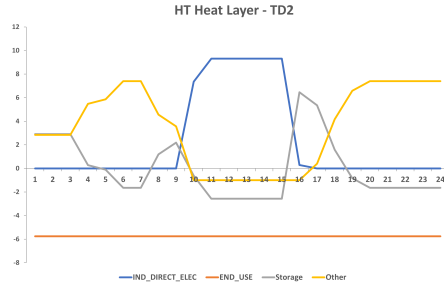


Figure 2.10: High temperature heat produced and consumed in GWh during TD 2

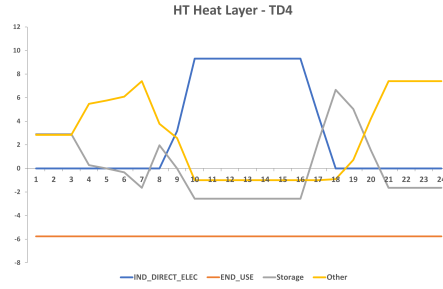


Figure 2.11: High temperature heat produced and consumed in GWh during TD 4

Freight

The freight mobility is totally the same with and without constraint on GWP limits.

Public Mobility

In the public mobility sector, compared to the scenario without restrictions, a big part (around 80%) of the CNG buses has been replaced by train.

Private Mobility

The private mobility sector in the optimal scenarios are the same with and without restrictions on the GWP limits, except that 25% of the H_2 production by natural gas reforming is replaced with electrolyzers, and 3% of H_2 is imported.

2.4 Optimal cost energy system for Belgium in 2035 with an aggressive CO2 policy scenario

With an additional constraint on the GWP emissions set to 10 Mt of CO2 equivalent, the optimal energy system given by ESTD is presented below and compared to the system without this constraint and with the constraint set to 40MT-eq.CO2. The parameters for the resources and technologies are the same as in section 1.3. Also, as in section 1.3, you will find the sankey Diagram in the Annex section in figure A.10

Electricity

The electricity layer in this scenario follows the same pattern as in the previous subsection : the renewable sources are set at their maximum capacity, the CCGTs are set to 0 and the gas and biomass CHP units capacities are even more increased as we can see on figure 2.12

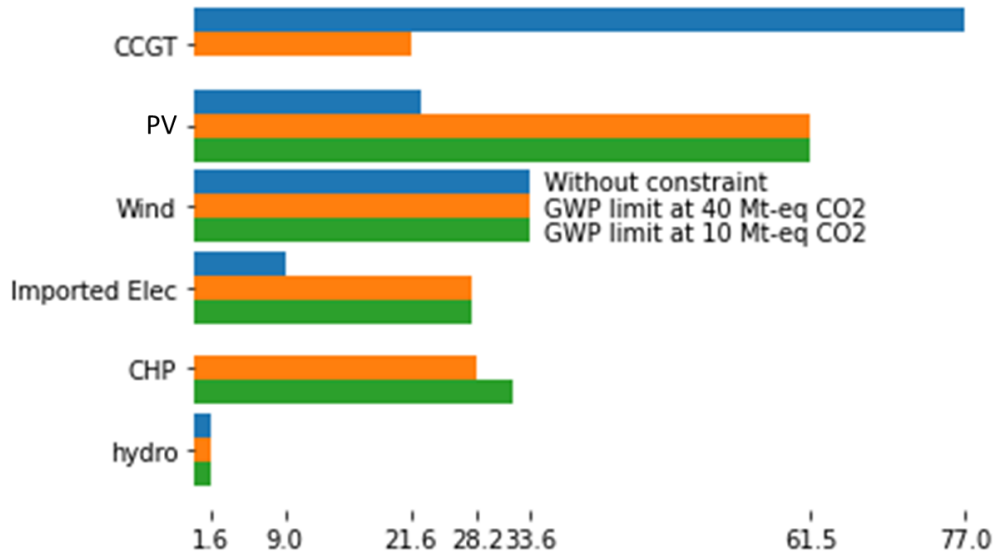


Figure 2.12: Comparison of the electricity produced in TWh by sources of the optimal energy system without constraint on the emission, with a constraint of 40MT of equivalent CO_2 and 10MT of equivalent CO_2 . Abbreviations : CCGT : Combined Cycle Gas Turbine, Solar : PV panels, Wind : Wind Turbines, Imported Elec : Imported electricity, CHP : Combined heat and power, Hydro : hydraulic turbines

Low temperature heat

The low temperature heat is exactly the same as in section 1.4.

High temperature heat

The high temperature heat layer is composed of the boilers using waste and wood as in the previous section, some gas CHP units and some direct production of heat from electricity. It is interesting to note that a part of the wood is not used in the boiler but transformed into gas, electricity and heat through a gas production unit and that the main part of the NG used is now synthesized natural gas (SNG) (around 80%).

As in the previous subsection, we observe in figures 2.13 and 2.14 that the overproduction of electricity by the PV panels leads to a reduction of the other means of electricity production and an increase of direct electric heat production which leads in figures 2.15 and 2.16 to a decrease of the other sources of heat.

Again, this HT heat production with electricity occurs only for large PV panels electricity production. Its capacity factor stays low (7%).

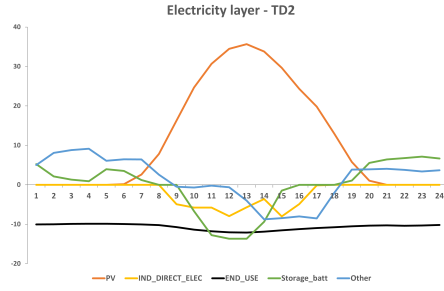


Figure 2.13: Electricity produced and consumed in GWh during TD 2

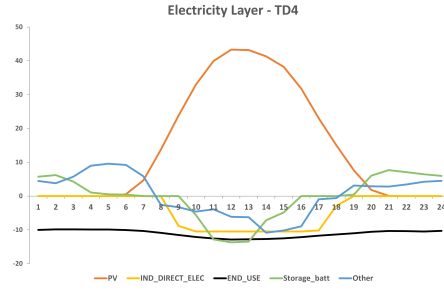


Figure 2.14: Electricity produced and consumed in GWh during TD 4

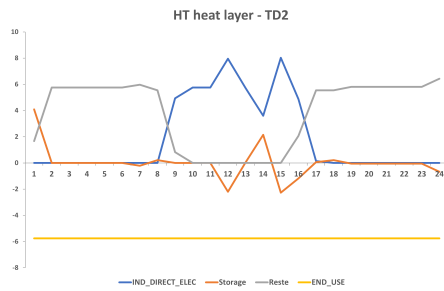


Figure 2.15: High temperature heat produced and consumed in GWh during TD 2

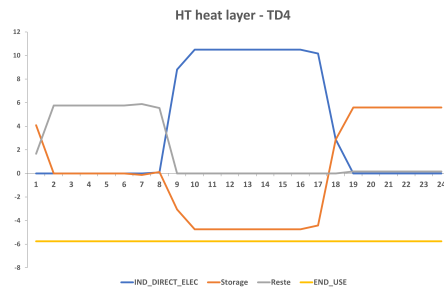


Figure 2.16: High temperature heat produced and consumed in GWh during TD 4

Freight

In the freight mobility sector we can observe the replacement of the natural gas boats by diesel boats for which the bio-diesel is imported . The rest is the same as in the optimal scenario with the GWP limit set to 40MT-eqCO₂.

Public Mobility

In the public mobility sector we can observe the replacement of the natural gas buses by hybrid diesel buses for which the bio-diesel is imported . The rest is the same as in the optimal scenario with the GWP limit set to 40MT-eqCO₂.

Private Mobility

The private mobility is exactly the same as in the scenario without constraint on the GWP. However, the H_2 used in the fuel cells of the cars is not made by natural gas

reforming anymore, but is totally imported. It is interesting to notice that the system does not use electrolyzers, unlike the mitigate CO_2 policy scenario.

3 Methodology

In this section we present the methodology used in order to get the results presented in the section 4.

The three methods used to get different solutions than the optimal one given by ESTD are briefly presented and then compared. If you want more information, you will find the details of the implementation in the Annex section.

3.1 Near-optimal solutions domain exploration methods

In order to reach different solutions than the optimal one, 3 methods have been developed :

1. Latin Hypercube Sampling (LHS) based method
2. Exclusion zone method
3. Modelling to Generate Alternatives (MGA)

These three methods will be presented in this section. The two first are based on the same principle : add constraints to the model, in particular to the sizing of the technologies, in order to expel the optimal solution of the feasible domain. However, the main difference between them is the nature of the constraints, and thus how the optimal solution is expelled of the feasible domain.

The last one also adds constraints to the model, but it also changes the objective function and its working principle is thus different.

The methods are not based on the selection of the typical days. Thus, from now on, we will consider EnergyScopeTD without this first step. We can thus resume EnergyScopeTD as shown in fig. 3.1.

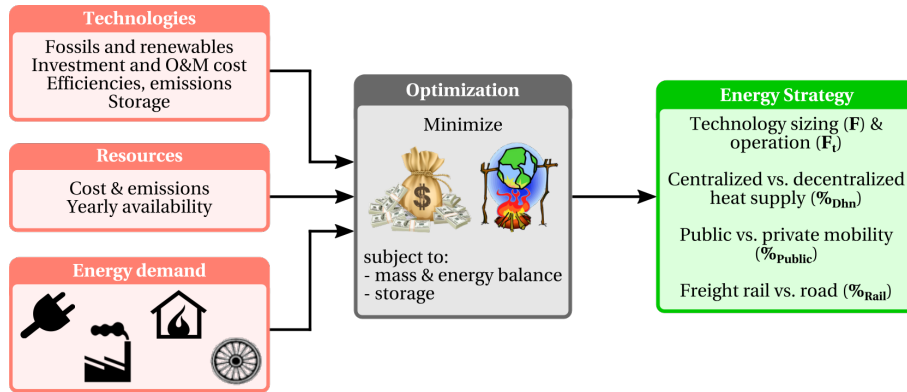


Figure 3.1: EnergyScope without the typical days selection

As the three methods try to forbid the solver to reach the optimum, their first step is the same : generate the optimum. Belgium energy system data for 2035 [5] is used to compute this optimum.

3.1.1 LHS method

This method is based on the latin hypercube sampling (LHS) [25]. The LHS is a statistical method to generate quasi-random samples of parameter values from a statistical distribution. In this work, the distribution used is the uniform distribution, and the parameters are the technologies sizing in EnergyScopeTD .

The idea of the LHS is to keep the randomness but to organise it in order to have representative samples. The LHS method has 2 steps :

1. Choose a random permutation of n (number of samples) cells, one per column and line
2. Choose a random coordinate in each cell.

This method allows to avoid confounding⁶ and does not suffer from curse of dimensionality.

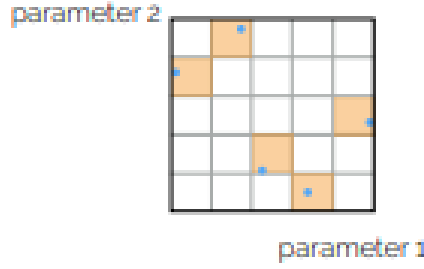


Figure 3.2: Illustration of the LHS method for 2 parameters. Here the chosen cells are highlighted and the blue points are the parameter values. There are 5 samples.

This method thus consists in adding new constraints in EnergyScopeTD on the sizing of chosen technologies. LHS method fixes the sizing of some technologies to suboptimal values.

The method is separated into 5 parts :

1. From the list of all technologies **used in the optimal energy system**, pick a number of n^7 technologies. This number has to be set experimentally depending

⁶Confounding occurs when the effect (synergetic or dysergetic) of some combination is not taken into account [33]

⁷For this work, we used 211

on the results wanted. The bigger n will be, the further from the optimum the new energy system will be. The technologies have been chosen randomly between all electricity, heating and mobility technologies in ESTD (see [5]).

2. Set a maximal variation $0 < var_{max} < 1$ for these technologies compared to the optimum.
3. Generate a n -space bounded dimensions. The bounds for each technology are computed as follow :

$$\text{upper bound} = \begin{cases} (1 + var_{max}) \times F_{optimum} & \text{if } (1 + var_{max}) \times F_{optimum} \leq f_{max} \\ f_{max} & \text{if } (1 + var_{max}) \times F_{optimum} > f_{max} \end{cases} \quad (3.1)$$

$$\text{lower bound} = (1 - var_{max}) \times F_{optimum} \quad (3.2)$$

4. Fill the n -space using LHS. Every point of the n -space represents a set of n^8 new constraints for ESTD. These constraints fixes the sizing of the technologies chosen.
5. Add the new constraints to the model and run ESTD. If ESTD finds a solution, we have found a new energy system with is cost suboptimal.

3.1.2 The exclusion zone method

In this section we will explain the working principles of the exclusion zone method.

Based on our observations during the development of other methods to find sub-optimums, we noticed that the optimizer had a tendency to find a solution that is close to the optimum in terms of technology used. So the idea of this method is to forbid the optimizer to use the technologies present in the optimal solution. To do so, we decide to create an "exclusion zone" around this optimal. The aim is then not to create constraints that will fix some parameters at a certain value, in opposition of the LHS method but to create an exclusion zone around the reference value.

Once we have obtained the reference scenario (optimal) without any supplementary constraint, to create this exclusion zone, we have to go through 2 steps :

1. **Selecting Technologies :** From this optimal reference, we have to select a set of technologies **that are installed** ($F \neq 0$) which we want to prevent to go into the exclusion zone. For example : 24 technologies are installed in the no CO_2 policy optimal scenario and we select a bunch of those technologies from 1 to 20 to guaranty the convergence of the solver. This selection was done randomly.
2. **Zone Sizing :** Once those technologies have been selected, we have to determine the size of the exclusion zone. It will be expressed relatively to the installed capacity. In our simulation we choose a relative distance which will be applied

⁸Practically, there are $2n$ new constraints as we can't fix a variable before running ESTD. We thus have to fix two parameters such that $f_{min,sub} = f_{max,sub} = F_{LHS}$

to the whole set of technology. For example : if we choose 10% of exclusion the exclusion zone for each technology will be $[0.9 * F_{ref}("tech"); 1.1 * F_{ref}("tech")]$

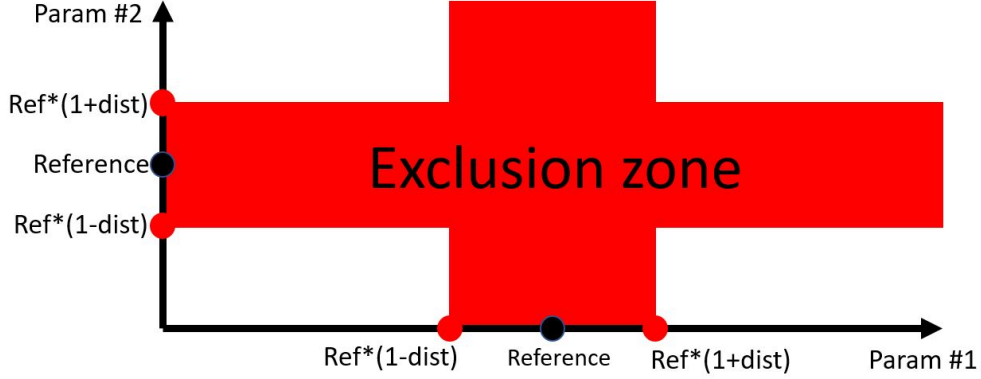


Figure 3.3: Illustration of an exclusion zone for 2 parameters

Basically the *Installed Capacity* F is constrained in the LP problem by :

$$F_{min}["tech"] \leq F["tech"] \leq F_{max}["tech"]$$

and now we have to impose the value of F to be between F_{min} and $(1 - dist) * F_{ref}$ or between $(1 + dist) * F_{ref}$ and F_{max} but it is not possible to implement an "OR" condition in linear programming so we have to use an artifice using a binary variable $Bin["tech"]$ for each technology. Thus the condition will be expressed by those 2 expressions :

$$(1 - dist) * F_{ref}["tech"] + (F_{max}["tech"] - (1 - dist) * F_{ref}["tech"]) * Bin_{tech} \geq F["tech"] \quad (3.3)$$

$$F_{min}["tech"] + ((1 + dist) * F_{ref}["tech"] - F_{min}["tech"]) * Bin_{tech} \leq F["tech"] \quad (3.4)$$

3.1.3 Modelling to Generate Alternatives (MGA) method

This method allows to find alternative solutions with a cost near the optimal one, but a maximum difference in the decision variables space. It is composed by 5 steps :

1. Obtain the initial optimal solution given by ESTD,
2. Add a user specified amount of slack to the value of the objective function (i.e. the total cost of the system),
3. Encode the adjusted objective function value(s) as an additional upper bound constraint,
4. Formulate a new objective function that minimizes the weighted sum of decision variables that appeared in the previous solutions,

5. Iterate the re-formulated optimization,
6. Terminate the MGA procedure when no significant changes to decision variables are observed in the solutions⁹.

Mathematically, the MGA problem is expressed as :

$$\begin{aligned}
& \text{minimize} && \sum_{k \in K} w_k X_k \\
& \text{Subject to} && f_j(\vec{x}) \leq T_j \quad \forall j \\
& && \vec{x} \in X
\end{aligned}$$

Where

- K = set of indices of the decision variables that are nonzero in all previous solutions (i.e. the installed capacity of the optimum technologies),
- X = set of feasible solutions based on the "technical" constraints of the model,
- w = weights,
- $\vec{x} \in X$ implies that the constraints of the original problem hold for the alternative solution,
- $f_j(\vec{x}) = j^{th}$ objective function in the original formulation,
- T_j = Target value for the j^{th} modeled objective. It is equal to the slack multiplied by the optimal cost.

While the new objective function ensures to find maximally different solutions in the decision variables space, the added constraint on the total cost of the system ensures that the solution lies in the near optimal solution space.

This method is thus different from the 2 first presented because it changes the formulation of the LP problem. The objective function is not the total cost of the system anymore but a weighted sum of the decision variables that appeared in the previous solutions. This weighted sum enforces that each new solution is maximally different from all the others.

The new objective function is however not unique. The one presented above is the most popular and has been introduced in [27]. However, other objective functions can be used. For example, in [28], they use the notion of Manhattan distances [35] (see figure 3.4)

$$\begin{aligned}
& \text{Maximize} && \alpha_j \\
& \text{where} && \alpha_j \leq D^{jk} \quad \forall j, k \\
& D^{j,k} = \sum_i \left| PE_i^j - PE_i^k \right|
\end{aligned}$$

⁹Practically, we generally observed no significant changes after 4 iterations

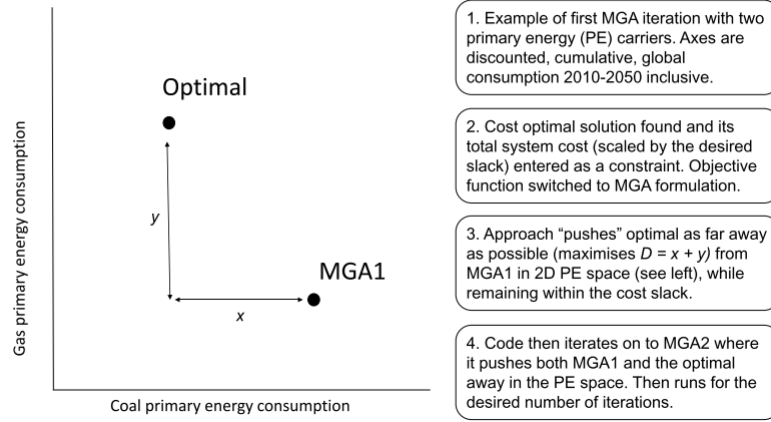


Figure 3.4: Schematic depicting an example of how the MGA method proceeds. In this case only two primary energy carriers are shown for diagrammatic simplicity. Source : [28].

We have implemented both formulations in ESTD, but the first one gave us the best results in addition to being computationally less complex.

The decision variables are a choice of the users and could be any variables of ESTD. However, to stay coherent, all variables in the weighted sum should have the same dimensions. Moreover, we noticed that taking as decision variables the installed capacity of technologies (in GW) could be a bad choice because all the capacity may not necessarily be used to meet the EUDs. We decided that the total activity of each technology (in GWh) was a more representative measure of a given technology's contribution to meet the EUDs.

Two sets of decisions variables have been implemented :

1. The total activity (i.e the total energy production over a year) of each technology in GWh, for the electricity and heat sectors
2. The total activity of each resource in GWh

To compute the weights, we used a method presented by Decarolis et al. called the normalized method[27].

This method starts with weights equal to their relative importance in their energy sector. For example, in the optimum energy system for Belgium in 2035, the CCGT activity represents 46% of the total activity of the electricity sector, its weight is thus 0.46. After the first run, if the new activity of CCGT is for example 0.20, then its weight becomes $0.46 + 0.20 = 0.66$.

This method allows to take into account not only the cumulative effect across the different MGA iterations but also the relative importance of each technology in its

sector¹⁰.

3.2 Comparison of the three methods

As said in section 2.1, the first two methods are based on the same principle and are thus very similar. They both have three important parameters :

- The choice of the technologies : both methods choose a number of n technologies, either to create the n -space for the LHS, or to create the exclusion zone.
- The number n of technologies : this number can vary. In order to get suboptimums enough different and meaningful for analysis, it should not be too low (typically, $n \geq 2$ for LHS and $n \geq 3$ for exclusion), and it should not be too high, otherwise the solver can't converge to a feasible solution (typically, $n \leq 14$ for LHS and $2 \leq n \leq 24$ for exclusion)
- The variation var_{max} for LHS and exclusion. Depending on this parameter, suboptimums will be more or less far than the optimum. For LHS, typical values used were 40% to 90%. For exclusion, typical values used were 0% to 5%. For the exclusion method, a too big variation could prevent the solver finding a solution.

Although both methods are very similar, the constraints they add to the model are fundamentally different. LHS method impose the sizing of the chosen technologies, while exclusion method forbids a range for the sizing of the chosen technologies.

As mentioned before, the exclusion method is way more computationally complex, but it explores more than LHS. By exploring, we mean that exclusion method can find more different suboptimums than LHS can.

LHS and exclusion methods can both generate large sample of cost suboptimal energy systems. These two methods will thus be used to generate results that will be analyzed under a statistical point of view. In the rest of this work, results coming from LHS or exclusion methods will not be differentiated.

The MGA method is different as it does not forbid the solver to reach the optimal solution, but it changes completely the LP problem.

This method has one major advantage compared to the LHS and exclusion methods : the new energy system obtained is maximally different from the previous solutions. This advantage allows to only generate a small number of sub-optimal energy systems that are suitable for "hand analysis".

However, it has also a big disadvantage : as the objective function is not the total cost anymore, we loose the link between the input and the output of the system. In the LHS and exclusion methods, there is a clear link between a variation of the input and the result on the output. The MGA is in this sense less intuitive.

¹⁰CHP technology will thus have 2 terms : one for its relative importance in the heat layer and another for the electricity layer

4 Results and analysis

This section is structured into 3 main parts, corresponding to the 3 different CO_2 policy scenarios : no policy, mitigate and aggressive policies.

The results for each part can further be classified into two categories that will be separated :

1. The results for a large sample of cost suboptimal scenarios generated with LHS and exclusion methods.
2. The results of for a smaller set of cost suboptimal scenarios, generated with the MGA method.

4 MGA runs with 4 different slacks will be studied for the 3 different CO_2 policy scenarios, for a total of $3 \times 4 = 12$ alternative energy systems.

After that, the results of the MGA applied to the 19 resources of the system will be given. Again, for each CO_2 policy scenario, 4 MGA runs with 4 different slacks will be given, for a total of 48 alternative energy systems. The different slacks considered are expressed in % and are defined as :

$$\text{slack} = 100 \times \frac{C_{tot,MGA} - C_{tot,opt}}{C_{tot,opt}} [\%] \quad (4.1)$$

Where

- $C_{tot,MGA}$ is the total cost of the energy system generated with the MGA method
- $C_{tot,opt}$ is the total cost of the optimal energy system

	No CO_2 emissions limit	Mitigate CO_2 policy	Aggressive CO_2 policy
Slack [%]	Total cost [M€]		
0 (optimum)	37 596	40 313	52 674
1	37 972	40 716	53 201
2	38 348	41 119	53 728
5	39 476	42 328	55 308
10	41 356	44 344	57 941

Table 4.1: Slacks used in the MGA method and their corresponding total costs for the 3 different scenarios

4.1 No CO_2 policy scenario

4.1.1 Results from LHS and exclusion methods

In this subsection, we are going to show the results obtain for suboptimums without constraint on the emissions limit. The results plotted are the share of energy produced by technologies in each of their own layer when the technology is installed.

The results have been divided in 4 categories according to their deviation from the total cost of the system : less than 1% deviation, between 1% and 2%, between 2% and 5% and between 5% and 10%. The distribution of the share is represented by a box plot, where the red line shows the share in the optimal scenario.

Also next to the technology name, the share of scenarios where this technology is installed is indicated as the number r :

$$r = \frac{\# \text{ Number of scenarios with the technology installed (i.e } F \neq 0)}{\# \text{ Total number of scenarios}} \quad (4.2)$$

The results shown here are composed of 550 scenarios generated with exclusion method and 1000 with LHS method.

Electricity sector

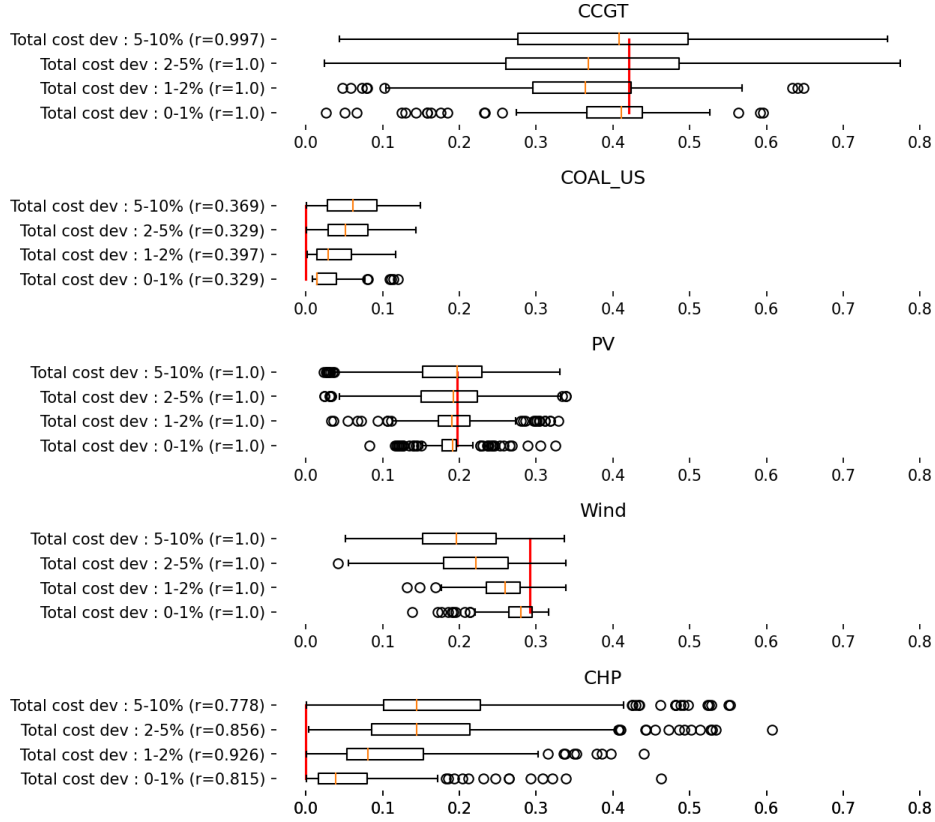


Figure 4.1: Variation of the different electricity sources productions for different total cost deviations. The red line corresponds to the optimum scenario. Abbreviations : CCGT : Combined Cycle Gas Turbine, COAL_US : advanced pulverized coal power plant, PV : photovoltaic panels, Wind : wind turbines, CHP : combined heat and power power plant

The first observation we can do in the electric layer in every generated scenarios is the appearance of CHP with a share that is globally increasing with the total cost deviation. It is very interesting to see that even with a low total cost deviation, the CHP can reach a very high share (more than 45%) of the sector. Also in figure 4.2, we can see that the share of CHP is correlated negatively with the share of CCGT and that it has a lower correlation with the emissions than the CCGT.

We can note that as the wind turbines are already at their maximum capacity it can only be decreased in suboptimal scenarios. (The rare increase of the wind share in

figure 4.3 is due to a decrease of the total electric layer, and not to an increase of the wind production itself). In those case it is compensated either by an increase of CHP, CCGT or PV.

The mean of the wind turbines can decrease more when the cost deviation increases. This observation is confirmed by the correlation matrix in figure 4.2 where the wind is negatively correlated to the total cost of the system. Although, the PV is not as much correlated with the total cost than the wind turbine because of its peak production. Indeed those peaks must be managed either by curtailment which lead to a pure loss of energy and efficiency or by adding a technology (i.e. heat production by electricity) to use this electricity which will increase the total cost of an increase of PV. To confirm that, we have run one simulation without wind turbines and one without PV pannels and we have observed an increase of 3.3% and 0.89% of the total cost respectively.

All those points may suggest that the CHP might be a cost-competitive and less polluting alternative to CCGT.

As the coal resource is limited we can see in figure 4.2 that the HT heat production using coal is totally correlated in opposition with the electricity production by coal but the use of one or the other technology is uncorrelated with the emissions as 100% of the coal available is always used due to its low price. It is interesting to note that the share of electricity produced by coal is increasing with the total cost deviation. It means that producing electricity with coal is not worth if the system can use CCGT or CHP units, and coal should thus always be used in boilers to produce HT heat.

In opposition to that, we can see that the the PV production is highly correlated to the emissions : an increase of PV leads to a decrease of emissions and vice versa. We can then imagine that the PV will have a higher share if the emissions should be reduced.

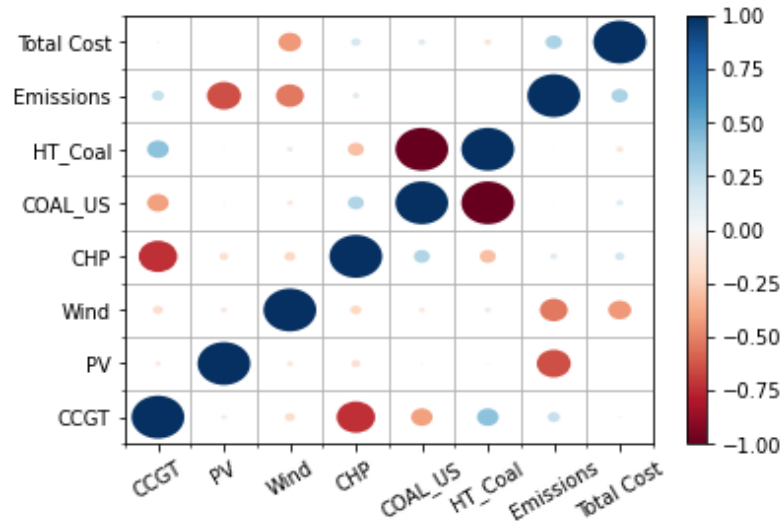


Figure 4.2: Correlation matrix of the energy production for each technology of the electric layer, one technology of the HT heat layer, and finally the emissions and the total cost. Abbreviations : HT_Coal : High temperature production with coal, COAL_US : advanced pulverized coal power plant, CHP : cogeneration heat and power, wind : wind turbines, PV : Photovoltaic panels, CCGT : combined cycle gas turbine

Industrial heat Sector

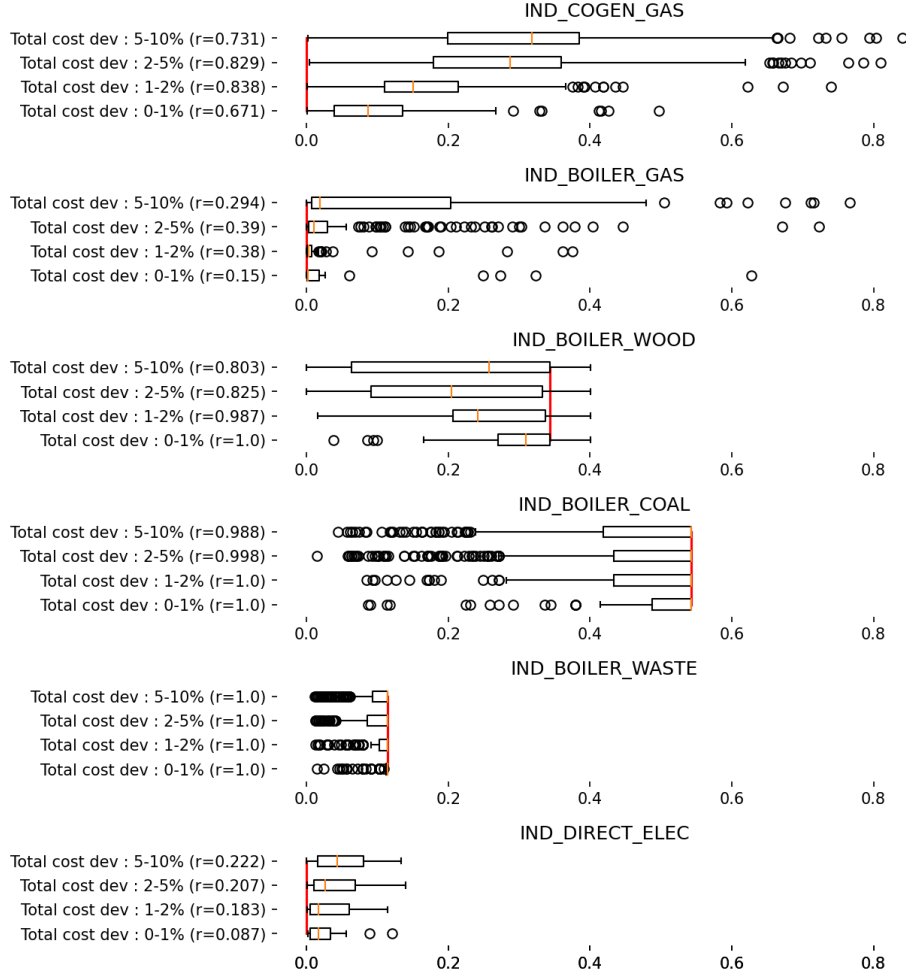


Figure 4.3: Variation of the different high temperature sources for different total cost deviations. The red line corresponds to the optimum scenario. Abbreviations : IND_COGEN_GAS : industrial heating gas cogeneration, IND_BOILER_GAS : Industrial heating gas boiler, IND_BOILER_WOOD : industrial heating wood boiler, IND_BOILER_COAL : industrial heating coal boiler, IND_BOILER_WASTE : industrial heating waste boiler, IND_DIRECT_ELEC : industrial heating with electricity

As observed in the electric sector, we see the apparition of gas CHP units in some suboptimal scenarios and the energy produced can reach a high penetration in the layer, around 50% with just a deviation of less than 1% from the total cost of the

system, and even more than 80% for a deviation of more than 5%. Also we can see that it is highly negatively correlated with wood and coal boilers, which can decrease very much even with a small total cost deviation. This point can lead us to conclude that coal and wood boilers are easily replaceable by gas CHP.

We can do the same observation for the gas boilers which reach a good share even for low total cost deviation. Its important to note that its way less often than for the cogeneration units but as observed in figure 4.4 it has a negative correlation with the decrease of coal boilers.

We can also see that the boilers using wood or coal can decrease a lot in a part of the scenarios generated, even not be installed with more than 5% total cost deviation.

All those points can lead us to conclude that coal and wood boilers are easily replaceable by gas CHP and gas boilers for a small total cost deviation. The waste boilers does not vary a lot and moves only when constrained by the model. This can be the sign of a very cost-competitive technology.

The direct electric heat production appears to produce heat when there is too much electricity in the network. It is confirmed by the correlation with the PV in figure 4.4 as the PV increases the electric heat production increases. This correlation is explained by the high PV electricity production during the day, as explained in sections 1.4 & 1.5.

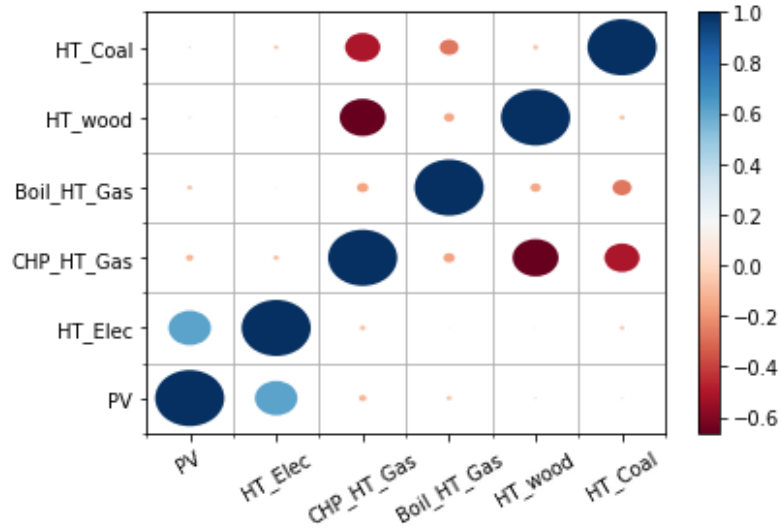


Figure 4.4: Correlation matrix of the energy production for technologies of the HT heat sector, and PV technology. Abbreviations : PV : photovoltaic panels, HT_Elec : High temperature heat generation directly with electricity, CHP_HT_GAS : High temperature heat generation with heat and power gas cogeneration units, Boil_HT_Gas : High temperature heat generation with gas boiler, HT_wood : High temperature heat generation with wood boiler, HT_coal : High temperature heat generation with coal boiler.

Heat low temperature sector

The first thing we can note from figure 4.5 is the high variability of the decentralized gas heat pump (gas HP), even with 1% total cost deviation, it can gain or loose 20% of the LT layer share and with 2% of total cost deviation, its share can almost go to 100% or decrease to less than 10%. In the same time, observing the correlation matrix in figure 4.6 leads us to understand that increasing the gas HP mainly decreases the centralized electric heat pumps and decreasing the gas HP mainly increases the decentralized electric heat pumps.

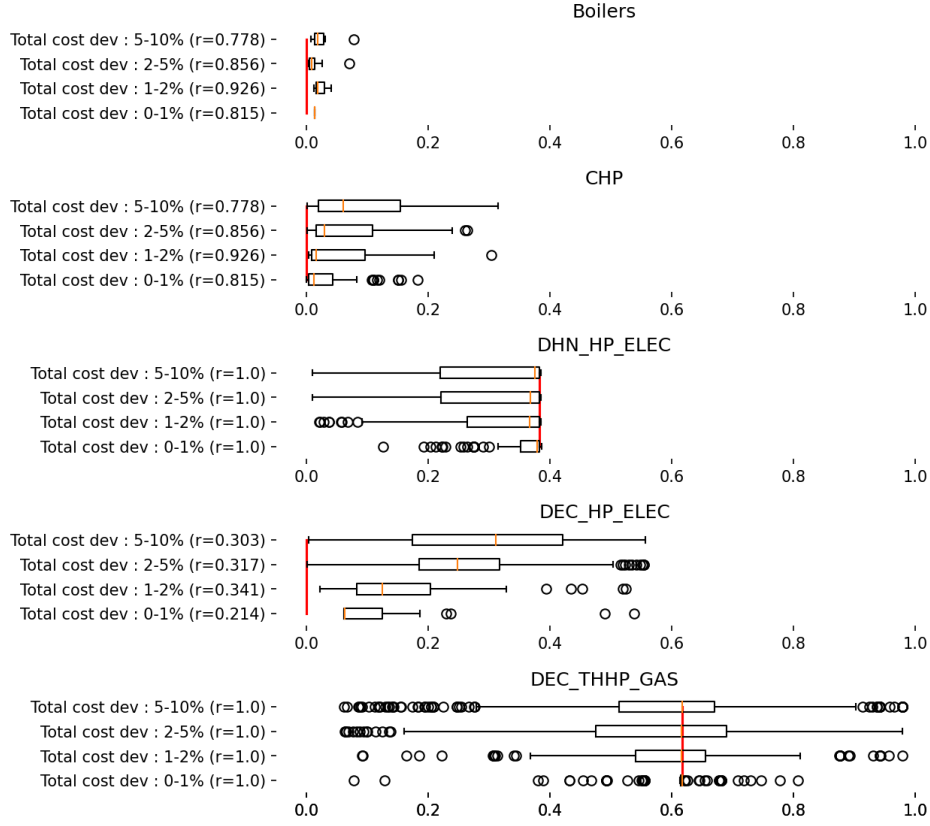


Figure 4.5: Variation of the different low temperature heat sources for different total cost deviations. The red line corresponds to the optimum scenario. Abbreviations : Boilers : sum of the different low temperature boilers, CHP : cogeneration heat and power plant, DHN_HP_ELEC : centralized heating with electric heat pump, DEC_HP_ELEC : decentralized heating with electric heat pump, DEC_THHP_GAS : decentralized heating with thermal gas heat pump.

Another correlation from figure 4.6 is the one between the centralized gas CHP and the centralized electric heat pumps. It lead us to the fact that the decrease of the heat pumps is mostly compensated by the centralized CHP units. Also it is showed that the presence of electric heat pumps have a good impact on the emissions (emissions are reduced when electric heat pumps are increasing). We can imagine that it will be a good choice in the case of a emissions reduction objective to use a mix composed of around 20% of gas CHP and 80% of gas and electric HP.

We also can see the appearance of boilers for high total cost deviation, which implies that it is not cost competitive.

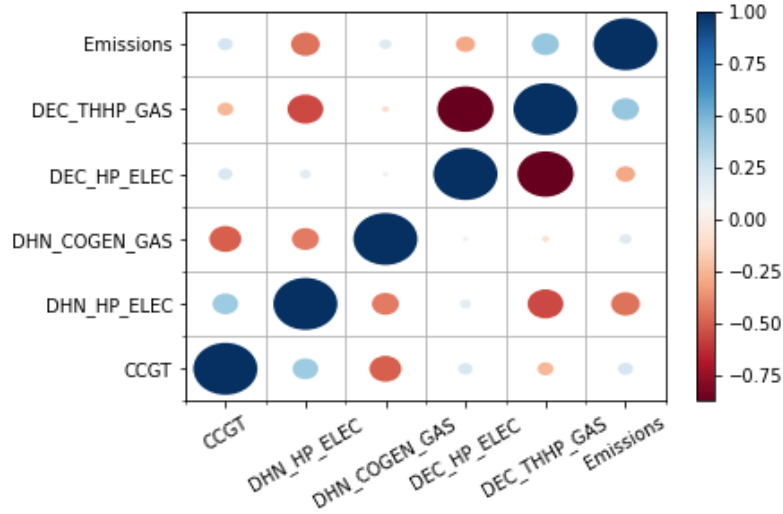


Figure 4.6: Correlation matrix of the energy production of technologies and emissions. Abbreviations : CCGT : combined cycle gas turbine, DHN_HP_ELEC : centralized electric heat pumps, DHN_COGEN_GAS : centralized gas cogeneration, DEC_HP_ELEC : decentralized electric heat pump, DEC_THHP_GAS : decentralized thermal gas heat pump.

Private Mobility

We can observe in the figure 4.7 that when the fuel cell cars are reduced from the optimal scenario, it is only replaced by Hybrid Electric Vehicles (HEV). The share of HEV cars stay moderate for low cost deviations (its mean is 20% for a cost deviation of 2%). However we see that when the costs deviation becomes larger, the HEV cars can become the main technology used for private mobility, but it does not happen often (the r is quite low). This suggests that HEV cars could be a complementary solution, but it is not the best economical solution for the future of private mobility as confirmed by the correlation matrix in figure 4.8.

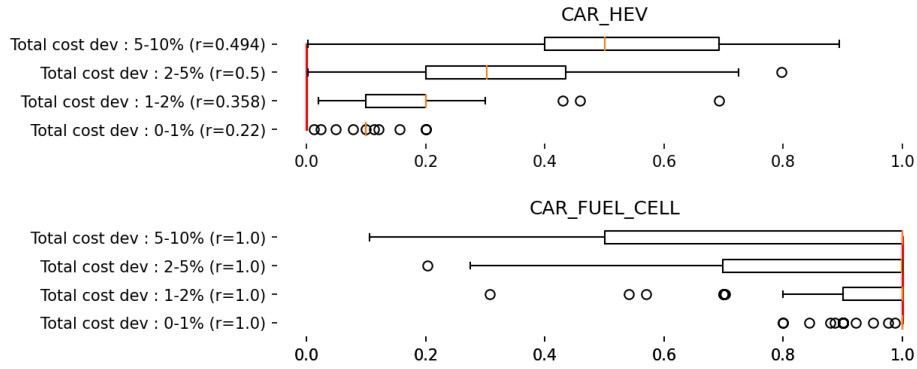


Figure 4.7: Variation of the different private transport technologies for different total cost deviations. The red line corresponds to the optimum scenario. Abbreviations : CAR_HEV : Hybrid electric car.

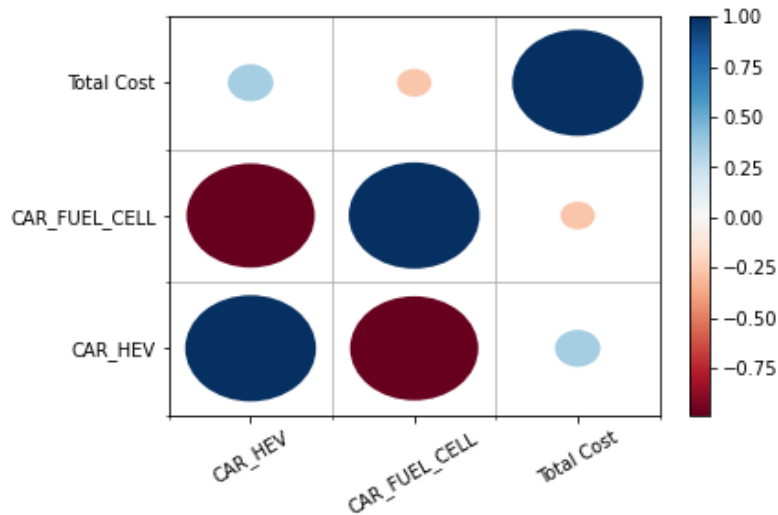


Figure 4.8: Correlation matrix between the capacities of private transport technologies and the total cost. Abbreviations : CAR_HEV : Hybrid electric car.

Public Mobility

The first element we can observe on figure 4.9 is that the tramway has a very small variance under 5% of total cost deviation and that there is no scenarios without tramway without a total cost deviation of 5%.

We can see on figure 4.10 that the CNG buses have a negative correlation with every

other technologies. As it is the only technology correlated with the tramway we can imagine that it is the only technology that replaces it when it is reduced. And as it has a negative correlation with diesel buses and electric train we can deduce that it is replaced when absent either by 1 or 2 of those 2 technologies.

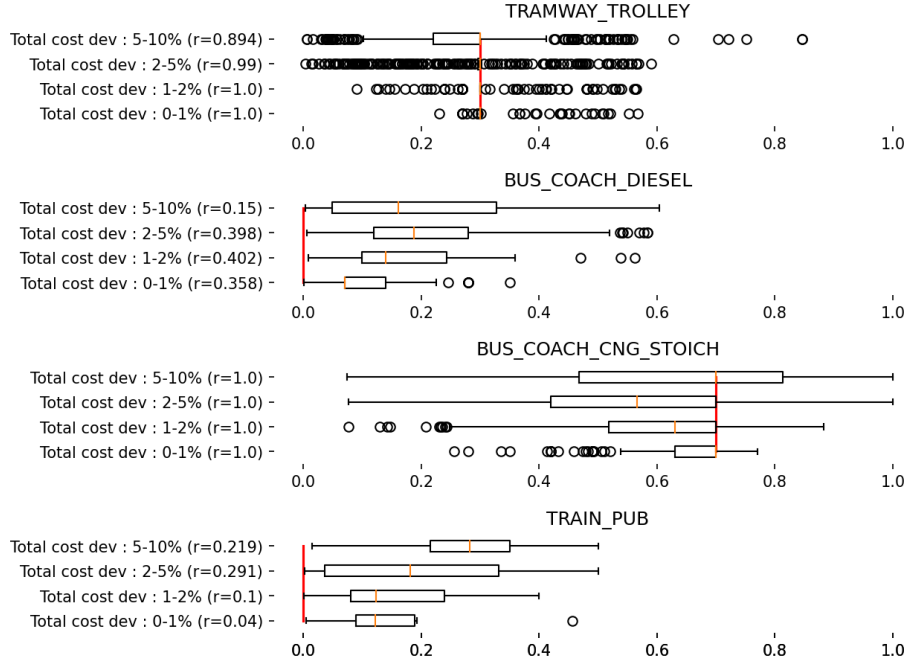


Figure 4.9: Variation of the different public transport technologies for different total cost deviations. The red line corresponds to the optimum scenario. Abbreviations : BUS_COACH_CNG_STOICH : compressed natural gas bus, TRAIN_PUB : public train

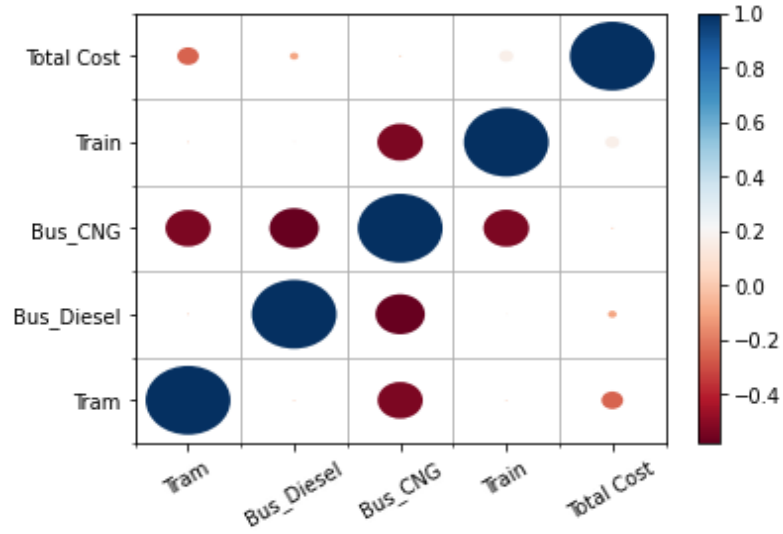


Figure 4.10: Correlation matrix between the capacities of public transport technologies and the total cost. Abbreviations : Bus_CNG : compressed natural gas bus.

4.1.2 Results from the MGA method

In order to get a first large view of the MGA results, three summarizing tables (corresponding to the electricity, LT heat and HT heat layers) are shown in figures 4.11, 4.12 & 4.13. These tables summarize the 16 alternative energy systems and compare them with the optimum. Each column represent a technology or a resource and each point of the table correspond to the relative importance of the technology activity in its sector (e.g. if the CCGT technology has produced 20% of the electricity then its abscissa will be 20).

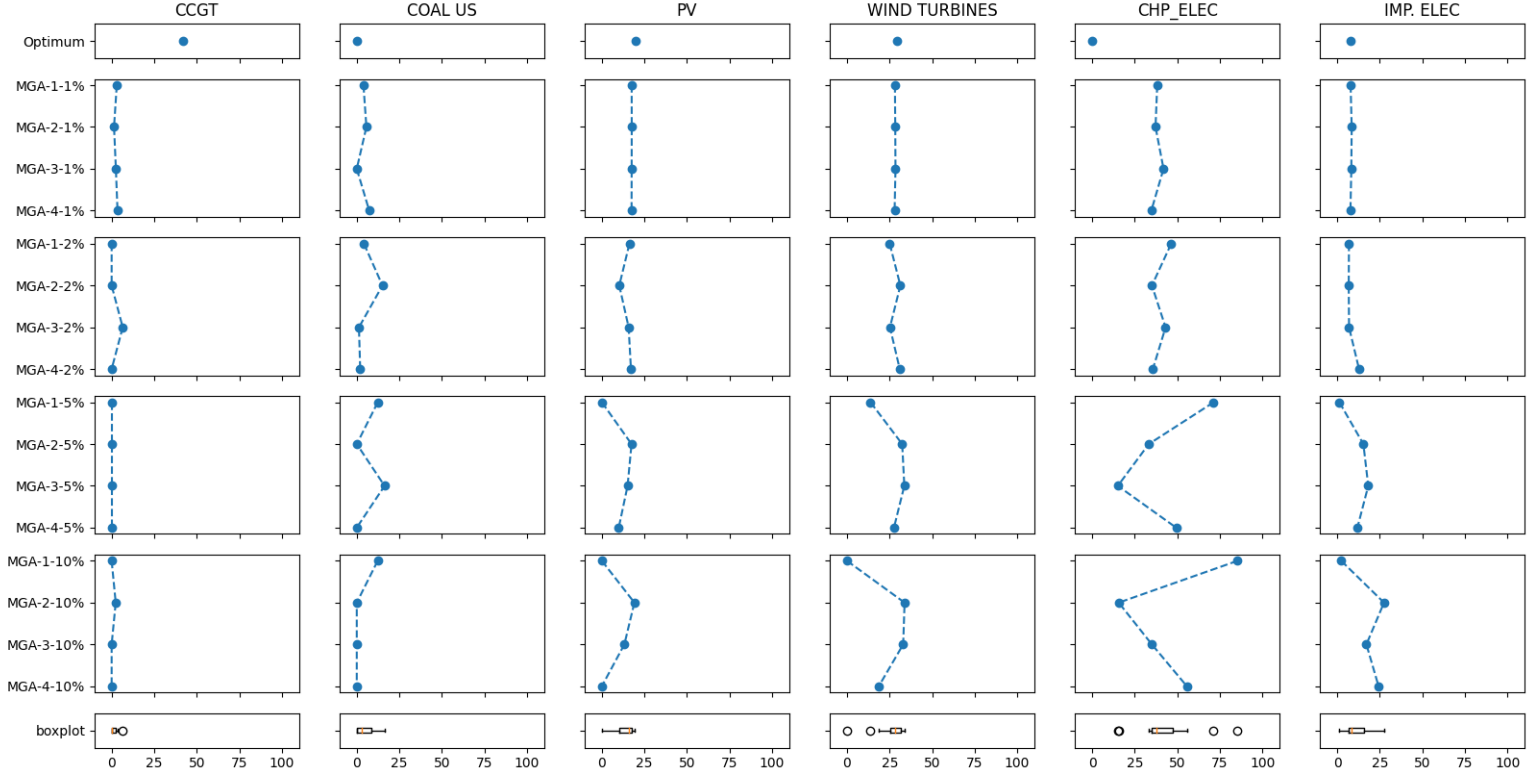


Figure 4.11: Summarizing results of the 16 MGA energy systems for the electricity layer. The vertical ticks indicate the model run, identified with their slack value and their model number. For example, MGA-1-1% corresponds to the first MGA run with a slack of 1%. Each slack contains 4 energy systems. The technologies chosen are the main contributors to the electricity layer. The last column represents the imported electricity. Each point represents its relative contribution to the total electricity layer in [%]. Boxplots summarizing the distribution of points across all models runs and each technology or resource is included at the bottom. Abbreviations : CCGT : combined cycle gas turbine, COAL-US : advanced pulverized coal power plant, PV : photovoltaic panels, CHP_ELEC : electricity production with cogeneration units, IMP.ELEC : imported electricity.

Electricity layer

We have seen in section 1.3 that CCGT produces almost 50% of the electricity of the optimum. We can see on figure 4.11 that this technology is actually easily replaceable. Indeed, for slack of only 1%, the system can already replace the major part of CCGT with mainly CHP. The CCGT decreases from 50% to almost 0% while CHP increases from 0% to approximately 40%, the rest is compensated with Coal_US. This suggests that there exist a cost-competitive alternative energy system based on CHP. For example, if we take a look at the energy system MGA-2-1%, we see that the CHP mainly replaces the CCGT in the electricity layer and the boilers in the HT heat layer. The LT heat and mobility layers stay the same. You will find the Sankey diagram of this energy system in figure A.11 in the Annex section.

We also notice that renewable sources (PV and wind turbines) tend to stay constant for low slacks. It is only when the slacks get bigger (5% and 10%) that the system starts to get rid of them. This is done with the compensation of CCGT and CHP, but this pair of technologies is not efficient at all from the economic point of view. For example, the 10% cost addition of the system MGA-2-10% comes from an increase of imported NG of approximately 35%. This increase comes from the consumption of the CCGT and the CHP due to the loss of wind and solar electricity. We also notice that the imported electricity decreases but this reduction is not sufficient to compensate the cost increase of NG, and thus the total cost of the MGA-2-10% system is larger. This shows a weakness in the electricity layer of the optimal energy system : the renewable sources are not easily replaceable. Even worse, the optimal capacity for wind turbines is at its maximum. This means that if for some reasons the development of renewable sources in Belgium does not go well, or if the energy demand is bigger than expected in the model, the result on the energy cost could be a problem. For example, if we enforce the system not to use solar and wind resources, the cost of the system increases by 4.5%.

changer ça Finally, as mentioned in section 1.3, we notice that the imported electricity completes the electricity layer when needed. Its importance in the electricity layer is however quiet low. Indeed, forbidding the system to import electricity results in an increase of 0.31% in the total cost. We will see that this conclusion becomes false when the system is decarbonated.

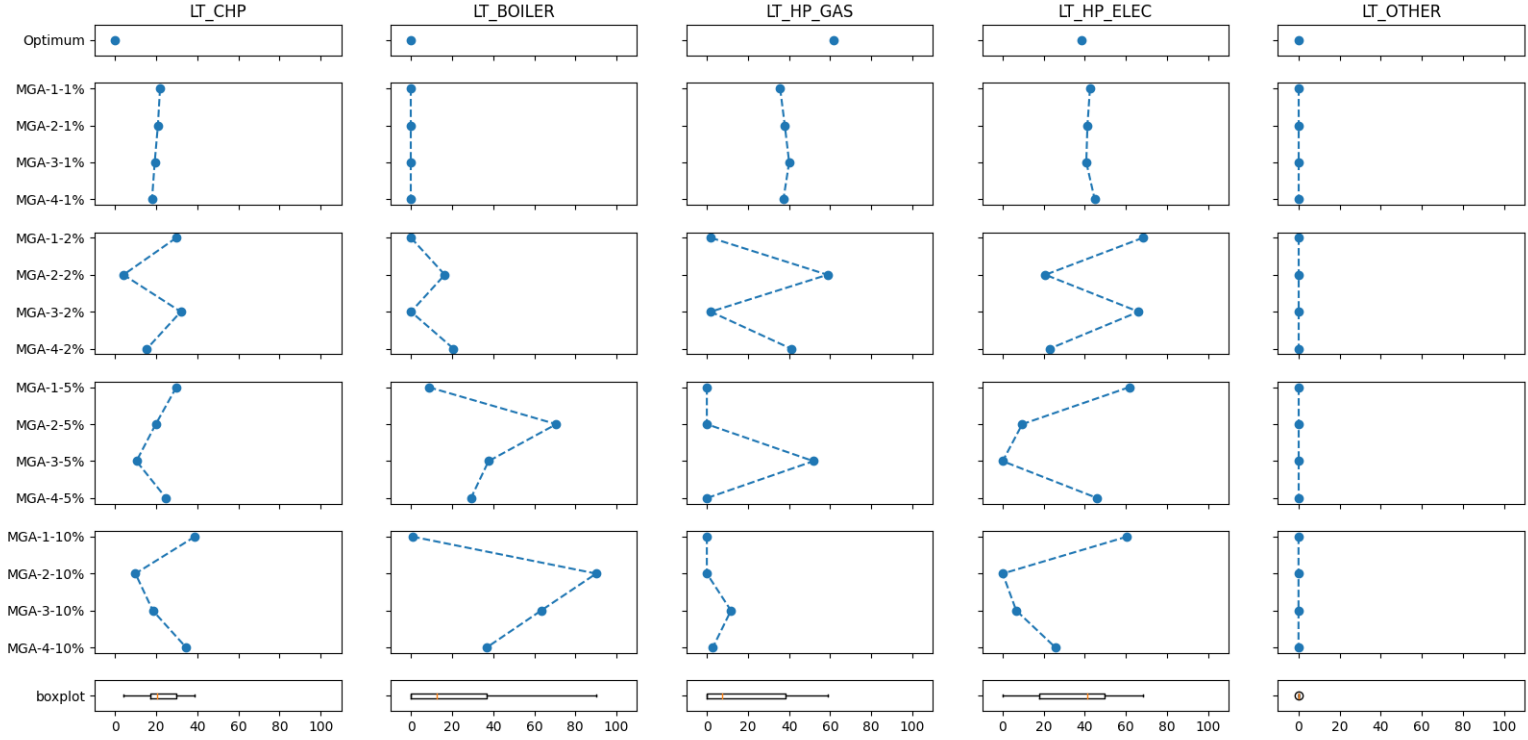


Figure 4.12: Summarizing results of the 16 MGA energy systems for the LT heat layer. The vertical ticks indicate the model run, identified with their slack value and their model number. For example, MGA-1-1% corresponds to the first MGA run with a slack of 1%. Each slack contains 4 energy systems. The technologies chosen are the main contributors to the LT heat layer. Each point represents its relative contribution to the total LT heat layer in [%]. Boxplots summarizing the distribution of points across all models runs and each technology or resource is included at the bottom. Abbreviations : LT_CHP : low temperature heating with cogenerations units, LT_BOILER : low temperature heating with boilers, LT_HP_GAS : low temperature heating with gas heat pumps, LT_HP_ELEC : low temperature heating with electric heat pump, LT_OTHER : all other technologies from the LT heat layer

LT heat layer

As mentioned in section 1.3, the only technologies used in the optimum to provide LT heat are centralized electric heat pumps (DHN_HP_ELEC, which accounts for 40%

of the LT heat) and decentralized thermal gas heat pumps (DEC_THHP_GAS, which accounts for 60% of the LT heat). For a 1% slack, we notice that the system adds CHP and reduces the heat pumps used in the optimum. However, it still lets the boilers to 0%. Indeed, gas HP are twice more efficient than gas boilers. Despite the fact that its investment and maintenance costs are cheaper, the system can't install boilers with a very low slack because of the increase of consumption in NG.

We have seen in figure 4.11 that there might exist a cost competitive energy system based on CHP. We see in this figure that part of the CHP in the electricity layer is used to provide LT heat.

When slacks get bigger, the system is more suited to decrease the heat pumps technology and add boilers. The boilers can even be the only technology used to provide LT heat at slack of 10%.

We also notice that CHP never gets more than 40% in the LT heat layer. Finally, the generation of LT heat directly with electricity is never used, even at slack of 10%.

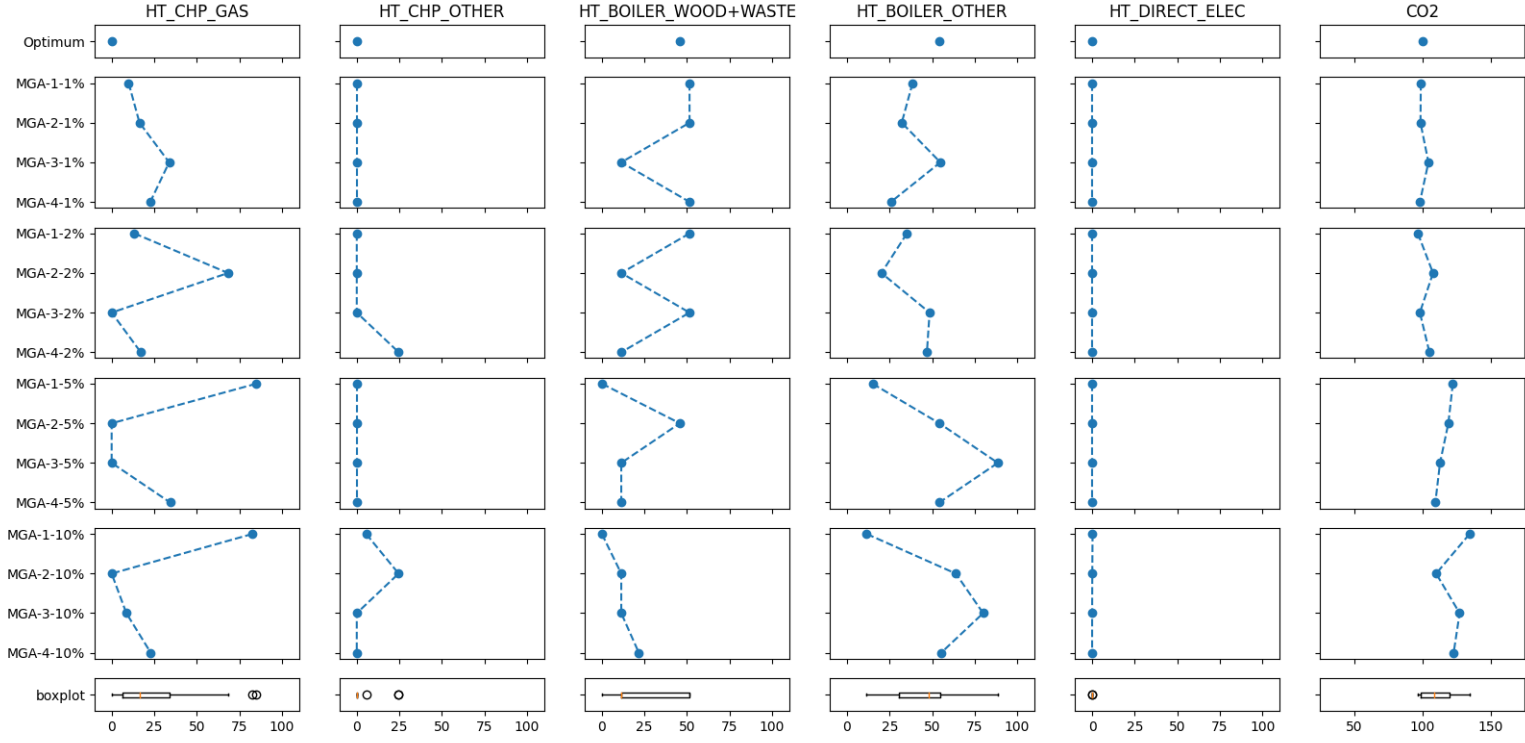


Figure 4.13: Summarizing results of the 16 MGA energy systems for the HT heat layer. The vertical ticks indicate the model run, identified with their slack value and their model number. For example, MGA-1-1% corresponds to the first MGA run with a slack of 1%. Each slack contains 4 energy systems. The technologies chosen are the main contributors to the HT heat layer. Each point represents its relative contribution to the total HT heat layer in [%]. Boxplots summarizing the distribution of points across all models runs and each technology or resource is included at the bottom. Last column shows the CO_2 emissions of each energy system relatively to the optimum. Abbreviations : HT_CHP_GAS : Industrial heating with gas cogeneration, HT_CHP_OTHER : industrial heating with all cogenerations except gas cogeneration, HT_BOILER_WOOD+WASTE : industrial heating with wood and waste boilers, HT_BOILER_OTHER : industrial heating with all boilers, except wood and waste boilers, HT_DIRECT_ELEC : industrial heating directly with electricity, CO_2 : CO_2 emissions.

HT heat layer

As mentioned in section 1.3, the optimum only uses boilers to provide HT heat.

This figure confirms however the remark done previously : there exists alternative energy systems where the boilers, and the CCGT in the electricity layer, are replaced with CHP. We notice that, even for a slack of 1%, it is possible to go from 100% boilers to only 60%, and this can even go to 20% for a slack of 2%.

We also notice that, when the system does not have any constraints on its CO_2 emissions, it will not install any HT heat production facilities directly by electricity, even with slacks of 10%. It means that this technology is not cost-competitive compared to CHP and boilers.

We also notice that, when the system uses CHP, it is generally gas CHP.

Finally, the different CO_2 emissions relatively to the optimum are shown in the last column. We notice that the optimum actually performs quite good in terms of emissions.

MGA method applied to resources

We analyze here the results of the MGA method applied to the primary energy carriers of ESTD (see table A.2).

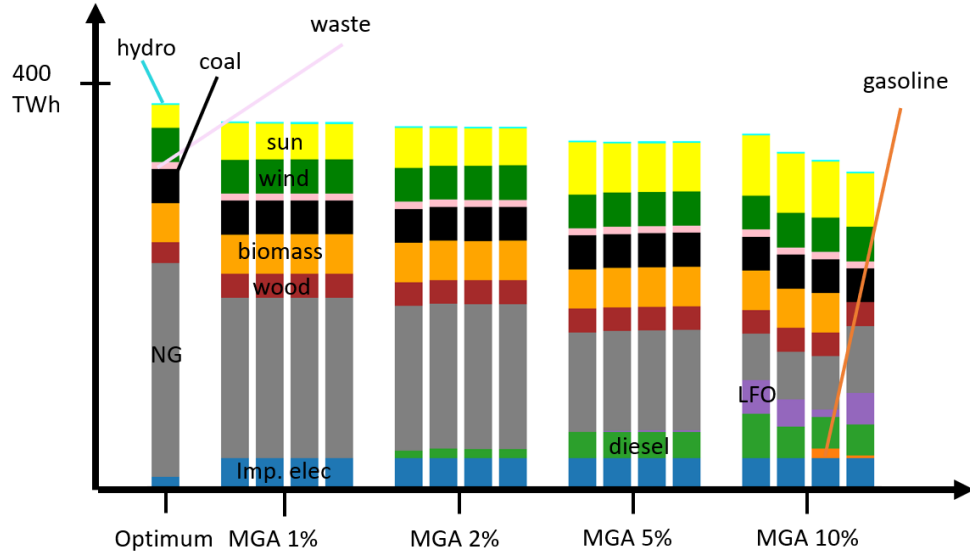


Figure 4.14: Results from applying MGA to the resources to the base case scenario. Legend from bottom to top : imp. electricity (blue), NG (grey), diesel (light green), LFO (purple), wood (red), wet biomass (orange), coal (dark), waste (pink), wind (dark green), sun (yellow), hydro (turquoise). The y-axis is the energy over a year. Abbreviations : NG : natural gas, Imp.elec : imported electricity, LFO : light synthetic fuel.

We see in figure 4.14 that, for a 1% slack, the system uses the same resources than in the optimum scenario. The only difference is that the imported electricity increased at the expense of NG. The difference between the total primary energy consumption comes from this increase of imported electricity. Indeed, the NG is mainly used in CCGT to provide electricity, and thus the yield is taken into account (0.63), while the imported electricity is accounted as a resource but is also directly an EUD.

For a 2% slack, the system stays the same except that the NG decreases a bit in favor of a new resource : the diesel.

For 5% slack, the diesel keeps increasing and replaces the NG, while the other resources stay the same.

For 10% slack, two new resources appear : gasoline and LFO. While the diesel has increased again, the LFO comes to replace a part of NG. We also notice that gasoline is used to replace NG. The other resources approximately stay the same. Finally, we see that the imported electricity stays approximately the same even at slack of 10%. As NG is the main resource in the optimum, its associated weight in the objective function is large and thus the system tries to replace it with other resources. The bigger the slack, the more the system can reduce the NG but even at slack of 10%, it cannot get rid of it. Its minimal penetration is about 14%. This shows a strong

dependancy of the Belgian energy system to NG. Indeed, if we enforce the system not to use NG, the total cost of the system increases of 16%. For more information on this free NG energy system, you will find its Sankey diagram in the Annex section in figure A.13.

4.2 Mitigate CO2 policy scenario

4.2.1 Results from LHS and exclusion methods

We are now going to show the results obtain for suboptimums with a constraint on the emissions limit of 40MT of equivalent CO2.

The results shown are composed of 700 suboptimums : 200 generated with the exclusion method and 500 with the LHS method.

Electricity sector

We can notice on figure 4.15 that PV and wind turbines have a very small variance for a 1% total cost deviation and this variance is increasing with the total cost deviation as the mean stays the same. Those informations lead to the fact that the PV and the wind turbines are essential to guarantee a system in a low total cost, there is no alternative.

We also can notice that CHP is present in every scenario and that it has also a low variance for a small price deviation. Also as it is the only technology to have an increasing mean under 5% we can say that it is the main replacing technology for a decrease of either the PV the wind or the CCGT. Indeed in the figure 4.16, we can see a highly negative correlation between CHP on one hand and on the other hand PV and wind turbines. But it is more correlated to the PV because the PV is linked to the HT heat production by electricity which is there to compensate the peak of electricity production created by the high amount of PV, thus decreasing the PV share also decreases the share of electric heat production which is better compensated by an increase of CHP.

It is interesting to notice that the CCGT is not present in every scenario and furthermore in scenario with a low total cost deviation which makes it more replaceable than in the scenarios without emission reductions. We can see in figure 4.16 that it is negatively correlated with PV and wind turbines. This is explained by its capacity to replace them and we note that it has a better replacing capacity for the wind than for the PV because of the link between PV and heat production explained previously.

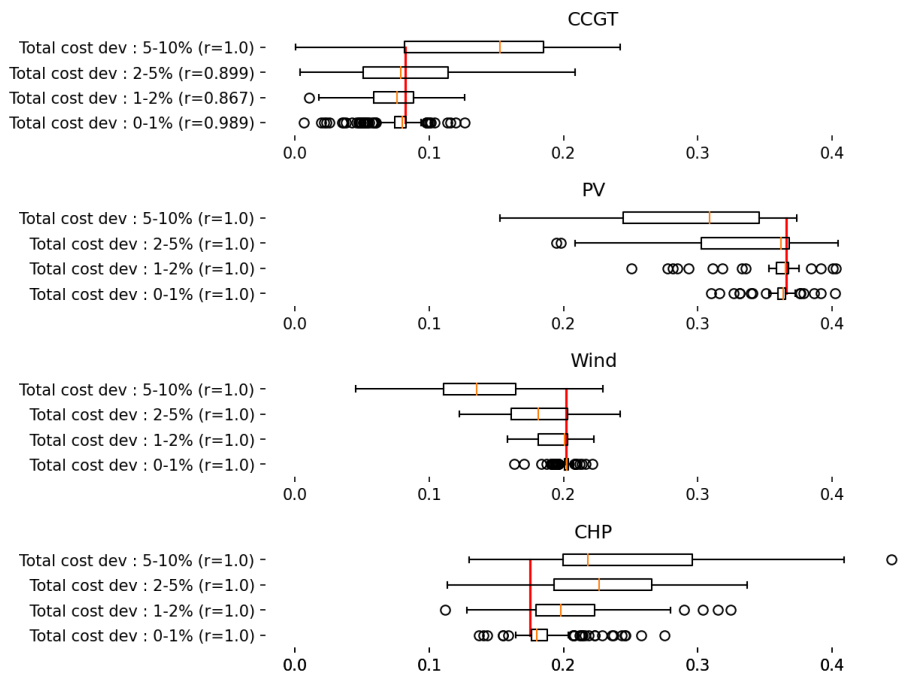


Figure 4.15: Variation of the share of different electricity sources for different total cost deviations.

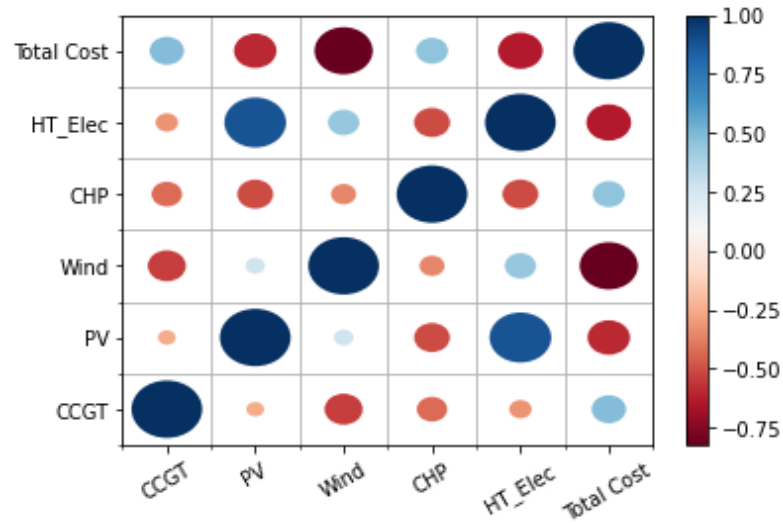


Figure 4.16: Correlation matrix between different technologies of the electricity layer, the HT heat production with electricity and the total cost.

Heat low temperature sector

We can observe in figure 4.17 that the technologies present in the optimal scenario (electric HP and bio-hydrolysis CHP) can't vary much from the optimal value even for a high total cost deviation. We however see that the electric heat pumps may have some rare variation which are compensated mainly by the addition of either gas CHP or gas HP (We can see a high negative correlation with electric HP in figure 4.18)

We can thus deduce that the electric HP and the bio-hydrolysis CHP are not replaceable for a low total cost deviation.

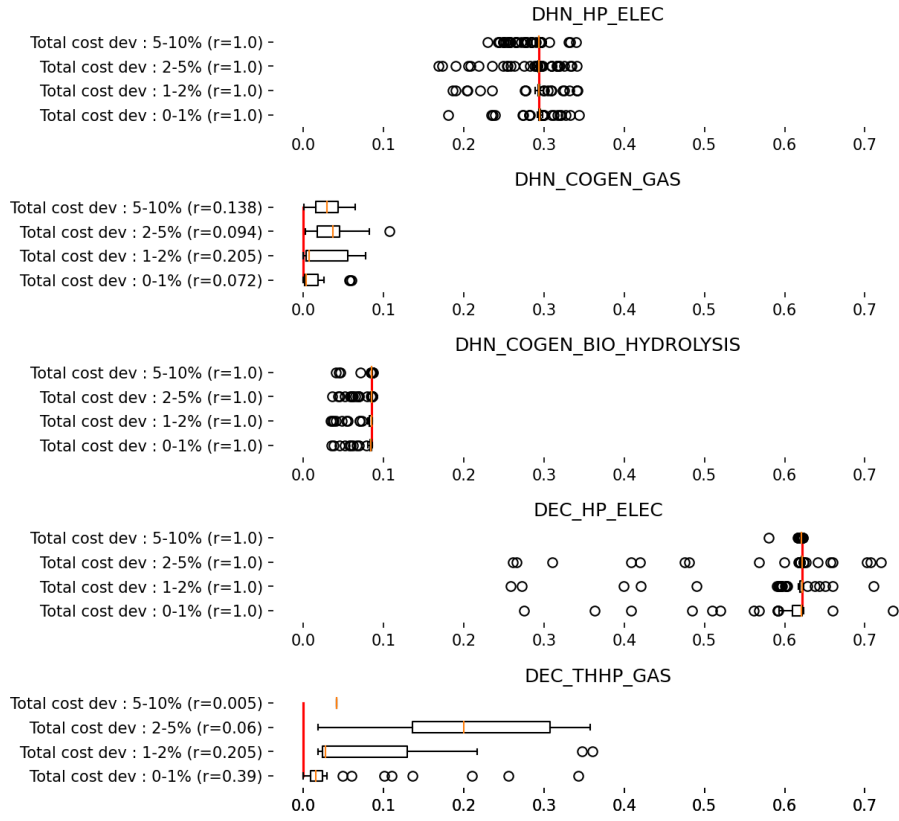


Figure 4.17: Variation of the share of different low temperature heat sources for different total cost deviations.

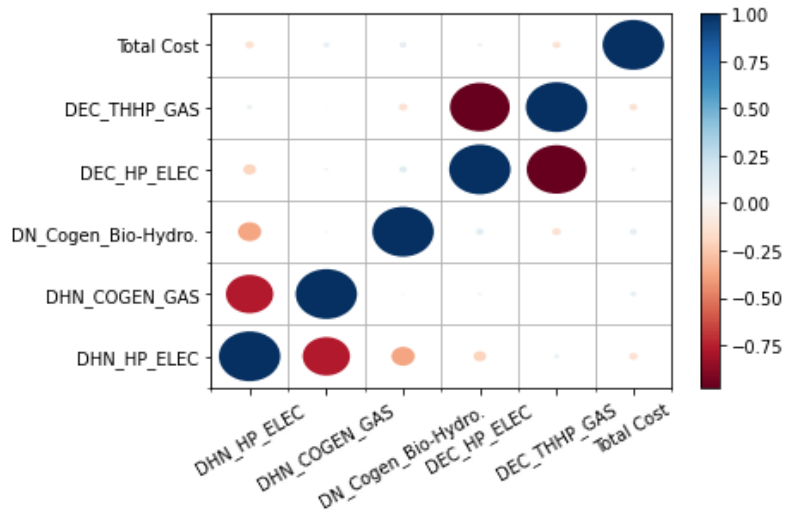


Figure 4.18: Correlation matrix between LT heat technologies and the total cost

Industrial heat Sector

We can notice the very low variation of waste boiler despite the low share. Indeed its low price is very interesting even though the waste resource is limited. We notice too that the waste boiler are not correlated with any other technology, it is logical because of its very low variation.

As explained in the electric sector the heat production by electricity is always present as it compensates the peak of electricity created by the high amount of PV.

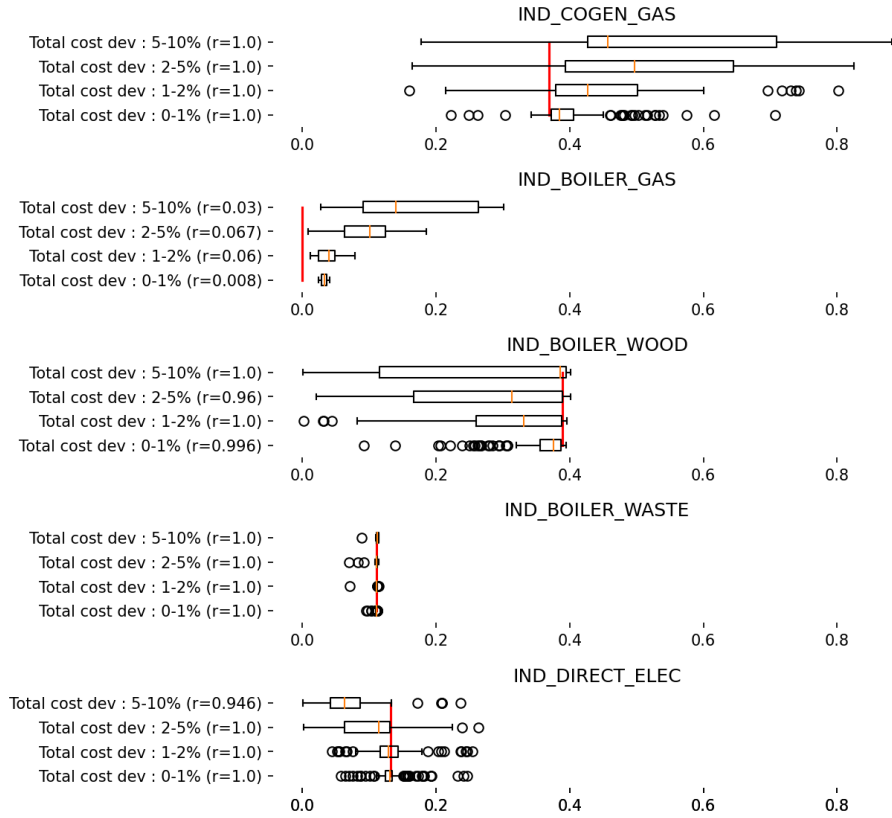


Figure 4.19: Variation of the share of different high temperature heat sources for different total cost deviations

On figure 4.16 we can observe the high negative correlation between gas CHP and wood boiler, the negative correlation between wood boiler and the total cost and the positive correlation between gas CHP and total cost. Those elements combined with the tendency to increase of the gas CHP with the increase of total cost deviation and the tendency to decrease of the wood boiler with the increase of total cost deviation presented on figure 4.17 leads us to conclude that to reduce the total cost of the system and lead to an optimal scenario we need to replace a maximum of the gas CHP by the wood boilers.

We conclude that the HT sector is way less tighten that the LT sector which makes the LT sector more influencing that the HT sector.

At this point we can also notice the total absence of the use of coal. This is logic as the coal emissions are not compatible with a reduction of the emissions.

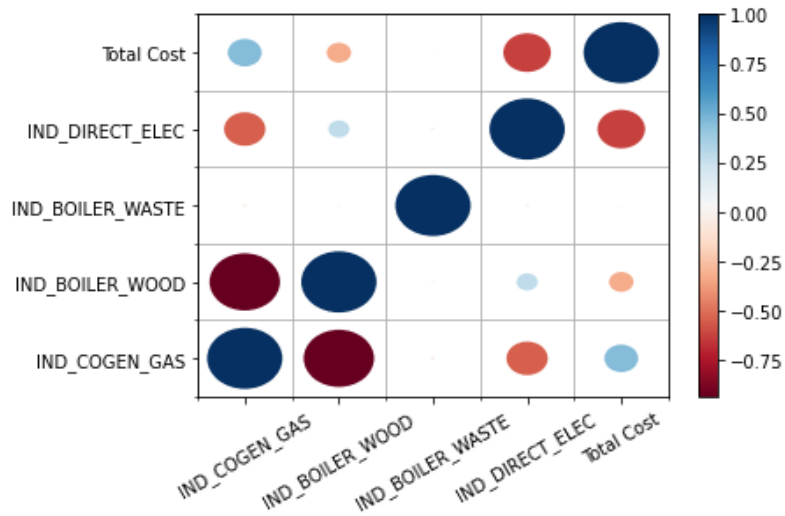


Figure 4.20: Correlation matrix between HT heat technologies and the total cost

Private Mobility

We observe the same behaviour as in the scenario without emission reduction policy : the fuel cell cars can be replaced by HEV but in this case we see a reduced frequency of the appearance of HEV in the mobility mix and a lower penetration.

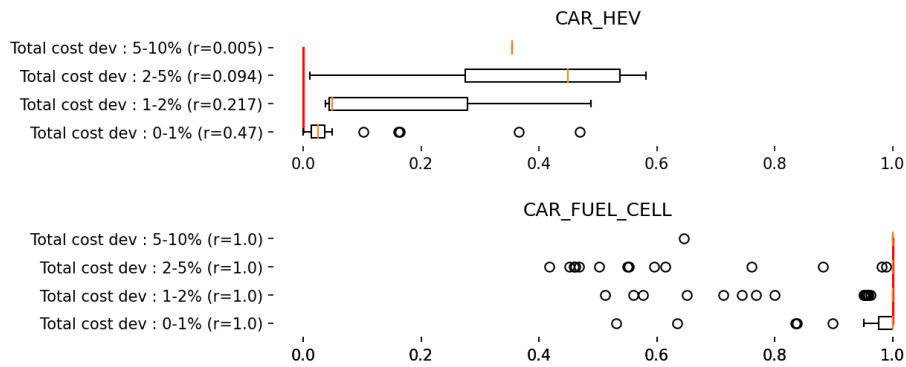


Figure 4.21: Variation of the share of different private transport technologies for different total cost deviations

Public Mobility

We can observe in figure 4.22 that we find again the same technology at 2 exception : The Diesel buses have been replaced by hybrid diesel buses and the train is now the main technology as it has a mean of 50% of the share.

We observe that the 3 technology installed on the optimal scenario a very small variance even at 10% of total cost deviation. And thus the hybrid diesel buses are use in only less than 10% of the scenarios even with a high total cost deviation.

We can thus conclude that there is not really a low cost alternative for the optimal solution.

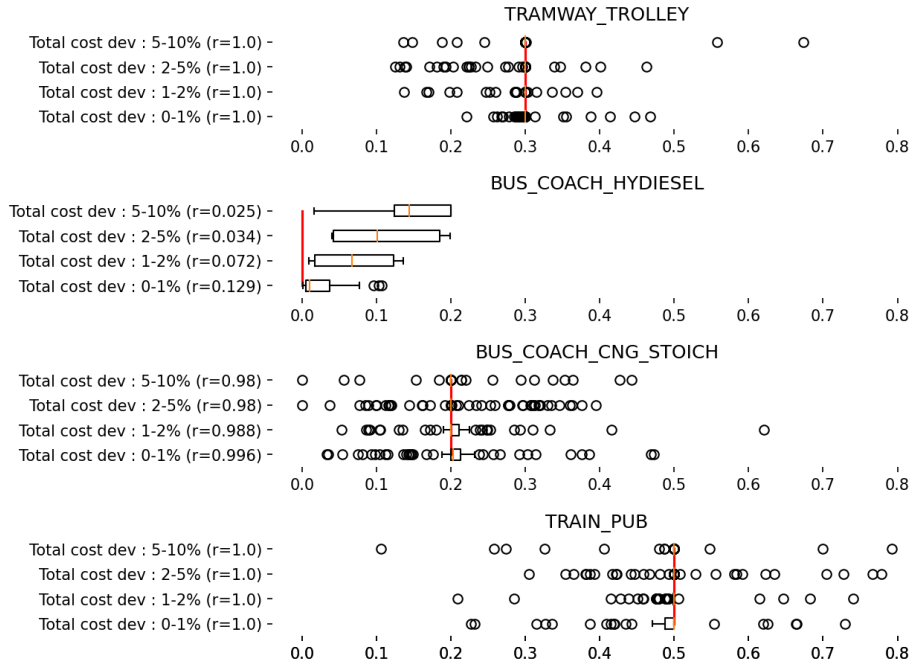


Figure 4.22: Variation of the share of different public transport technologies for different total cost deviations

4.2.2 MGA results

The optimal energy system with a 40 MtCO₂ emissions limit has been presented in section 1. We analyze here the 16 energy systems obtained with the MGA method applied to the technologies activities (in GWh).

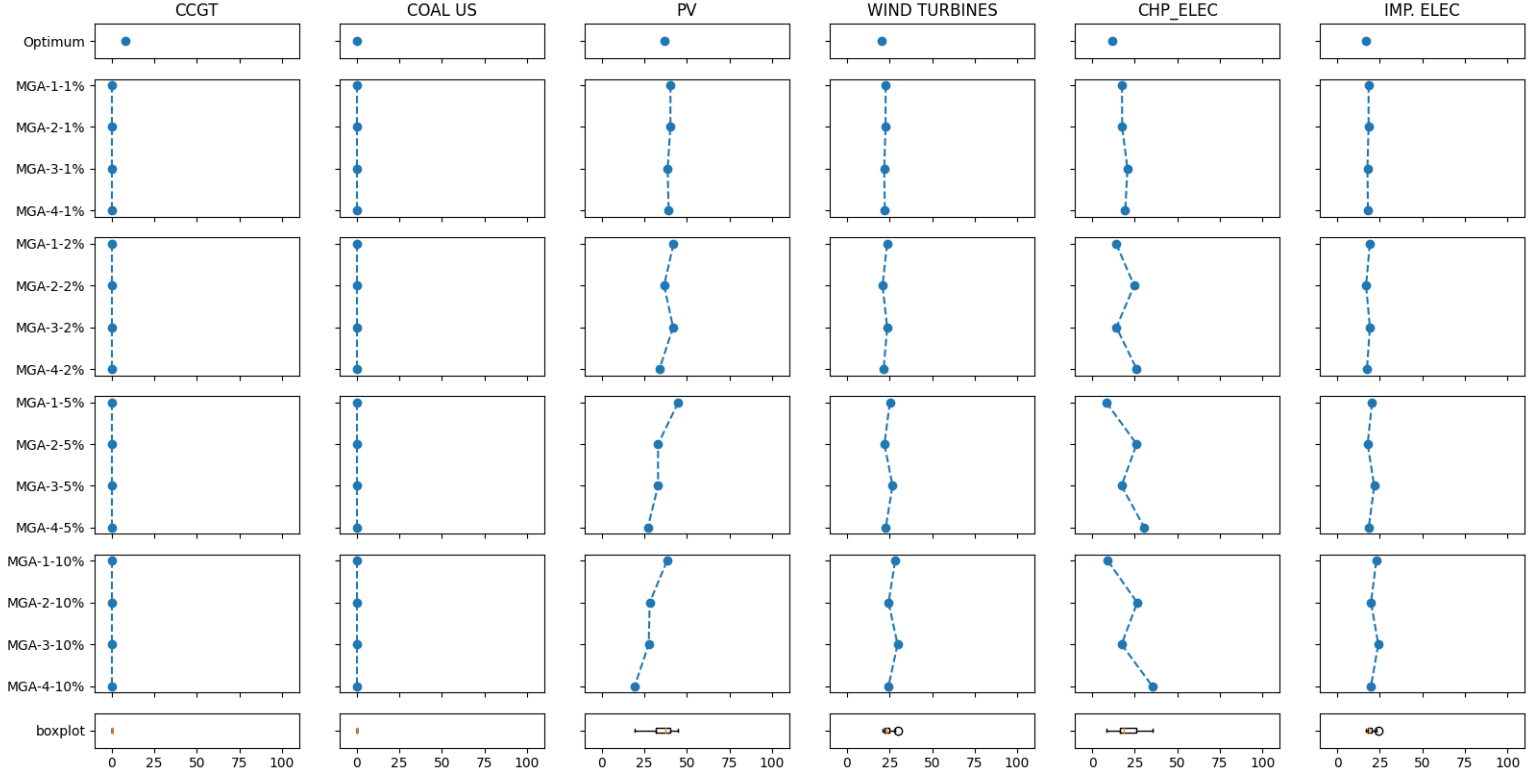


Figure 4.23: Summarizing results of the 16 MGA energy systems for the electricity layer with a mitigate CO_2 policy scenario.

Electricity layer

As the CO_2 emissions are reduced by almost 50%, the system does not have as many technological choices as without a CO_2 emissions limit. This means that it will be harder to minimize the weighted sum during the MGA process. This can be seen in figure 4.23 in the boxplots. Indeed, compared to figure 4.11, the boxplots have reduced which means that the variations in the distribution during the MGA runs have decreased. When the slacks increase, the system is allowed to make bigger variations of some technologies for another, but the energy system for the electric layer globally stays the same : the PV and the wind decrease a bit in favour the the CHP but there are no new technologies installed. This observation confirms what has been obtained

with LHS and exclusion methods, where we saw that the system prefers to replace PV with CCGT as PV is strongly correlated to the HT heat production.

We can conclude that, for this mitigate policy CO_2 scenario and for the electricity layer, there is no cost-competitive alternative energy system than the system presented in section 1.4. We see that CHP could increase up to almost 40% of the electricity share, however there are no new technologies and PV and wind turbines are irreplaceable for slacks lower than 10%.

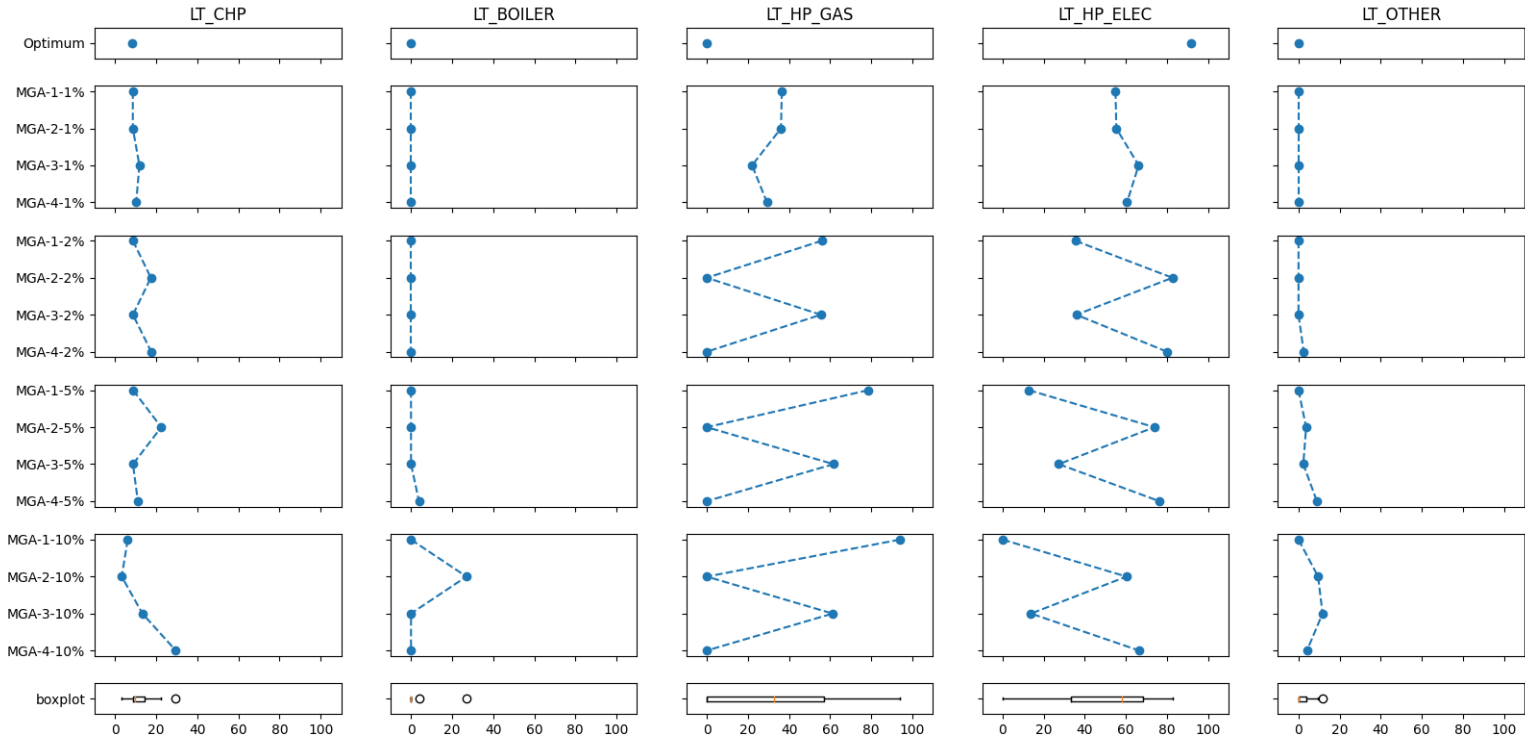


Figure 4.24: Summarizing results of the 16 MGA energy systems for the LT heat layer with a mitigate CO_2 policy scenario.

LT heat layer

For the LT heat layer, we see in figure 4.24 that the system mainly uses HP, and sometimes reduces HP in favor of CHP. The system can change electricity HP for gas HP and vice-versa more and more when the slack gets bigger, and can even totally

replace electric HP for gas HP (and CHP) when the slack hits 10%. This is interesting because this de-electrification of the LT heat layer results in an electrification of the HT heat layer, as we will see below.

We also notice that, compared to the no CO_2 policy scenario, the boiler technology has far less variance. The system really prefers to use HPs as the efficiency of HP is approximately twice the efficiency of boilers. The MGA-2-10% system is an exception with the boilers producing more than 30% of the LT heat. This system actually uses all wood and waste available to produce 80% of LT heat and 20% of HT heat. This is a quite different configuration than the optimum, where all wood and waste available were used to produce HT heat. However, we recall that this system leads to an increase of 10% of the total cost of the system. This seems to mean that boilers should not be used to produce LT heat but only HT heat.

Finally, we also notice that when the slack gets bigger (5% and 10%), the system adds a new technology never used before. This technology is the centralized heating.

It is interesting to notice that this technology is not always used because, despite its low investment and maintenance costs, its GWP is larger than the GWP for electric heat pumps, and as its capacity factor depends on the meteorological conditions and is thus lower than 1, the electric heat pumps are more suitable.

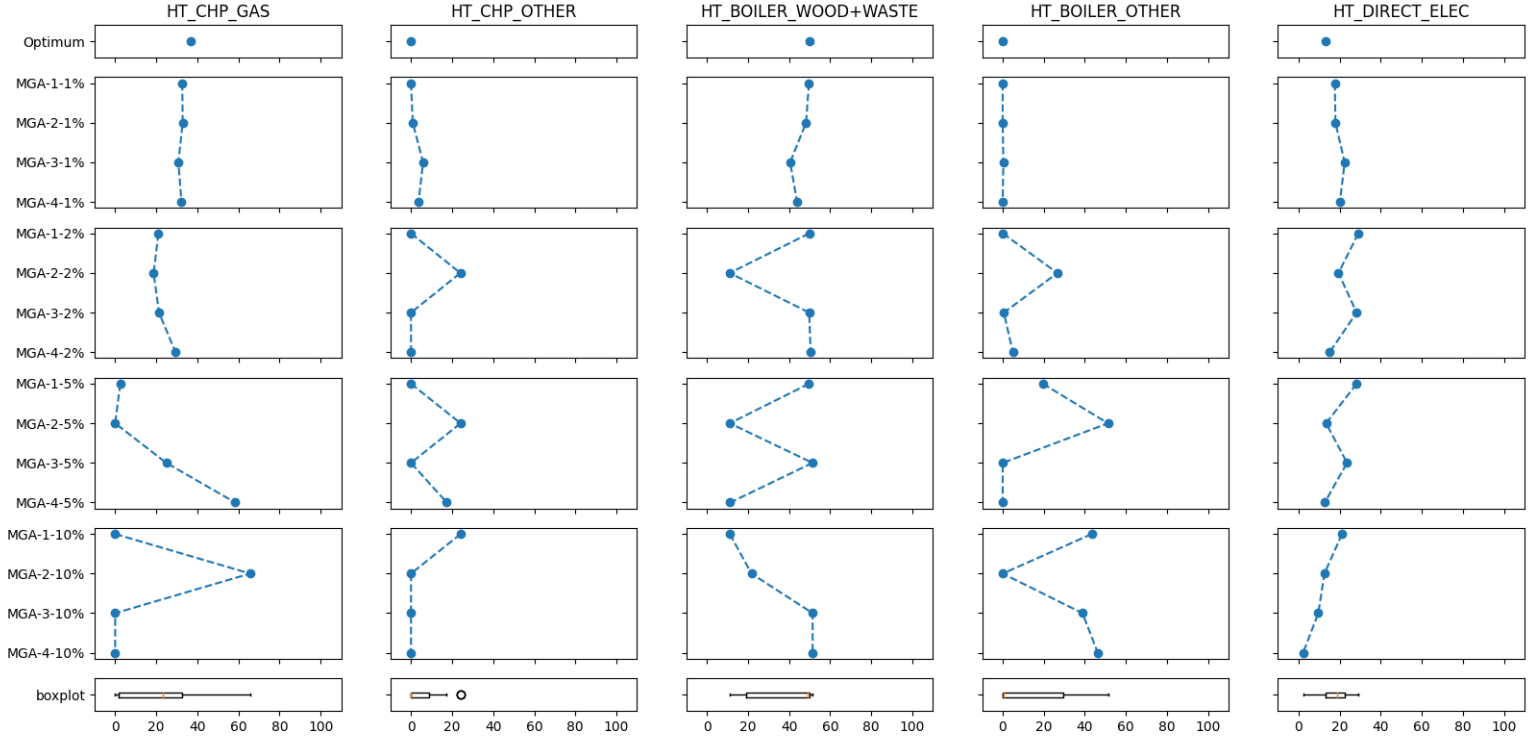


Figure 4.25: Summarizing results of the 16 MGA energy systems for the HT heat layer with a CO_2 limitation of $40\text{Mt}CO_2\text{eq}$.

HT heat layer

We see in figure 4.25 that, even for low slacks (1% and 2%), the system can decrease the part of boilers and CHP to add direct electricity generation. However, this variation stays moderate.

When the slack reaches 5%, the system can almost totally remove the CHP units or the boilers. For example, the system MGA-4-5% is a system with almost no boilers, and the HT heat is mainly provided with CHP and a bit of direct electricity generation.

When the slack reaches 10%, the system can even totally removes the CHP and direct electricity generation to only use boilers (see the system MGA-4-10%). This kind of HT heat layer reminds the HT heat layer of the cost-optimal scenario when no CO_2 policy were applied. However, we notice here that this system does not economically perform very well. For the mitigate CO_2 policy, the use of boilers to cover the HT

heat demand thus must be accompanied with CHP to stay economically competitive. Indeed, the wood and the waste are not sufficient to cover the whole HT heat demand, and it is more cost-competitive to add gas CHP than gas boilers. Finally, we have seen in figure 4.24 that the LT heat layer could easily be de-electrified, and this release of electricity benefits the HT direct electricity generation which can increase.

MGA method applied to resources

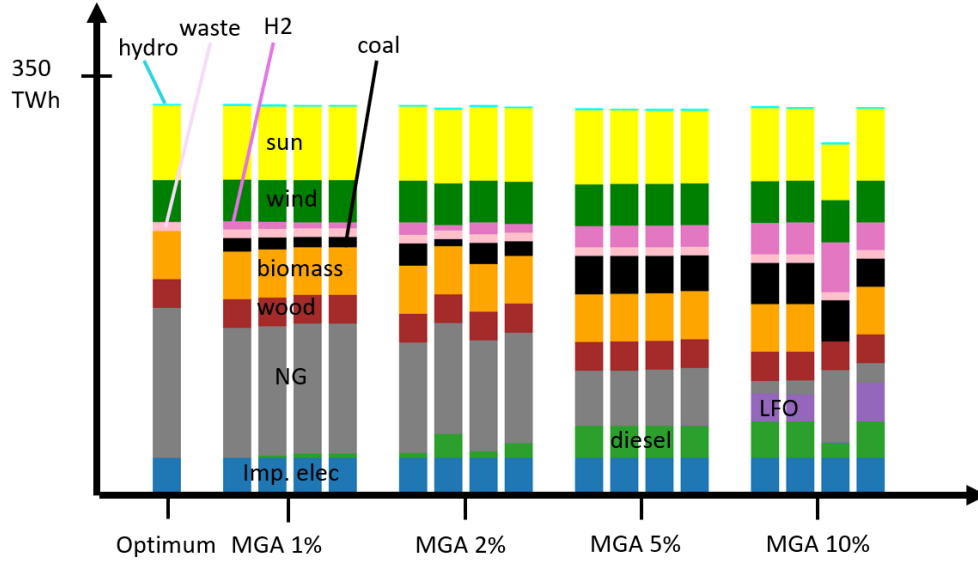


Figure 4.26: Results from applying MGA to the resources to the CO_2 mitigate policy scenario. Legend from bottom to top : imp. electricity (blue), NG (grey), diesel (light green), LFO (purple), wood (red), wet biomass (orange), coal (dark), waste (pink), H_2 (dark pink), wind (dark green), sun (yellow), hydro (turquoise). The y-axis is the energy over a year.

Analysis of figure 4.26

We notice that, even for 1% slack, the system adds three new resources compared to the optimum : diesel, H_2 and coal. These three resources are mainly used to decrease NG and a bit the biomass.

For 2% slack, we notice that diesel, H_2 and coal can increase a bit but there is no major differences with a 1% slack. This conclusion is also valid for 5% slack.

For 10% slack, we notice that the H_2 has increased and is now a major resource of the system. Furthermore, a new resource is added : LFO. The other resources tend

to stay the same, except for the third energy system in MGA 10%, where the biomass has disappeared, in favour of NG.

The NG is still a major resource of the optimal energy system, and we see that, even at slack of 10% the system cannot completely get rid of it. However, for this slack, NG can be reduced to only 3.5% of the primary energy consumption. If we enforce the system not to use NG, the total cost of the system increases of 18%.

The imported electricity is at its full potential and does not vary in any runs of the MGA. This indicates a dependency on imported electricity.

Finally, we notice a drop of approximately 50TWh of primary energy consumption compared to the no CO_2 policy scenario. This comes from the increase of PV and imported electricity, and thus the decrease of NG. Indeed, NG is mainly used to produce electricity via CCGT or CHP and thus the yield is taken into account (yield of CCGT = 0.63 and yield of CHP = 0.44). The yield considered for PV, wind and imported electricity is 1 between the resource and the electricity production. This explains the decrease of primary energy consumption.

4.3 Aggressive CO2 policy scenario

4.3.1 Results from LHS and exclusion methods

In this subsection we are going to present you the suboptimal scenarios generated with an emission limits of 10 MT of equivalent CO_2 .

Those scenarios are composed of 200 generated by the exclusion method and 500 with the LHS method.

Electricity sector

We can observe on figure 4.27 that for a small deviation of the total cost there is no big modification possible for the electric sector, as in the previous subsection but in a more important way. In some rare scenarios we can see the apparition of CCGT but at a far lower level than in the previous subsections. But with a higher deviation, the presence of CCGT is more frequent. This is confirmed by the correlation matrix on figure 4.28 where we can find a high negative correlation between PV or wind turbines and the total cost of the system.

Also one big observation is that wind turbines and PV shares have a tendency to decrease for system with higher total cost. CHP share, on the other hand, has a tendency to increase. This element is confirmed and more explicit by the figure 4.28 where we can see that the CCGT is more negatively correlated with the Wind turbines and the PV with the CHP.

Those elements lead us to assume that PV and wind turbines are essential to ensure a high decarbonation of the electric sector for a competitive total cost. To complete the demand, the CHP seems to be the preferable alternative to renewable sources, while CCGT is less often used ($0.1 \leq r \leq 0.6$ for CCGT and $r = 1$ for CHP).

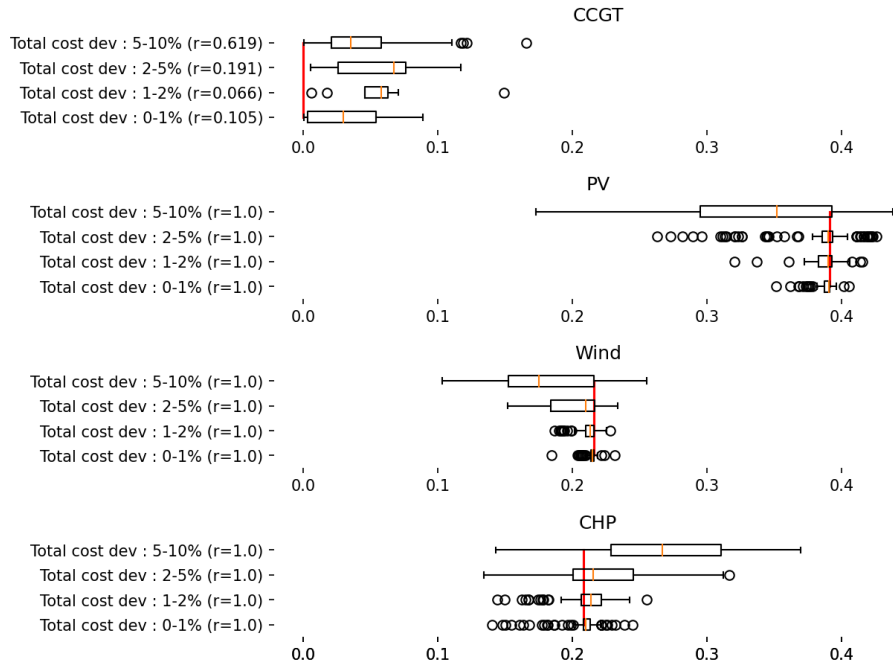


Figure 4.27: Variation of the share of different electricity sources for different total cost deviations.

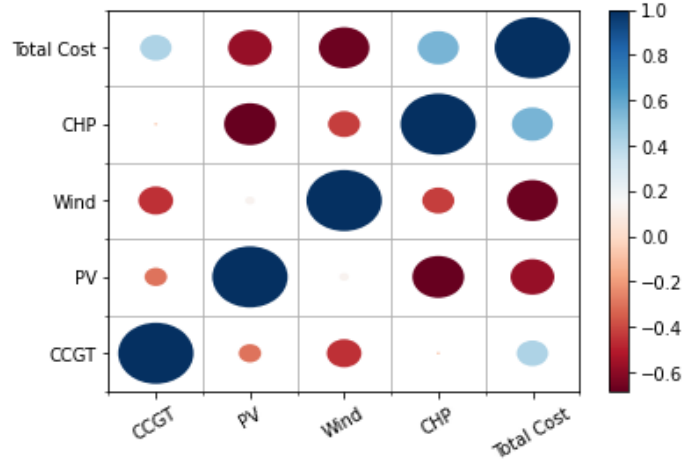


Figure 4.28: Correlation matrix for different electricity production technologies and the total cost.

Industrial heat Sector

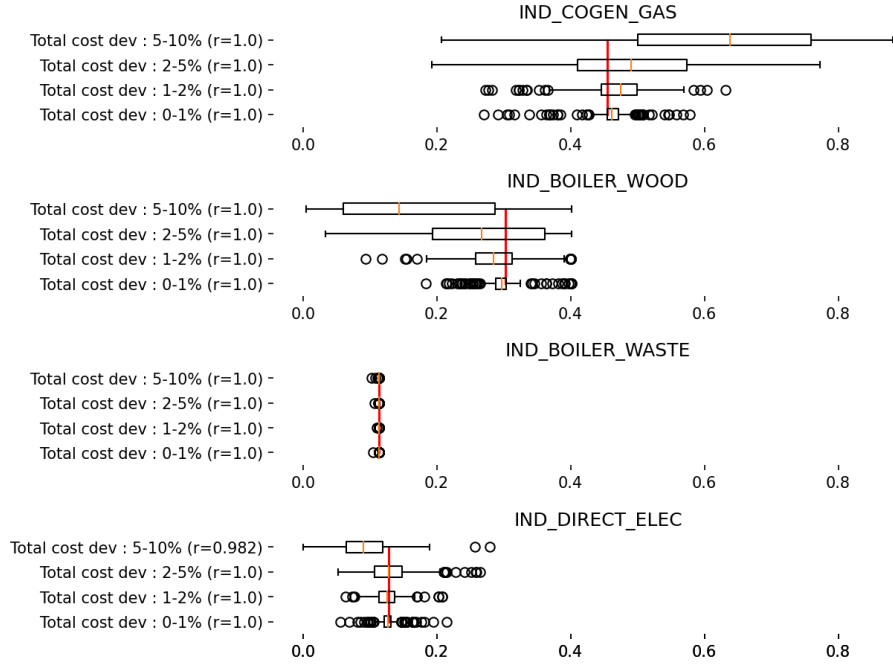


Figure 4.29: Variation of the share of different high temperature heat sources for different total cost deviations.

We can observe in figure 4.29 that no other technologies than the one present in the optimum scenario are installed.

We can observe that the Waste boiler is really constant, indeed it is the only installed technology in every scenarios to use the waste resources, which makes it a very constant technology. The low price of the waste resources makes it a hard to replace technology, even for large cost deviations.

As in the previous subsection, the heat production by electricity is directly linked to the amount of PV installed, it can be confirmed in the figure 4.30 where the correlation is high. It has then the same behaviour as the PV and thus globally the same correlation with the CHP.

Also we can see in the figure 4.30 that the CHP and the wood boilers have a highly negative correlation which indicates that one is replacing the other with an increasing variance as the total cost deviation increases.

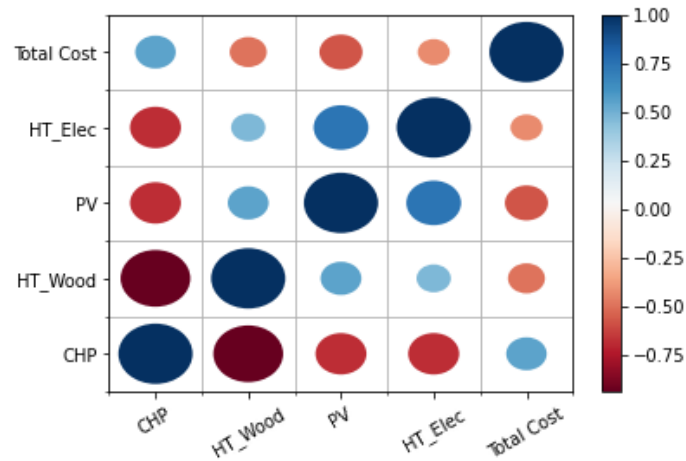


Figure 4.30: Correlation matrix for different high temperature heat production technologies and the total cost.

Heat low temperature sector

We can observe in figure 4.31 that the technologies are very tighten. The small variance of the electric HPs indicates that they are vital to stay in a good range of total cost.

Also the Bio-Hydrolysis CHP have a low share but the small variance makes it a essential technology.

We can note the rare appearance of the gas HP and as we can note on figure 4.32 it is highly negatively correlated with the electric HP.

The solar heat production is appearing only in a few scenarios with a high total cost deviation, this is due to its very low load factor due to the meteorological condition in Belgium. Those elements makes it a bad solution for low temperature heat production.

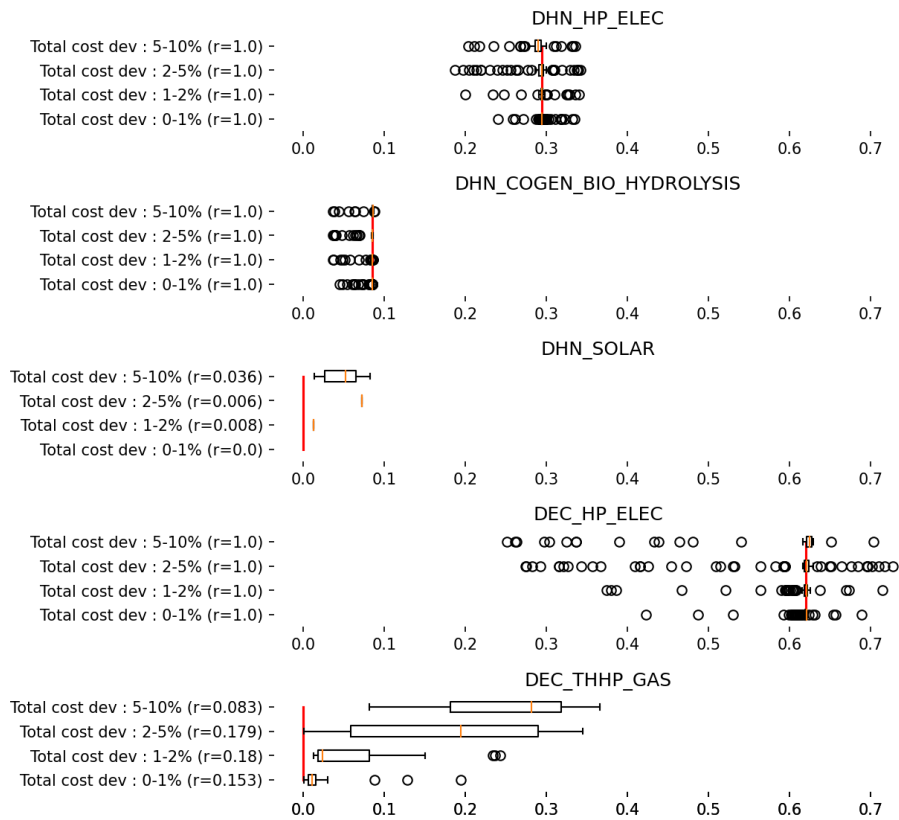


Figure 4.31: Variation of the share of different low temperature heat sources for different total cost deviations.

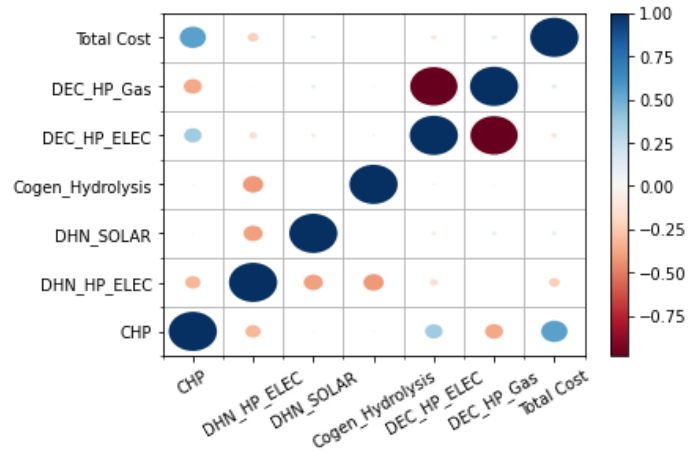


Figure 4.32: Correlation matrix for different low temperature heat production technologies and the total cost.

Private Mobility

As in the 2 previous subsection, we see that the share of the fuel cell cars is replaced by hybrid electric vehicles. The mean and the variance are very low for small price deviation which implies that the use of HEV, wont simplify the total cost reduction of the system.

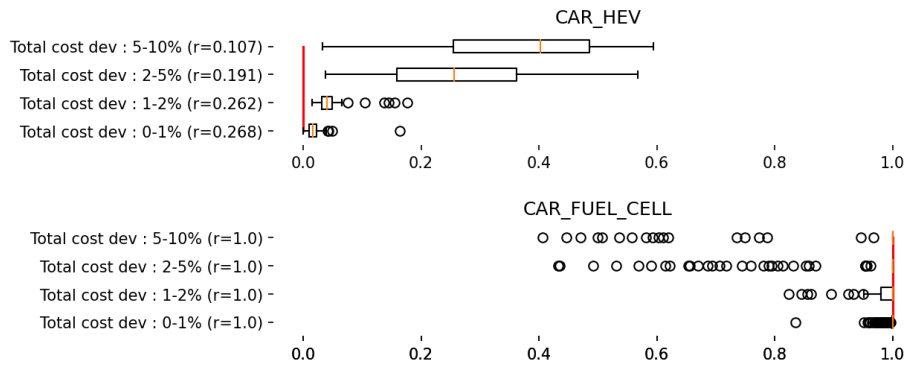


Figure 4.33: Variation of the share of different private transport technologies for different total cost deviations.

Public Mobility

We can observe in figure 4.34 that, as in the private mobility sector, the technologies are very tight with small variance, even with a high total cost deviation. This implies that there is not really some different solution for this sector with a low price deviation.

What is interesting to notice here is that the buses are powered by hybrid diesel motors contrarily to the mitigate emission reduction scenarios where the fuel cell buses where the best solution.

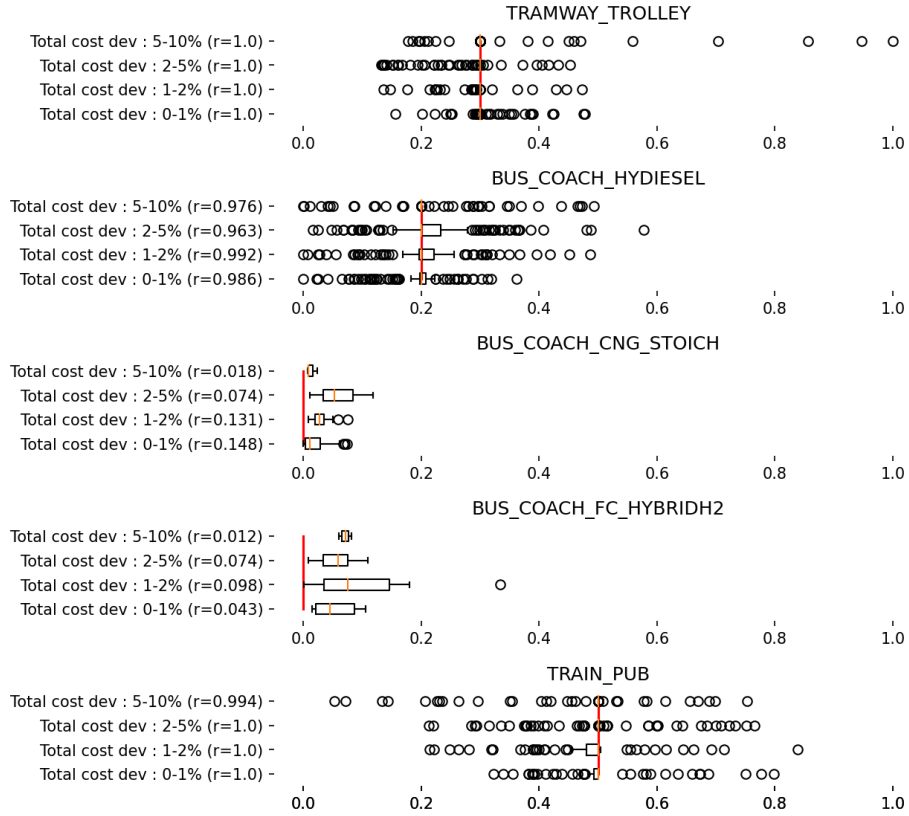


Figure 4.34: Variation of the share of different public transport technologies for different total cost deviations.

4.3.2 MGA results

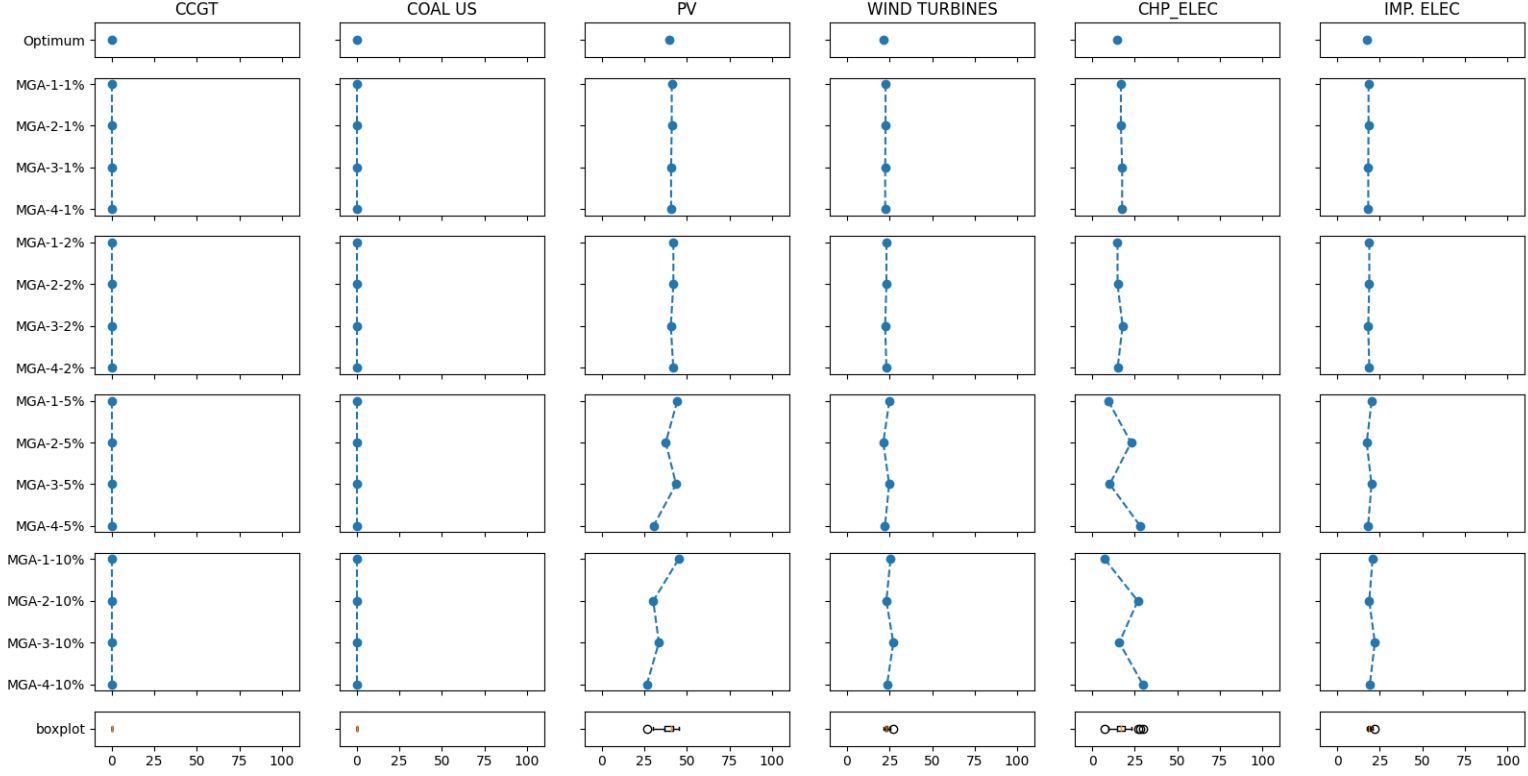


Figure 4.35: Summarizing results of the 16 MGA energy systems for the HT heat layer for an aggressive CO_2 policy.

HT heat layer

We see on figure 4.35 that there are no major changes in the electricity layer, even for slacks of 10%. We notice however that the system can decrease a bit the PV and wind turbines in favor of CHP for slacks of 5% and 10%. This observation confirms the results obtained with the LHS and exclusion methods, where we saw that the system usually prefers to replace PV production with CHP. As shown in figure 4.28, the PV is strongly linked to the direct electricity generation and thus replacing it with CHP allows to cover the loss of heat indirectly generated by the loss of PV. This is also why

the system does not install CCGT in any MGA runs.

From this figure 4.35, we can conclude that there are no big alternatives for the electricity layer. The CHP could increase of about 10% at sufficient slack but there are no cost competitive technologies that could replace PV and wind turbines.

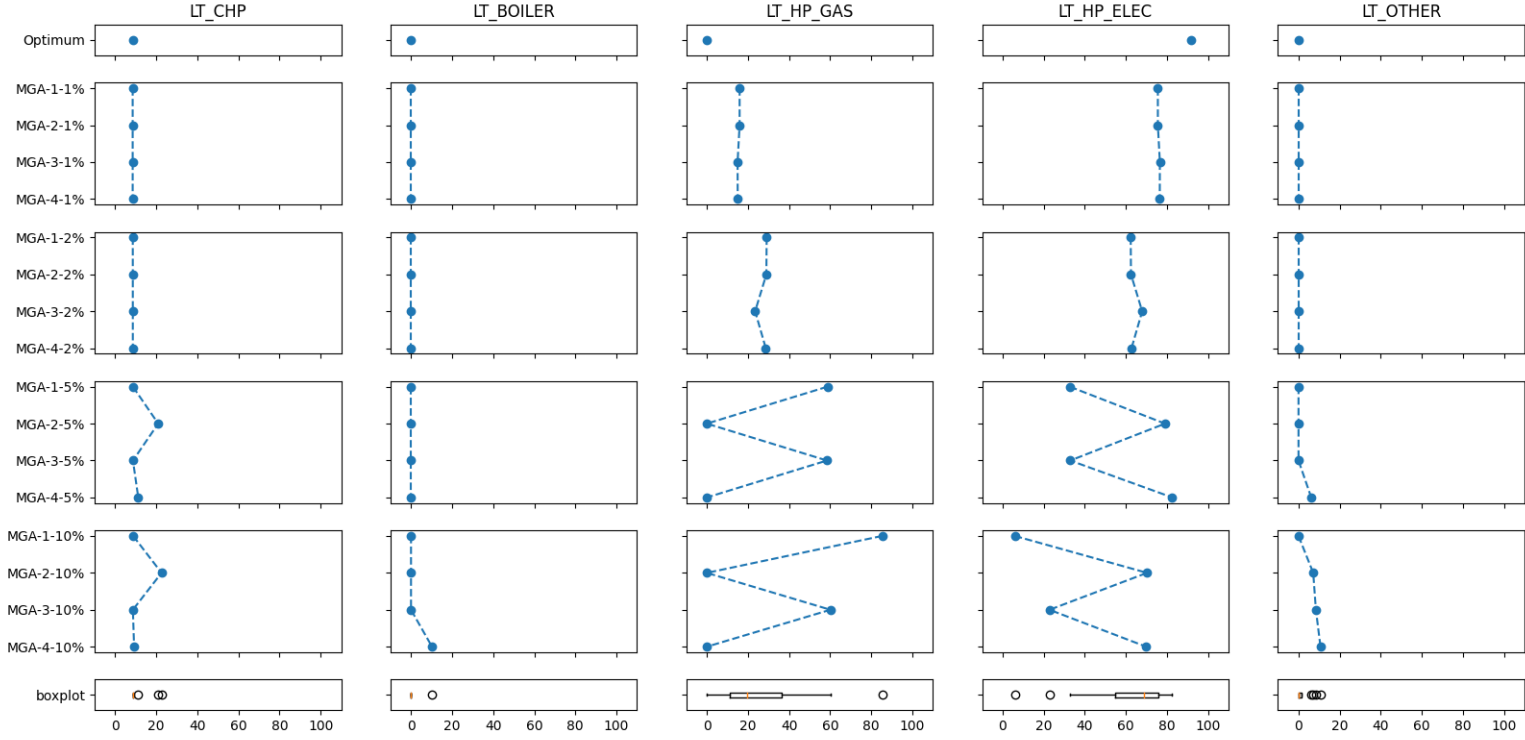


Figure 4.36: Summarizing results of the 16 MGA energy systems for the HT heat layer for an aggressive CO_2 policy.

LT heat layer

The HP technology is extremely important in this layer. We see that it can be replaced a bit with CHP (up to 20% for a 10% slack). However, at low slacks, the LT heat layer only shows very small variations.

However, even for slacks of 1 and 2%, we see that the electric HPs can be replaced with gas HPs, and even fully replaced when the slack increases to 10%. We will see when we will analyze the HT heat layers that this de-electrification actually leads to

an important electrification of the HT heat layer.

We also notice that, for slacks of 5 and 10%, the system starts to use a new technology. This technology is the solar centralized heating. It is interesting to notice that this technology is not always used because, despite its low investment and maintenance costs, its GWP is larger than the GWP for electric heat pumps, and as its capacity factor depends on the meteorological conditions and is thus lower than 1, the electric heat pumps are more suitable.

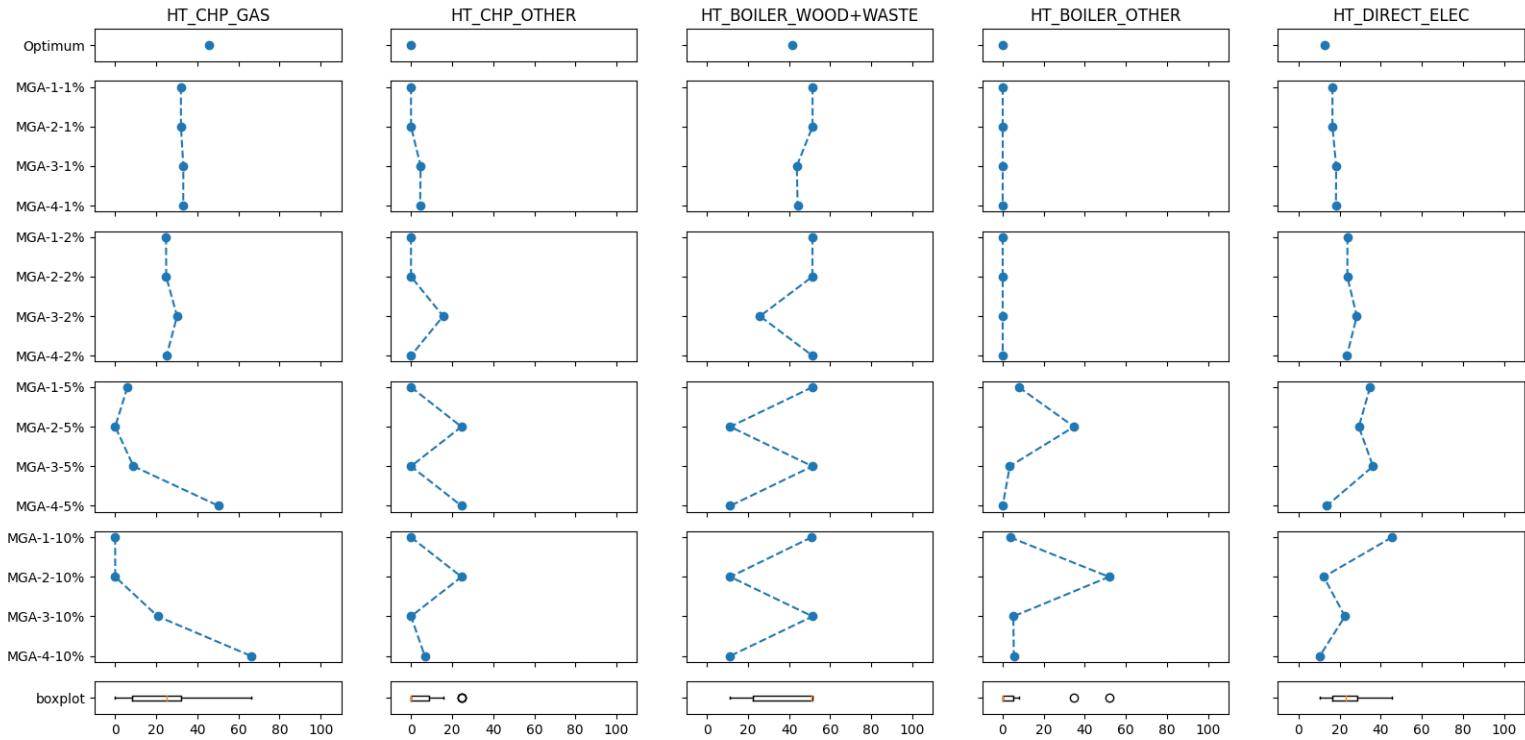


Figure 4.37: Summarizing results of the 16 MGA energy systems for the HT heat layer for an aggressive CO_2 policy.

HT heat layer

We see that the CHP and boilers technology are still complementary, and the direct elec technology comes to complete the layer. However, when the slacks get bigger, the

system is more allowed to add direct elec generation. This electrification of the HT heat layer, which increases with slack, result in a gasification of the LT heat layer. Indeed, when the slack gets larger, the system can evolve from a CHP-boilers system to a boilers-direct_elec system and completely remove the CHP units (see MGA-1-10%). Actually, if we look back at figure 4.36, we see that the LT heat layer has gone from fully electric HPs to fully gas HPs. This releases electricity available for the HT heat layer, and thus the system can produce almost 50% of its HT heat with direct electricity generation.

We also notice that, for low slacks, the CHP is gas CHP, while the boilers are wood and waste boilers. This indicates that NG or SNG is better used in CHP, while wood and waste are a more useful resources in boilers.

Finally, we see that at low slacks (1 and 2 %), the HT heat layer is mainly composed of a mix between CHP and boilers, with some direct_elec. However, when the slack hit 5% and 10%, the main part of the CHP (resp. the boiler) can be replaced by boiler (resp. CHP). This confirms what has been said in the mitigate CO_2 policy analysis : to be cost competitive, the HT heat layer must be a mix between mainly CHP and boiler, completed by direct_elec.

MGA applied to resources

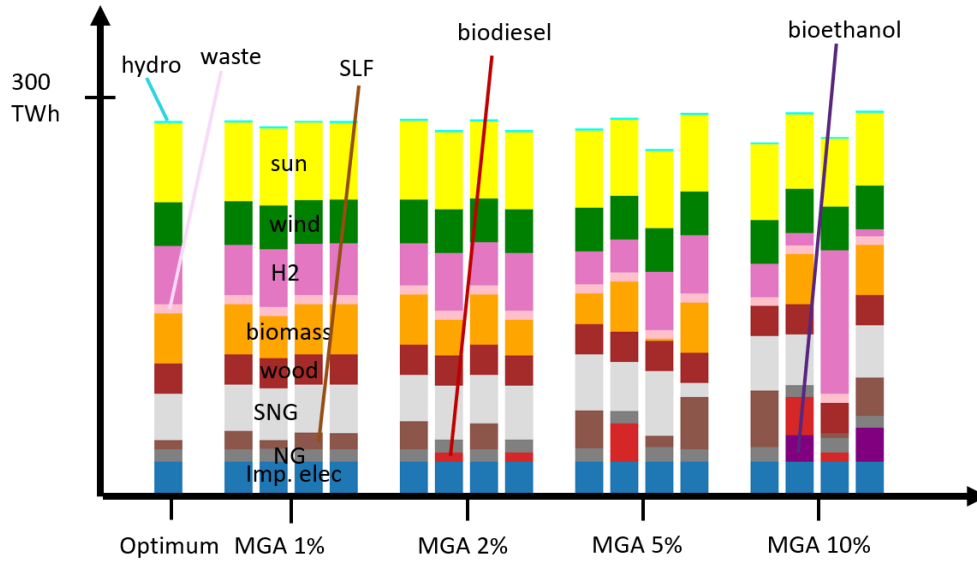


Figure 4.38: Results from applying MGA to the resources to the baggressive CO_2 policy scenario. Legend from bottom to top : imp. electricity (blue), bioethanol (dark purple), biodiesel (light red), NG (grey), SNG (brown), wood (dark red), wet biomass (orange), waste (light pink), H_2 (dark pink), wind (dark green), sun (yellow), hydro (turquoise). The y-axis is the energy over a year.

At a slack of 1%, only small variations in the resource occur. the SLF increase a bit at the expense of SNG.

However, at slack of 2%, we notice that biodiesel starts to be used. This biodiesel fully replaces SLF.

We see that, for 5% slack, the SLF or the biodiesel can increase. It is also interesting to notice that the third energy system has almost taken the biomass off, in favor of H_2 .

Finally, at slack of 10%, the bioethanol appears. We also notice that, at this slack, the H_2 can become the major resource.

We notice that, despite the fact that sun and wind are main resources, their penetration in the energy mix does not change during the runs. Indeed, these two resources are crucial for the cost of the system. The absence of the wind or the sun leads to an increase of respectively 17% and 22% of the system cost.

5 Discussion

In this section we will discuss the results from section 4. This discussion aims at underlying the important results, and give a further thought on it. The main limitations of our methods will be address and with them, the possible future work that could be done in order to overcome these limitations.

This sections will be divided into 4 subsections : the first three sections will discuss the results for each CO_2 policy, and the last section will discuss the limitations and the future work that could eventually be done.

5.1 Scenarios without emissions reduction policy

As explained in section 2.3, the coal and waste are used at 100% of their availability, while the wood is almost used at 90% in the HT heat layer of the optimal scenario. Considering the great level of uncertainty that apply to ESOM, the idea of an industry which relies on limited resources (i.e. coal wood and waste) for its heating needs and which availability does not offer large error margins (see section 2.3), could scare decision makers.

This is where the near-optimal solutions space analysis steps in to show that there is actually an alternative. While the optimal cost scenario does not include any CHP technologies, our results show that this technology could actually be a cost competitive alternative for many technologies used in the optimum. We have shown that CHP can easily (i.e. without a large cost increase) replace electrical and heating technologies such as CCGT, gas heat pumps and boilers.

Concerning the private mobility, the current trend is towards hybrid and electric vehicles. Our results however seem to indicate that the best cost-competitive technology are the fuel cell cars. Also we have seen that, in some suboptimums, hybrid vehicles can be a complementary solution even going high penetration with a higher total cost deviation, but it is far from being a complete cost competitive alternative.

Two more important insights have emerged from this analysis :

1. We have seen a strong negative correlation between PV panels and CO_2 emissions. While this information is quite obvious, the analysis also showed a strong correlation between PV panels and industrial heating with electricity. This means that decarbonizing the electricity layer by investing in PV panels must be accompanied by an investment in the direct electricity heat generation because this technology is going to be cost competitive when installing large amount of PV panels.
2. For the LT heat, there is an important negative correlation between electric heat pumps and the CO_2 emissions. This shows that, in the context of a reduction of the CO_2 emissions, investing in electric heat pumps will be crucial to decarbonize the LT heat layer.

5.2 Scenarios with mitigate emissions reduction policy

The three methods (LHS, exclusion and MGA) give the same trend : there are less possibilities for the energy system than in the case without CO_2 policy. This is particularly true for the electricity layer, where we noticed that, for low cost deviation (less than 2%), the only way to fulfill the demand is to set the renewable sources at their maximum potential, import the maximum electricity potential from neighbour countries, and complete the layer with CHP.

We have seen that, if for example the renewable potential of Belgium were overestimated, its best alternative is to replace the missing PV capacity with CHP and missing wind capacity with CCGT. However, we have also seen that these alternatives are not cheap and result in cost deviation of at least 5%.

Furthermore, as observed in figure 4.26, this mitigate scenario is strongly dependant on imported electricity. It implies that, if Belgium wants to decarbonate its energy system, it will be dependant on neighbour countries for its electricity supply.

While our analysis can give the best technologies to use and some alternatives, it can also indicate which technology not to use. For example, we have seen that the use of boilers in the LT heat layer usually comes with a large cost increase. In other words, Belgium should highly recommend the use of heat pumps instead of boilers for domestic heating.

5.3 Scenarios with aggressive emissions reduction policy

The case with an aggressive policy is in some way the continuation of what has been observed for the mitigate policy. The system is even more constrained and thus the electric layer, as for the mitigate policy, shows no alternatives.

For small cost deviations (1% to 2%), the HT and LT heat layers do not show any alternatives either.

While the LT heat layer was almost fully electric (electric HP) and the HT heat was mainly provided with gas, wood and waste, we have shown that, if the cost deviation increases, this electrification of the LT heat layer could move to the HT heat layer. Indeed, the electric heat pumps are replaced with gas heat pumps in the LT heat layer and this release of electricity is used in the HT heat layer with direct electricity generation. This variation is quite low for moderate cost deviation but becomes bigger when the cost deviation increases. This seems to indicate that, in the context of a decarbonization, the electrification of the LT heat layer must be the priority because electrifying the HT heat layer first is not the best solution from an economic point of view.

5.4 Limitations and future work

A first limitation of this kind of analysis is the different parameters used in the simulation that are subjectively chosen. Indeed, the slack for MGA, the technologies used for MGA, the number of technologies for LHS and exclusion methods, their range

of variation, etc are all parameters that are subjectively chosen by the user. These choices could result in a miss of getting new insights about the energy system. Our conclusion on the mitigate and aggressive policy is that there are no cost-competitive alternatives, but we can not be totally sure that we did not miss something. We could for example change the MGA objective function, the technologies used for LHS, etc and maybe get different results.

To go a step further, the user could for example perform sensitivity analysis on these parameters. It is also possible to target certain technologies in the MGA runs in order to find new scenarios.

Another limitation is the lack of flexibility of the MGA. Indeed, the objective function used here worked well when applied to the technologies energy production. However, we saw that when applied to the resources, it had a tendency to stay stuck at the same energy system. This means that, depending on the model you use, you should tune differently your objective function in order to get consistent results. This method is thus quite specific to only one model and cannot be easily used for many different models.

Finally, there is a real lack of information on the plausibility of the different alternative systems. The r criteria presented in equation 4.2 is mainly conditioned by the technologies used for the LHS or the exclusion methods, and does not give a real plausibility of the entire scenario. A future work could be to evaluate the plausibility of the different key alternative scenarios and classify them.

6 Conclusion

The new report of the Intergovernmental Panel on Climate Change (IPCC) on the climate change is clear : humanity, through its activity, largely influences the climate and the global warming is a real threat for our societies [3].

In this context, as energy infrastructures are often expansive and long-lived, there is a real need of models that can help the decision makers to plan for the long term the energy strategy of their country. However, these models aim at representing complex systems with many different engineering knowledge and different decision makers. These models are thus subject to lots of uncertainties.

These uncertainties are classified into two categories : parametric and structural. The former refers to uncertainties on empirical values of parameters of the model while the latter refer to the imperfect and incomplete nature of the set of equations describing the system.

Some studies try to take into account parametric uncertainties with sensitivity analysis, Monte-Carlo analysis or stochastic programming. However, these methods do not capture structural uncertainties and these uncertainties are often neglected in scientific literature.

The objective of this work was to address all type of uncertainties by using the model in an innovative way. Instead of considering only the optimized solution, this work considers the near cost optimal solutions space. Considering uncertainties, all these solutions could perfectly be the right candidate for a decision maker who is concerned with many unmodeled factors.

In order to obtain near optimal solutions, 3 methods have been developed :

1. LHS method
2. Exclusion zone method
3. MGA method

The two first are used to generate large sample of near optimal solutions. These sample are then used in statistical analysis to get new insights on the energy system and alternative energy systems that could be preferred to the optimum. The MGA method, for its part, does not generate large sample of solutions but rather a small set of near optimal solutions with a maximum difference in the decision space.

These two approaches have been confronted and the main results are very similar. Moreover, one approach could sometimes provide insights that were not accessible in the other approach. This was often the case with the correlation matrix.

We have shown in section 5.1 that the cost optimal solution, without CO_2 policy, could actually be a bad choice for the industrial heating. However, a very cost competitive alternative exists in the cogeneration units. This result is validated by both approaches and illustrates the great potential in exploring the near optimal solutions space.

Our analysis have also shown that the private mobility should strongly develop fuel

cell cars, and that the second alternative could lie in the hybrid electric car. However, if possible, all private mobility should focus only on fuel cell cars, as hybrid electric cars are positively correlated with the total cost of the system (see figure 4.8).

Interesting insights have also emerged from our results : we have seen that a decarbonization of the electricity layer by installing PV panels had to be accompanied with development of direct electricity heating for industries, we have also seen that the decarbonization of the LT heat layer has to be done with the development of electric heat pumps.

Some technologies on the other hand gave us bad results in terms of cost variation : the boilers used for the domestic heating (LT heat) seems to be a bad choice compared to heat pumps. The electrification of the domestic heating should take priority over the electrification of the industrial heating in the context of a cost competitive decarbonization.

While there were clear cost competitive alternatives for the optimal cost scenario without CO_2 policy, it is difficult to imagine that Belgium in its near future is not going to fix strong objectives of CO_2 emissions reduction. Our results showed us that the decarbonization of the Belgian energy system decreases the cost competitive alternatives. We have shown for example that, in a mitigate or aggressive policy, the electricity layer had absolutely no cost competitive alternatives. Moreover, Belgium will depend on neighbour countries to fulfill a non negligible part of its electricity demand. However, the actual situation about nuclear power is still subject to discussion and a new analysis with a part of nuclear production could be considered.

All these analysis use ESTD as a tool to provide insights, but not to provide a perfect forecast of which energy system Belgium should reach. It is important to insist on the fact that ESOM in general are not and will never be perfect forecasters. They are much better used as a tool to provide insights to analysts in order to better apprehend the complexity of energy systems. ESOM used as a forecaster could mislead decision makers and the result on the energy system could be problematic, considering the high level of uncertainties that affect these models.

This work is just the beginning of a work that energy analysts should provide to decision makers. These analysis can for example be improved with parametric studies. Moreover, we have seen that changing for example the MGA objective function could lead to different results. In this work we have not targeted any specific technologies but it could be interesting to adapt the MGA objective function in order to reach different scenarios with new technologies.

The near optimal solutions space still has a huge potential for further analysis. For example, it is possible to define relevant metrics, based on the near-optimal solutions, to quantify the cost robustness of one optimum. This has been done in Annex section A.4 for 5 optimums with different CO_2 emissions limit. The conclusion is similar to the one obtained in section 4. The cost robustness metric R decreases when the CO_2 emissions limit decreases. This indicates less cost competitive alternatives, as said earlier.

Finally, the three methods developed in this work are functional and useful to give new

insights in the complexity of ESTD solutions. All the codes used for our simulations are available at : github.com/andevresse/Master-thesis.

A Appendix

A.1 EnergyScope TD

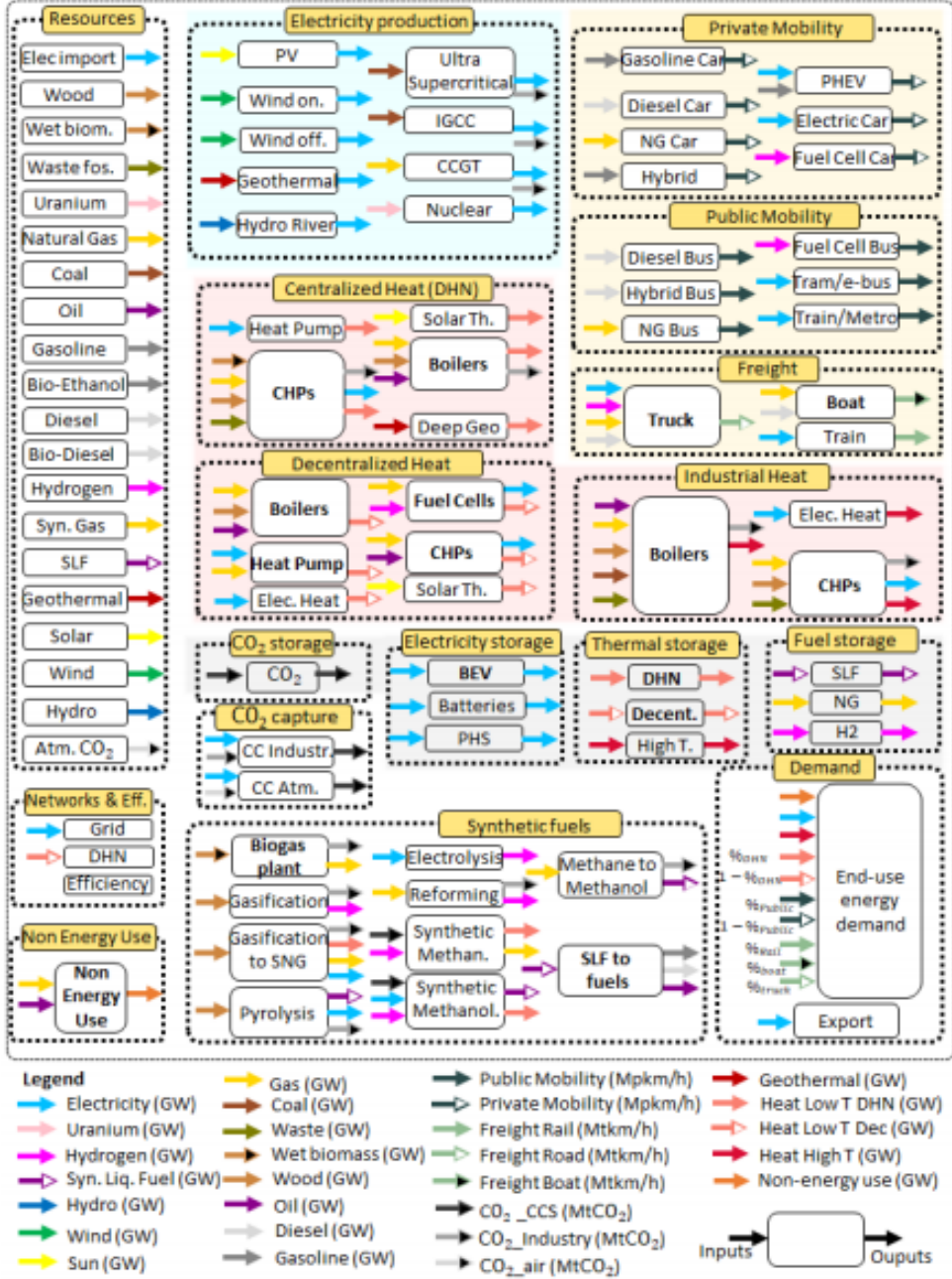


Figure A.1: Overview of the different technologies, resources and demands implemented in ESTD. Technologies in **bold** represent technologies with different energy inputs (e.g. oil boilers, coal boilers, etc). "Decent" represents the thermal storage for each decentralised heat production technology. Abbreviations : synthetic liquid fuel (SLF), Atm (atmospheric), hydrogen (H_2), photovoltaic (PV), integrated gasification combined cycle (IGCC), combined cycle gas turbine (CCGT), carbon capture and storage (CCS), cogeneration of heat and power (CHP), heat pump (HP), natural gas (NG), plug-in hybrid electric vehicle (PHEV), district heating network (DHN), battery electric vehicle (BEV), pumped hydro storage (PHS), power to gas (PtG), carbon capture (CC), methan. (methanisation), onshore (on.), offshore (off.), decentralised (decent.)

	Name	Description
Ind. var.	Share_mobility_public	Ratio [0; 1] public mobility over total passenger mobility
	Share_freight_train	Ratio [0; 1] rail transport over total freight transport
	Share_freight_road	Ratio [0; 1] Truck transport over total freight transport
	Share_freight_boat	Ratio [0; 1] boat transport over total freight transport
	Share_heat_dhn	Ratio [0; 1] centralized over total low-temperature heat
	F	Installed capacity
	F_t	Operation in each period
	Storage_in	Power input to the storage in a certain period
	Storage_out	Power output from the storage in a certain period
	Power_nuclear	Constant load of nuclear
	Shares_mobility_passenger	Constant share of passenger mobility
	Shares_mobility_freight	Constant share of freight mobility
	Shares_lowT_dec	Constant share of heat Low T decentralised
	F_solar	Solar thermal installed capacity per heat decentralised technologies
	F_t_solar	Solar thermal operating per heat decentralised technologies
Dep. var.	End_uses	total demand for each type of end-uses (hourly power)
	TotalCost	Total cost of the system
	C_inv	Total investment cost of each technology
	C_maint	Total O&M cost of each technology (excluding resource cost)
	C_op	Total O&M cost of each resource
	TotalGWP	Total global warming potential (GWP) emissions in the system
	GWP_constr	Total emissions of the technologies
	GWP_op	Total yearly emissions of the resources
	Network_losses	Losses in the networks (normally electricity grid and DHN)
	Storage_level	Energy stored at each period

Table A.1: 25 type of variables in ESTD. Ind. var. is independant variables and Dep. var. is dependant variables.

Resources		availability [TWh]	Emissions [$ktCO_{2eq}/GWh$]	Op. cost [$M\text{€}/MWh_{fuel}$]
Gasoline	Fossil	∞	0.3448	82.4
Diesel		∞	0.3148	79.7
LFO		∞	0.3115	60.1
NG		∞	0.2666	41.5
Coal		∞	0.4014	17.6
Elec. import	others	27.5	0.2065	84.3
Uranium		∞	0.0039	3.9
Waste		17.8	0.1501	20
Wood	Renew	23.4	0.0118	32.8
Wet biomass		38.9	0.0118	5.8
Wind		∞	0	0
Solar PV		∞	0	0
Hydro		∞	0	0
Geothermal		∞	0	0
Bio-ethanol		∞	0	225.7
Bio-diesel		∞	0	240
Hydrogen		∞	0	177.1
SNG		∞	0	197.1
SLF		∞	0	211.4

Table A.2: Resources parameters for the reference energy system

param:	c_{inv}	c_{maint}	gwp_{constr}	$lifetime$	c_p
NUCLEAR	4845.73462	102.930986	707.88	60	0.849
CCGT	771.99176	19.5520259	183.79	25	0.96153846
COAL_US	2516.70568	29.383767	331.6	35	0.868
COAL_IGCC	3245.80953	48.4202238	331.6	35	0.856
PV	870	9.93546687	2081.43	25	1
WIND_ONSHORE	1040	2.83442308	622.85	30	1
WIND_OFFSHORE	4974.63394	9.57379518	622.85	30	1
HYDRO_RIVER	5044.91994	50.4447982	1262.82	40	1
GEOHERMAL	7488	139.1104	24929.09	30	0.95
IND_COGEN_GAS	1408.03446	90.5068571	1024.32	25	0.85
IND_COGEN_WOOD	1080.79408	39.5704399	165.33	25	0.85
IND_COGEN_WASTE	2927.86778	107.936516	647.82	25	0.85
IND_BOILER_GAS	58.891282	1.17988576	12.32	17	0.95
IND_BOILER_WOOD	115.179324	2.30358648	28.87	17	0.9
IND_BOILER_OIL	54.8553235	1.17988576	12.32	17	0.95
IND_BOILER_COAL	115.179324	2.30358648	48.18	17	0.9
IND_BOILER_WASTE	115.179324	2.30358648	28.87	17	0.9
IND_DIRECT_ELEC	332.343852	1.5076318	1.47	15	0.95
DHN_HP_ELEC	344.760745	11.6905347	174.79	25	0.95
DHN_COGEN_GAS	1254.49012	36.6786131	490.88	25	0.85
DHN_COGEN_WOOD	1080.79408	39.5704399	165.33	25	0.85
DHN_COGEN_WASTE	2927.86778	107.936516	647.82	25	0.85
DHN_COGEN_WET_BIOMASS	1374.44386	111.858244	1024	25	0.75
DHN_COGEN_BIO_HYDROLYSIS	4536.89973	221.689419	647.8	15	0.85
DHN_BOILER_GAS	58.891282	1.17988576	12.32	17	0.95
DHN_BOILER_WOOD	115.179324	2.30358648	28.87	17	0.9
DHN_BOILER_OIL	54.8553235	1.17988576	12.32	17	0.95
DHN_DEEP_GEO	1500	56.2011765	808.76	30	0.85
DHN_SOLAR	362	0.42698611	221.22	30	1
DEC_HP_ELEC	492.040453	20.5154739	164.89	18	1
DEC_THHP_GAS	315.684989	9.22648759	381.93	20	1
DEC_COGEN_GAS	1408.03446	90.5068571	1024.32	20	1
DEC_COGEN_OIL	1305.56232	80.1017715	1024.32	20	1
DEC_ADVCOGEN_GAS	7242.27924	134.969226	2193.45	20	1
DEC_ADVCOGEN_H2	7242.27924	134.969226	2193.45	20	1
DEC_BOILER_GAS	158.535443	4.75699972	21.09	17	1
DEC_BOILER_WOOD	462.440303	16.1812904	21.09	17	1
DEC_BOILER_OIL	142.382246	8.54012548	21.09	17	1
DEC_SOLAR	719.07482	7.97827512	221.22	20	1
DEC_DIRECT_ELEC	39.9756532	0.17474215	1.47	15	1
TRAMWAY_TROLLEY	625	12.5	0	30	0.34246575
BUS_COACH_DIESEL	611.111111	30.5555556	0	15	0.29680365
BUS_COACH_HYDIESEL	833.333333	33.3333333	0	15	0.29680365
BUS_COACH_CNG_STOICH	611.111111	30.5555556	0	15	0.29680365

Table A.3: EnergyScope TD all technologies parameters. c_{inv} is the annual investment cost, c_{maint} is the annual maintenance cost, gwp_{constr} is the global warming potential for the infrastructure construction and c_p is the maximal performance coefficient (part1).

param :	c_{inv}	c_{maint}	gwp_{constr}	$lifetime$	c_p
BUS_COACH_FC_HYBRIDH2	1041.66667	31.25	0	15	0.29680365
TRAIN_PUB	1506.0241	54.3527493	0	40	0.27507289
CAR_GASOLINE	420.286358	13.7975247	342	10	0.05136986
CAR_DIESEL	434.453584	14.7048704	346	10	0.05136986
CAR_NG	429.375804	17.8185491	342	10	0.05136986
CAR_HEV	429.411554	8.97736817	519	10	0.05136986
CAR_PHEV	456.367081	9.50498939	519	10	0.05136986
CAR_BEV	449.824825	6.86853663	385	10	0.05136986
CAR_FUEL_CELL	434.77406	2.6878298	786	10	0.05136986
TRAIN_FREIGHT	104.415584	2.08831169	0	40	0.34246575
BOAT_FREIGHT_DIESEL	76.3888889	3.81944444	0	40	0.11415525
BOAT_FREIGHT_NG	76.3888889	3.81944444	0	40	0.11415525
TRUCK_DIESEL	371.111111	18.5555556	0	15	0.09259259
TRUCK_FUEL_CELL	402.222222	12.0666667	0	15	0.09259259
TRUCK_ELEC	771.111111	23.1333333	0	15	0.09259259
TRUCK_NG	371.111111	18.5555556	0	15	0.09259259
NON_ENERGY_OIL	0	0	0	1	1
NON_ENERGY_NG	0	0	0	1	1
EFFICIENCY	3200	0	0	1	1
DHN	825.882573	0	0	60	1
GRID	74919.0636	0	0	80	1
MOTORWAYS	339	11.865	0	60	1
ROADS	2800	98	0	60	1
RAILWAYS	1780	62.3	0	60	1
H2_ELECTROLYSIS	696.202532	19.1455696	0	15	0.9
H2_NG	681.243562	62.8658412	0	25	0.86
H2_BIOMASS	2525.38627	177.910768	0	25	0.86
GASIFICATION_SNG	2743.8056	137.751662	0	25	0.85
PYROLYSIS	1344.21762	61.0969703	0	25	0.85
ATM_CCS	5160	128.088	0	40	1
INDUSTRY_CCS	2580	64.044	0	40	1
SYN_METHANOLATION	1679.65165	47.6648671	0	20	0.95
SYN_METHANATION	262.196835	66.9927632	0	40	1
BIOMETHANATION	986.047383	13.6590909	0	20	0.85
BIO_HYDROLYSIS	1591.90936	108.53745	0	15	0.85
METHANE_TO_METHANOL	958.582264	41.9152035	0	25	0.85
SLF_TO_DIESEL	0	0	0	1	1
SLF_TO_GASOLINE	0	0	0	1	1
SLF_TO_LFO	0	0	0	1	1
BATT_LI	302	0.46689884	61.3	15	1
BEV_BATT	0	0	0	1	1
PHEV_BATT	0	0	0	1	1
PHS	58.8	0	8.33	50	1

Table A.4: EnergyScope TD all technologies parameters. c_{inv} is the annual investment cost, c_{maint} is the annual maintenance cost, gwp_{constr} is the global warming potential for the infrastructure construction and c_p is the maximal performance coefficient (part2).

param :	c_{inv}	c_{maint}	gwp_{constr}	$lifetime$	c_p
TS_DEC_DIRECT_ELEC	18.9718138	0.1328027	0	20	1
TS_DEC_HP_ELEC	18.9718138	0.1328027	0	20	1
TS_DEC_THHP_GAS	18.9718138	0.1328027	0	20	1
TS_DEC_COGEN_GAS	18.9718138	0.1328027	0	20	1
TS_DEC_COGEN_OIL	18.9718138	0.1328027	0	20	1
TS_DEC_ADVCOGEN_GAS	18.9718138	0.1328027	0	20	1
TS_DEC_ADVCOGEN_H2	18.9718138	0.1328027	0	20	1
TS_DEC_BOILER_GAS	18.9718138	0.1328027	0	20	1
TS_DEC_BOILER_WOOD	18.9718138	0.1328027	0	20	1
TS_DEC_BOILER_OIL	18.9718138	0.1328027	0	20	1
TS_DHN_DAILY	3	0.0086	0	40	1
TS_DHN_SEASONAL	0.54	0.00295833	0	25	1
TS_HIGH_TEMP	28.03	0.3	0	25	1
SEASONAL_NG	0.051158	0.00130916	0	50	1
SEASONAL_H2	6.19	0.39	0	20	1
CO2_STORAGE	49.5	0.495	0	30	1
SLF_STO	0.00635	0.000397	0	20	1

Table A.5: EnergyScope TD all technologies parameters. c_{inv} is the annual investment cost, c_{maint} is the annual maintenance cost, gwp_{constr} is the global warming potential for the infrastructure construction and c_p is the maximal performance coefficient (end).

A.2 Implementation of the LHS method

EnergyScope TD runs thanks to a .run file which consists of all commands one after the other. This file loads the model data and constraints, and asks to AMPL [29] to solve the LP problem.

The idea of the LHS method is to first generate the constraints, and then modify the .run file to add the constraints directly in it.

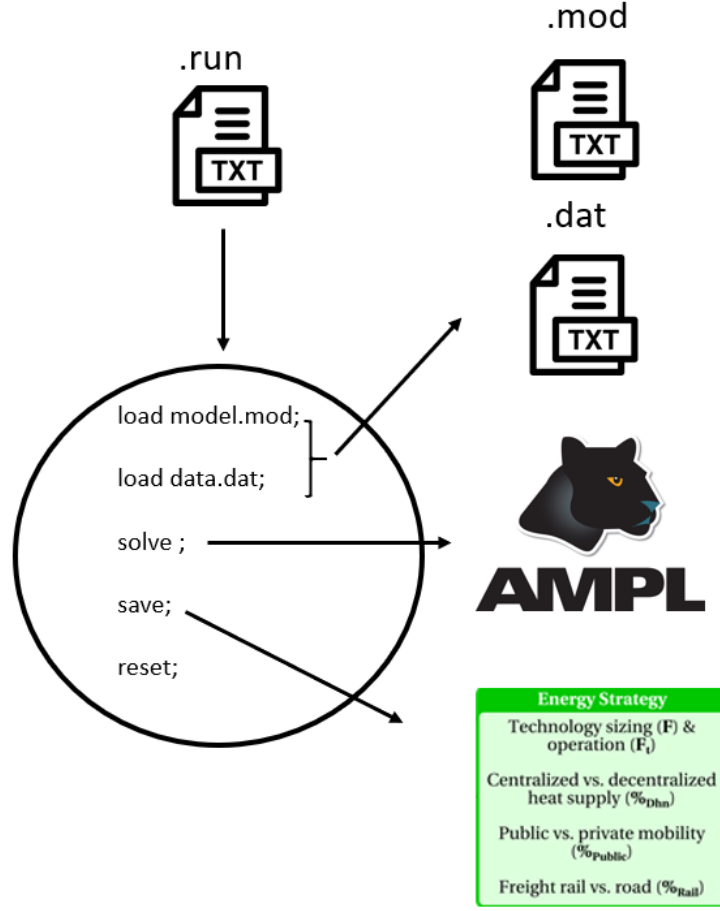


Figure A.2: Working principle of EnergyScope TD. First, the model and the data are loaded, then a solver (AMPL) is called to solve the LP problem. Finally, the output is saved and the model is reset to load the next one

Generation of the constraints

To generate the constraints, a first script called LHS_space.py will generate the n -space described in section 2. This script chooses the technology used for LHS, then it creates an empty n -space with the upper and lower bounds of equations 3.1 & 3.2 and then fills it using LHS. All the values assigned to each technology chosen for the LHS are then stocked in an array of dimensions $n_{tech} \times n_{sub}$.

A second script, called Write_Constraints.py, will copy the reference .run file, add the constraint for each technology of the i^{th} suboptimum of the array and repeat for every

suboptimums of the array.

The modified .run file is a huge file where all instructions to generate each suboptimum of the array are included.

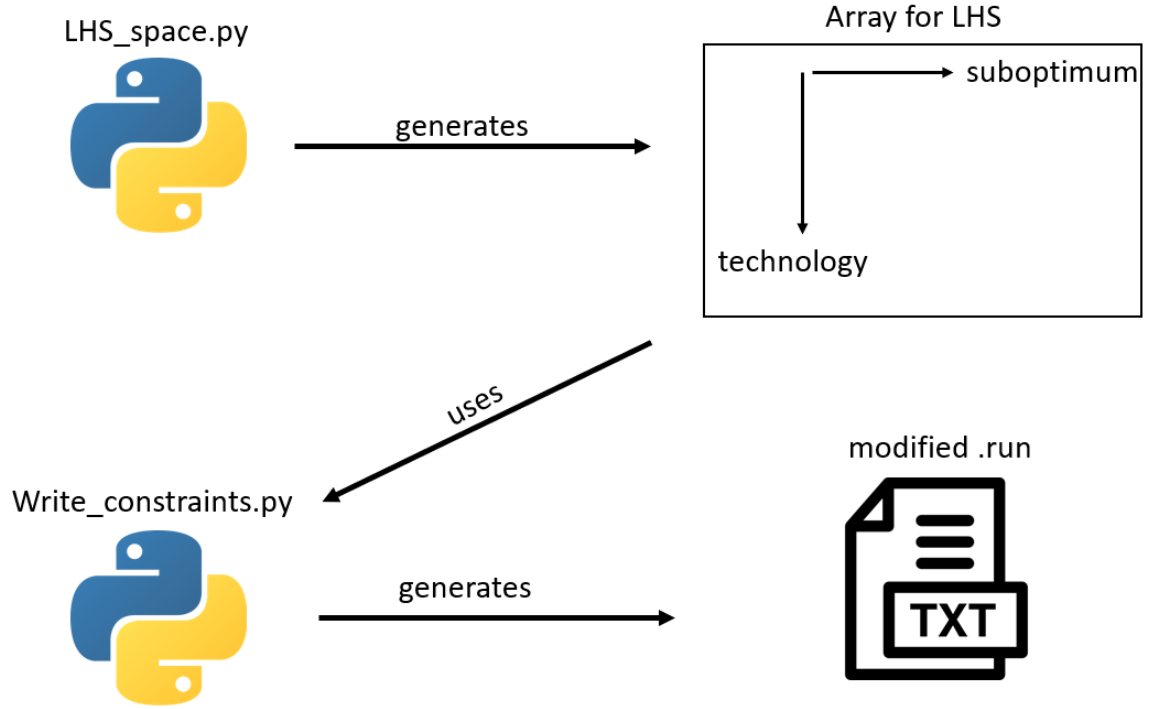


Figure A.3: Implementation of the LHS method

A.3 Implementation of the MGA method

In this section we describe with more details the implementation of the MGA method. As said in section 2, two different objective functions have been implemented. The first one, from [27], is a weighted sum of all previous decision variables that appeared in the previous solutions (the optimum and the MGA runs).

The second one is based on Manhattan distances [35] and states that the distance between the actual MGA run decision variables and all previous solutions must be maximized. This one is far more computationally complex. Indeed, as we have to maximize the absolute value of a variable, it requires to add 4 constraints for each iteration, with a binary variable [34]. It thus divides each problem in 2 different subproblems and lead to a greater computational cost. This is why this method has

only been tested on the resources and not the technologies activities. There are way too many technologies to achieve a simulation like that. Here below we explain with more details the implementation of these two methods.

Implementation of the MGA method from [27]

First, the optimum is computed with ESTD. After that, the script "main.py" calls the script "Write_mod.py" and this script computes the weights based on the optimum and returns it to the main. The script Write_mod.py also modifies the ESTD model in order to add the new objective function (based on the weights it has computed) and the new constraints (based on the total cost of the system and the slack). Then the script "main.py" calls Amplide to solve the new model from ESTD, and this is iterated 4 times. It is important to notice that the weights are not refreshed at each iteration, they stay the same (saved in the main script) and the script "Write_mod.py" modifies them in order to take into account the last solution given by ESTD. This explanation is schematized in figure A.4 and each step is numbered.

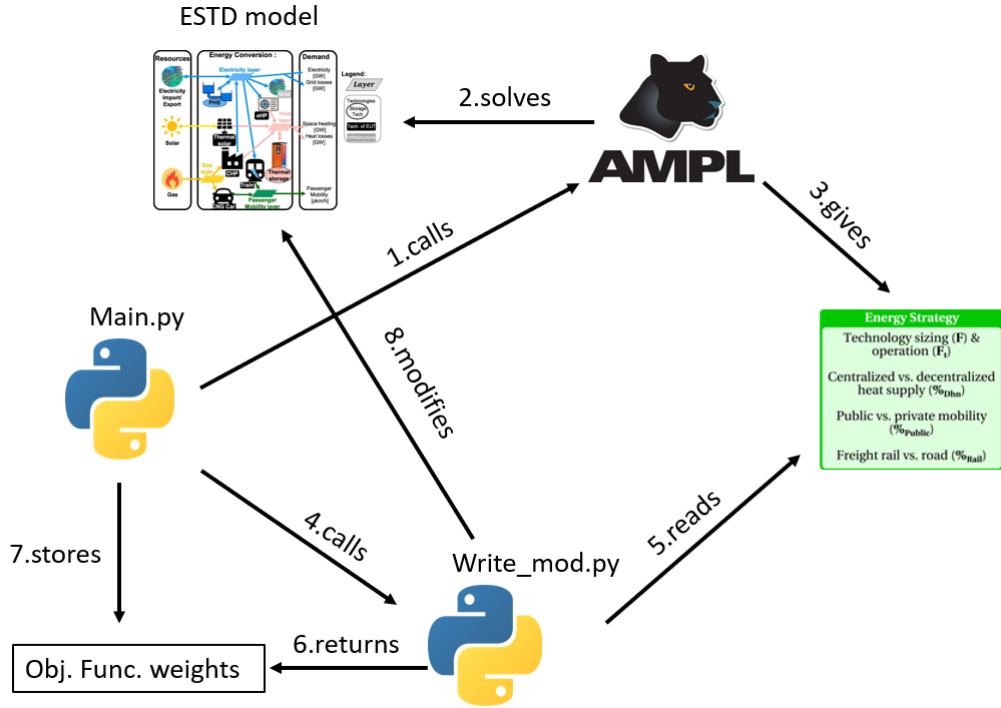


Figure A.4: Schematic of the implementation of the first MGA method from [27] in ESTD

Implementation of the MGA method from [28]

The implementation here is almost the same than the previous one, except that there is no need to compute and return any weights (the objective function does not have any weights) and the script `Write_mod.py` also modifies the `.dat` file from ESTD. The `.dat` file is a data file in ESTD where all numerical values of the parameters are memorized. As the objective function from [28] has all the previous solutions decisions variables in it, we decided to write these solutions in a parameter. This parameters is called `A.i[resource]` where `i` is the `i`th iteration and `resource` is one resource from the ESTD resources set (see A.2).

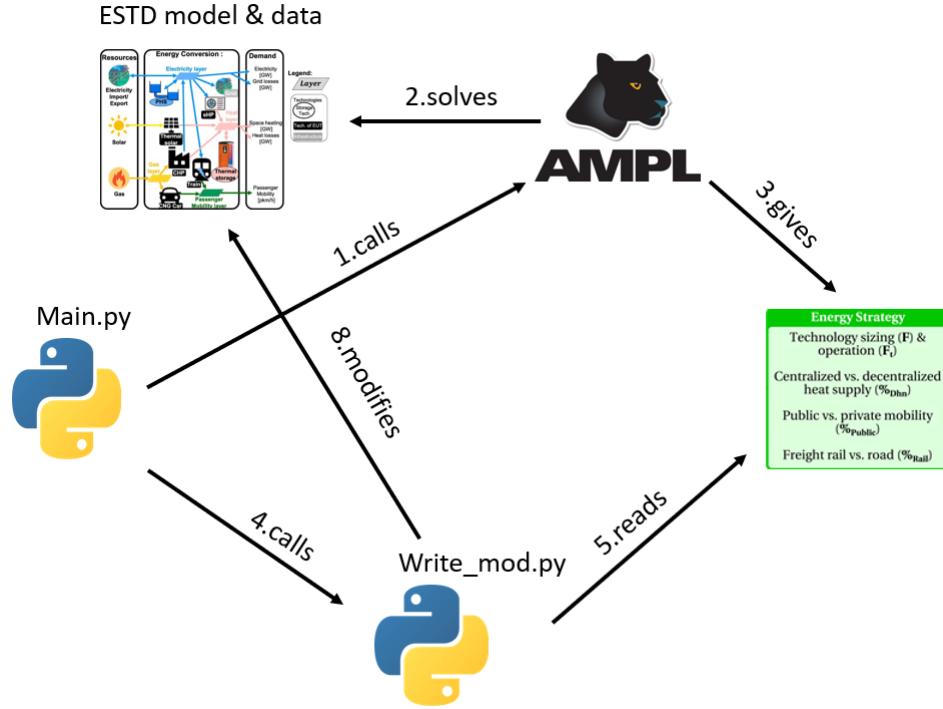


Figure A.5: Schematic of the implementation of the second MGA method from [28] in ESTD

A.4 The cost robustness metric R

First, we define the annual total cost of an energy system. The total cost of an energy system will be the sum for each technology of 3 contributions :

- The total investment cost of the technology C_{inv} , related to the sizing of the technology (F)

- The total operation cost of the technology C_{op} , related to the hourly operation of the technology ($\mathbf{F}_t$)
- The total maintenance cost of the technology C_{maint} , related to the hourly operation of the technology ($\mathbf{F}_t$)

We have thus for the total annual cost of an energy system

$$C_{tot} = \sum_{i=1}^{n_{tech}} \left(C_{inv,i} + C_{op,i} + C_{maint,i} \right) = \sum_{i=1}^{n_{tech}} C_i \quad (\text{A.1})$$

where $C_i = C_{inv,i} + C_{op,i} + C_{maint,i}$ is the total cost of the i -th technology and n_{tech} is the number of technologies (here we have $n_{tech} = 128$).

The costs difference between a suboptimum and an optimum will thus be

$$\Delta C = C_{tot,sub} - C_{tot,opt} = \sum_{i=1}^{n_{tech}} \left(C_{sub,i} - C_{opt,i} \right) \quad (\text{A.2})$$

Notice that ΔC , as defined here, will always be positive as a suboptimum will always have a higher cost than the optimum.

$$\Delta C \geq 0 \quad (\text{A.3})$$

Secondly, we need a variable to quantify how far a suboptimum is from the optimum. We define the transition cost C_T , which is an estimation of the real transition cost between the 2 systems, as :

$$C_T = \sum_{i=1}^{n_{tech}} \left(\max(C_{inv,sub,i} - C_{inv,opt,i}; 0) + (C_{maint,sub,i} - C_{maint,opt,i}) + (C_{op,sub,i} - C_{op,opt,i}) \right) \quad (\text{A.4})$$

C_T corresponds to the sum, for each technology, of 3 terms :

1. The first term is the maximum between the difference of investment costs between the 2 systems, and 0. Indeed, if the suboptimum has a higher installed capacity on a technology, then the transition of investment is 0 as it can just lower the production of the technology. **mieux écrire ça**
2. The second term is the difference between the maintenance costs
3. The last term is the difference between the operational costs

From equations A.2 & A.4, we understand that C_T is an upper bound for ΔC .

$$0 \leq \Delta C \leq C_T \quad (\text{A.5})$$

This upper bound is shown in figure A.6 as an illustration.

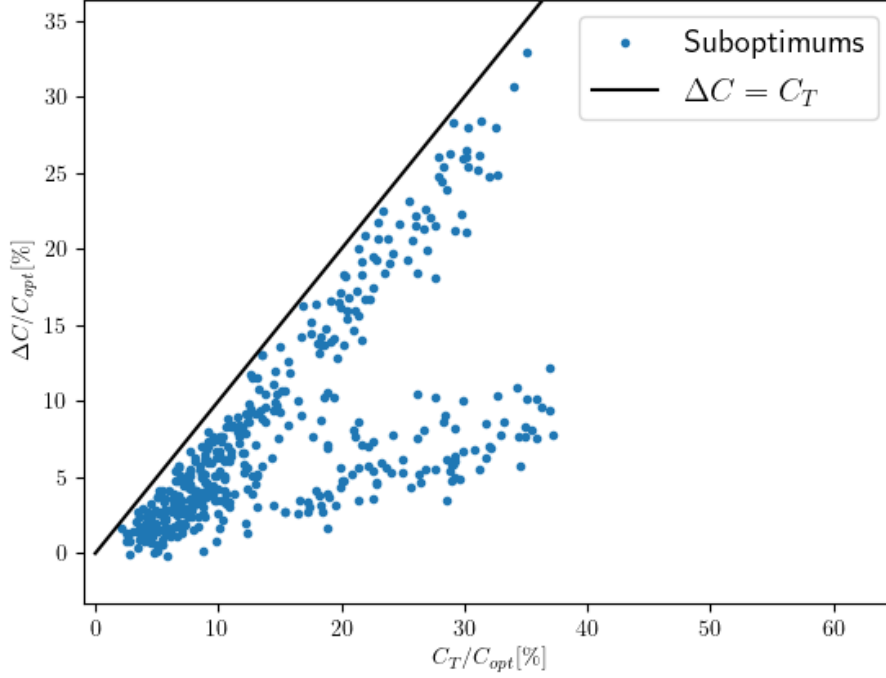


Figure A.6: Illustration of the theoretical limit between ΔC and C_T . Blue points are 500 suboptimums generated with the LHS method. Dark line is the theoretical limit from equation A.5. C_{opt} is the optimal cost. C_T and ΔC are expressed as relative variations compared to C_{opt} .

This upper bound is useful to quantify the robustness of an optimum. For each suboptimum different than the optimum ($C_T \neq 0$), there are 2 extreme cases corresponding to equations A.3 & A.5 :

1. $\Delta C = 0$ means that every cost variation in C_T has been handled perfectly and the total cost is the same than the optimum
2. $\Delta C = C_T$ means that all technologies have a higher investment cost in the suboptimum. This means that, despite the increase of some technologies capacities, ESTD could not decrease others.

Intuitively, the first case corresponds to optimum cost robustness while second case corresponds to optimum cost weakness.

From these 2 extreme cases, we define a variable R that will be bounded between 0

and 1 :

$$R = 1 - \frac{\Delta C}{C_T} \quad (\text{A.6})$$

Thus, $R = 0$ corresponds to the case $\Delta C = C_T$ (weak) and $R = 1$ corresponds to the case $\Delta C = 0$ (robust)

Generating lots of suboptimums around an optimum and computing R for each one allows to define the cost robustness of the optimum :

$$\text{Robustness} = \sum_{i=1}^{n_{sub}} \frac{R_i}{n_{sub}} \quad (\text{A.7})$$

The cost robustness of an optimum is simply the mean of R for all suboptimums around it.

The results for 5 optimums with different CO_2 emissions limit are shown in figure A.7. We see that the cost robustness increases when the GWP limit increases. This confirms what has been observed in section 4.

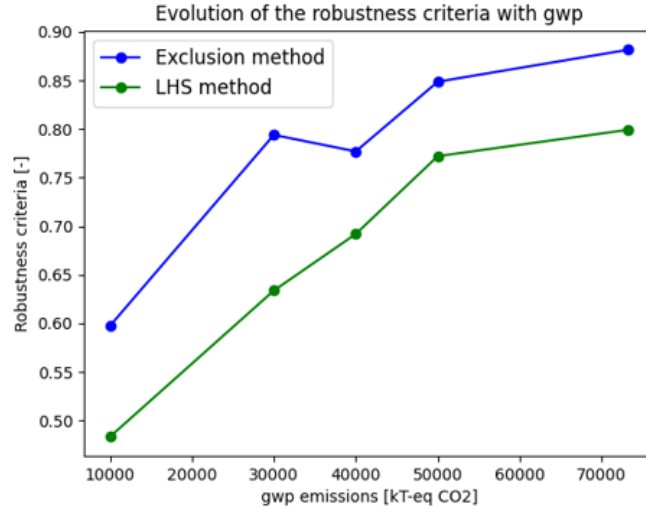


Figure A.7: Evolution of the R metrics with the CO_2 emissions limit for LHS and exclusion methods. 1500 (1000 for the LHS and 500 for the near optimal solutions) have been used for every cost-optimal scenarios

A.5 Sankey diagram

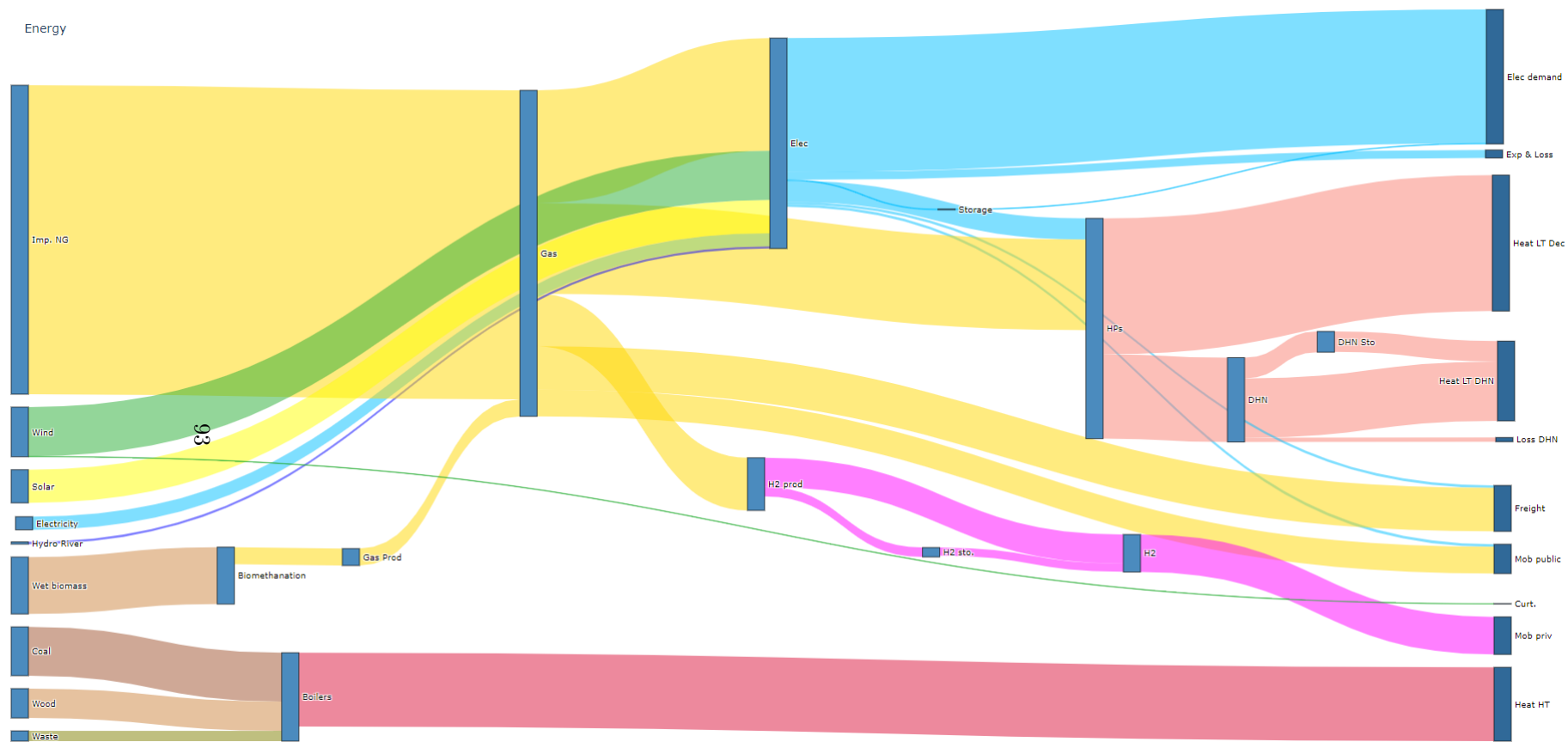


Figure A.8: Sankey diagram : energy flows in a scenario representing the cost optimal Belgian energy system in 2035, without CO_2 policy. Left side gathers all the resources and right side gathers the final energy consumption. In between, the conversion technologies are aggregated by families. Abbreviations: mobility (mob), private (priv), exports and losses (Exp & Loss), natural gas (NG), hydrogen (H2), storage (sto.), cogeneration of heat and power (CHP), electricity (Elec), heat pump (HP), district heating network (DHN), low temperature (LT), high temperature (HT).

Energy

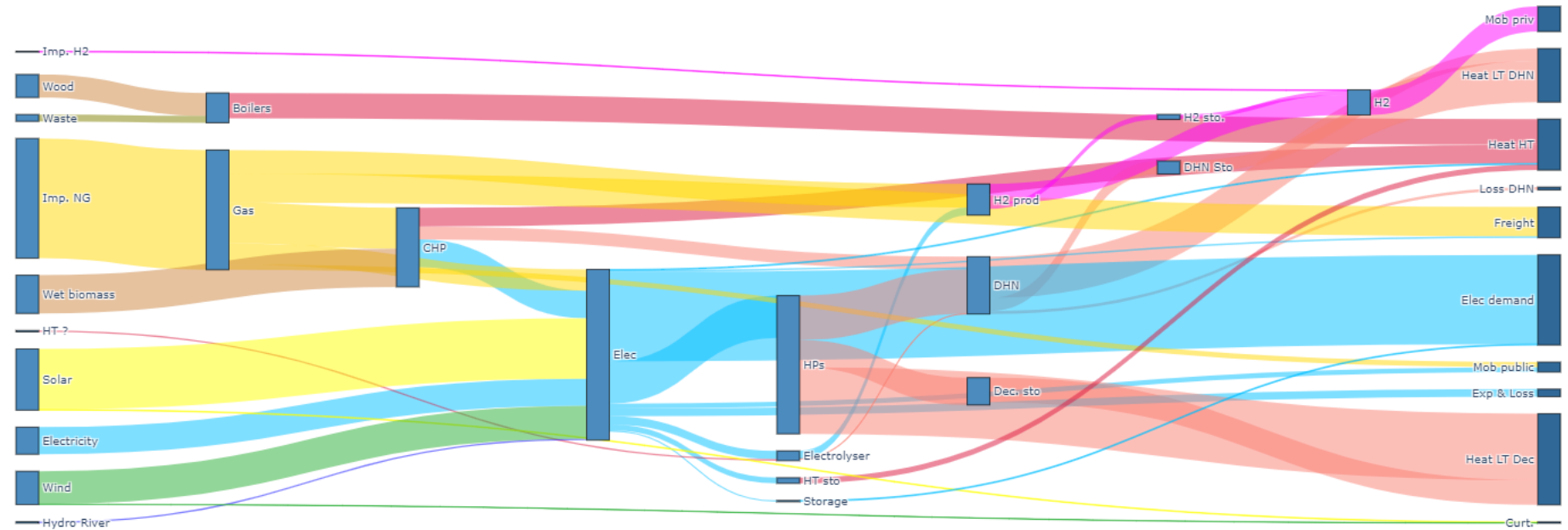


Figure A.9: Sankey diagram : energy flows in a scenario representing the cost optimal Belgian energy system in 2035 with an emission limit of 40MT of CO_2 equivalent. Left side gathers all the resources and right side gathers the final energy consumption. In between, the conversion technologies are aggregated by families. Abbreviations: mobility (mob), private (priv), exports and losses (Exp & Loss), natural gas (NG), hydrogen (H2), storage (sto.), cogeneration of heat and power (CHP), electricity (Elec), heat pump (HP), district heating network (DHN), low temperature (LT), high temperature (HT).

Energy

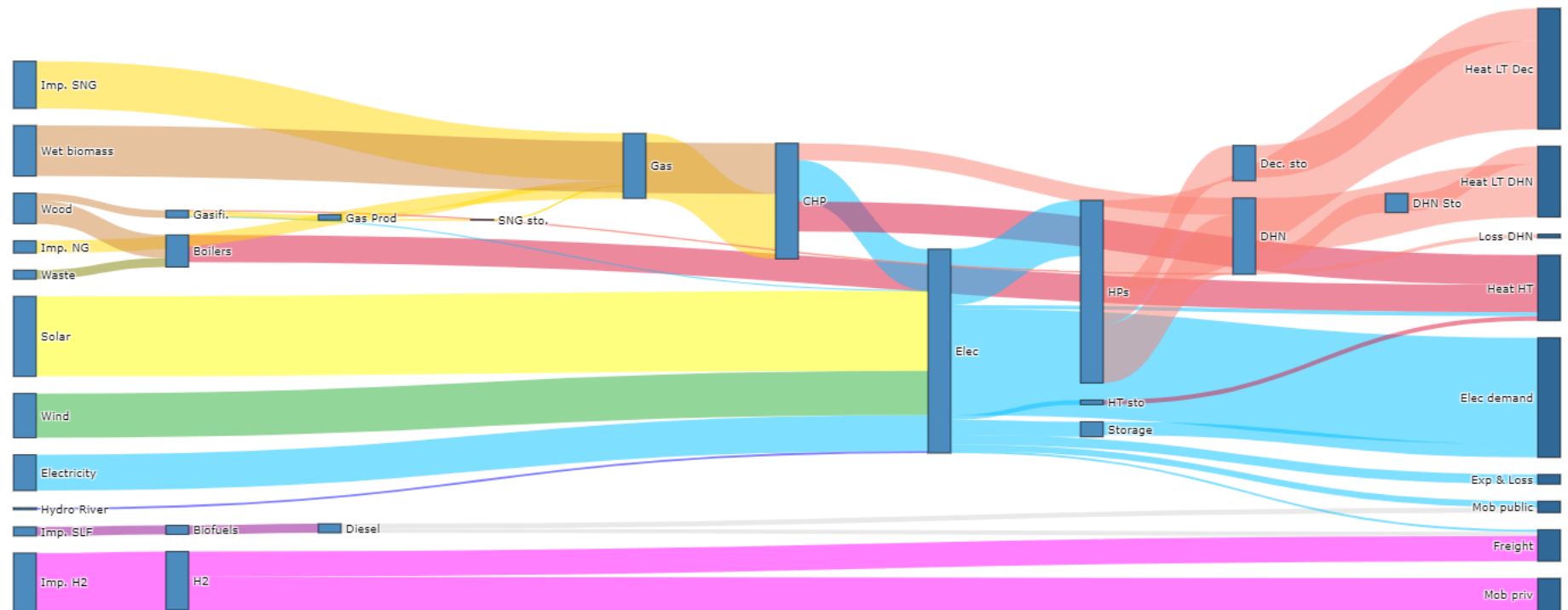


Figure A.10: Sankey diagram : energy flows in a scenario representing the Belgian energy system in 2035 with an emission limit of 10MT of CO_2 equivalent. Left side gathers all the resources and right side gathers the final energy consumption. In between, the conversion technologies are aggregated by families. Abbreviations: mobility (mob), private (priv), exports and losses (Exp & Loss), natural gas (NG), hydrogen (H2), storage (sto.), cogeneration of heat and power (CHP), electricity (Elec), heat pump (HP), district heating network (DHN), low temperature (LT), high temperature (HT).

Energy

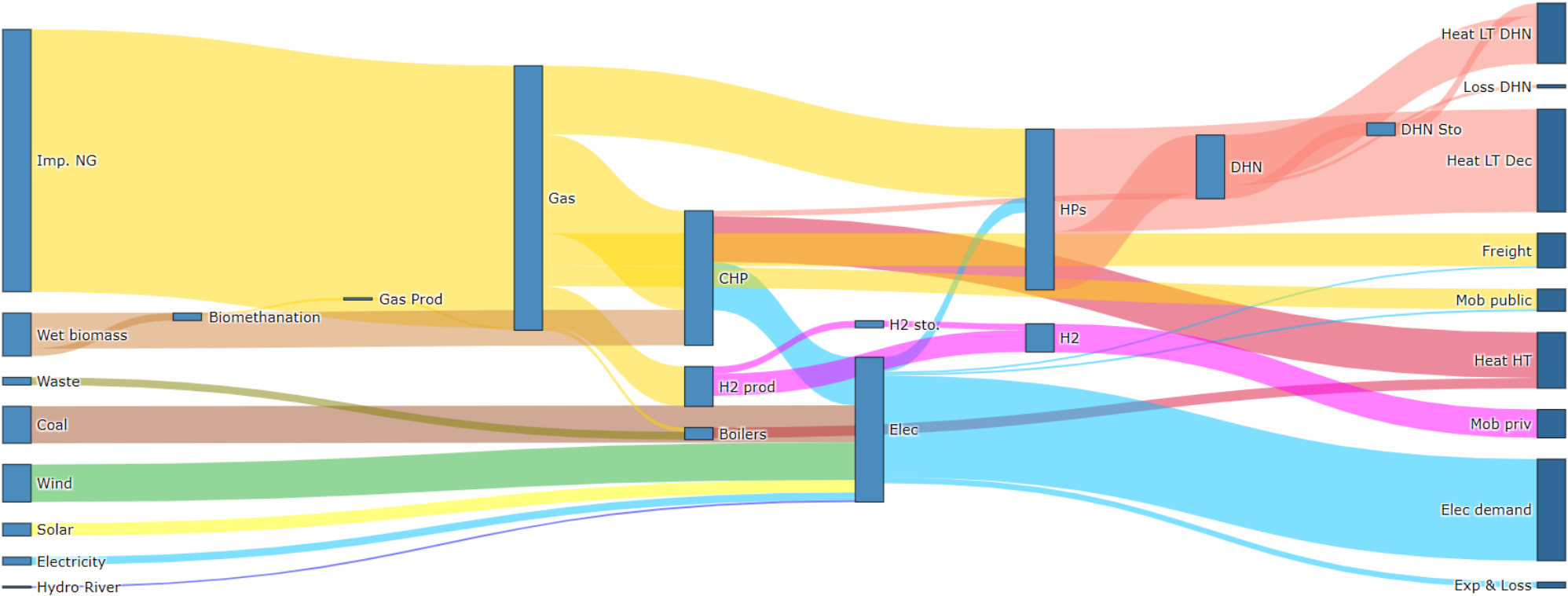


Figure A.11: Sankey diagram of the MGA-2-1% energy system.

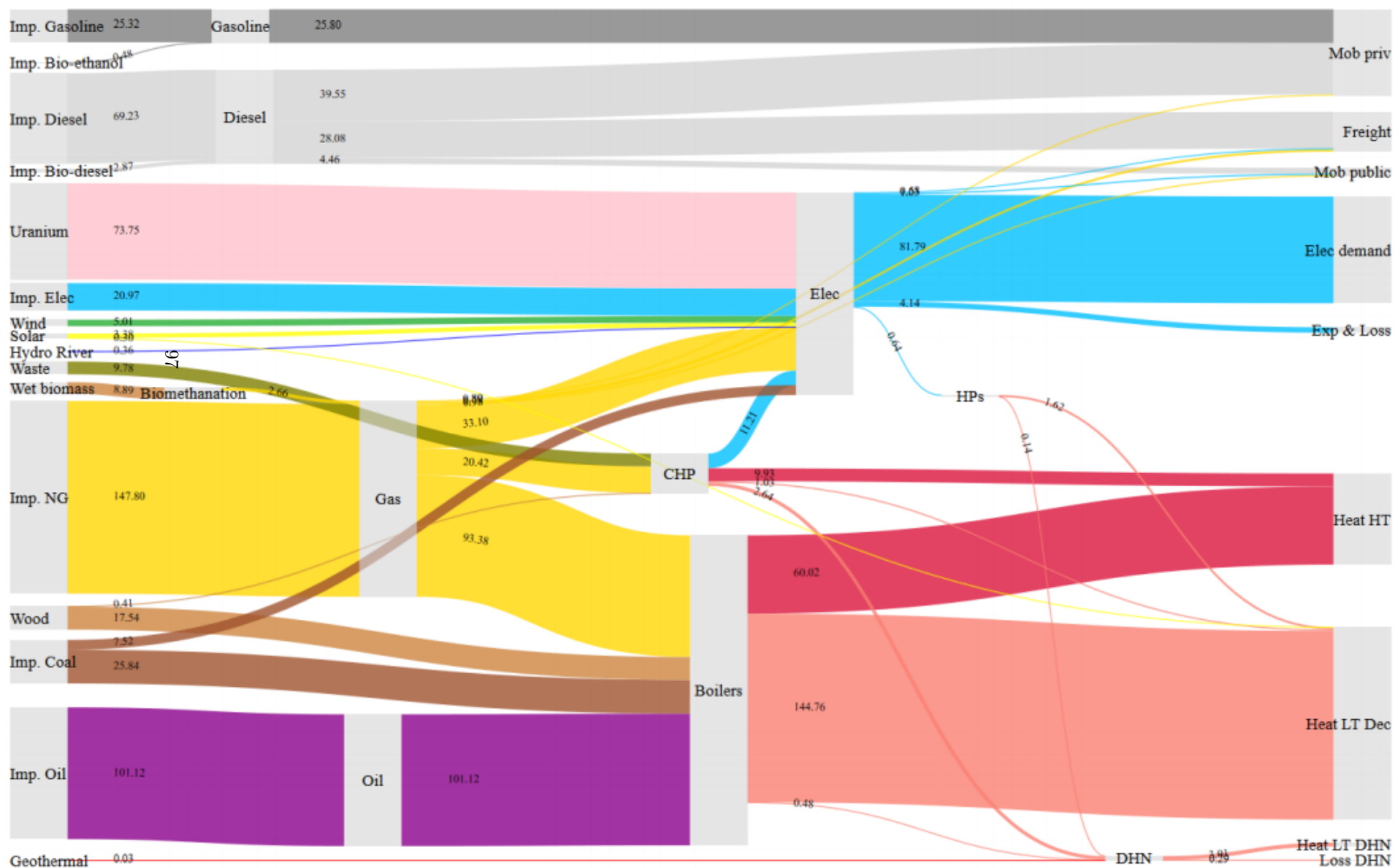


Figure A.12: Sankey diagram of the 2015 Belgian energy system

Energy

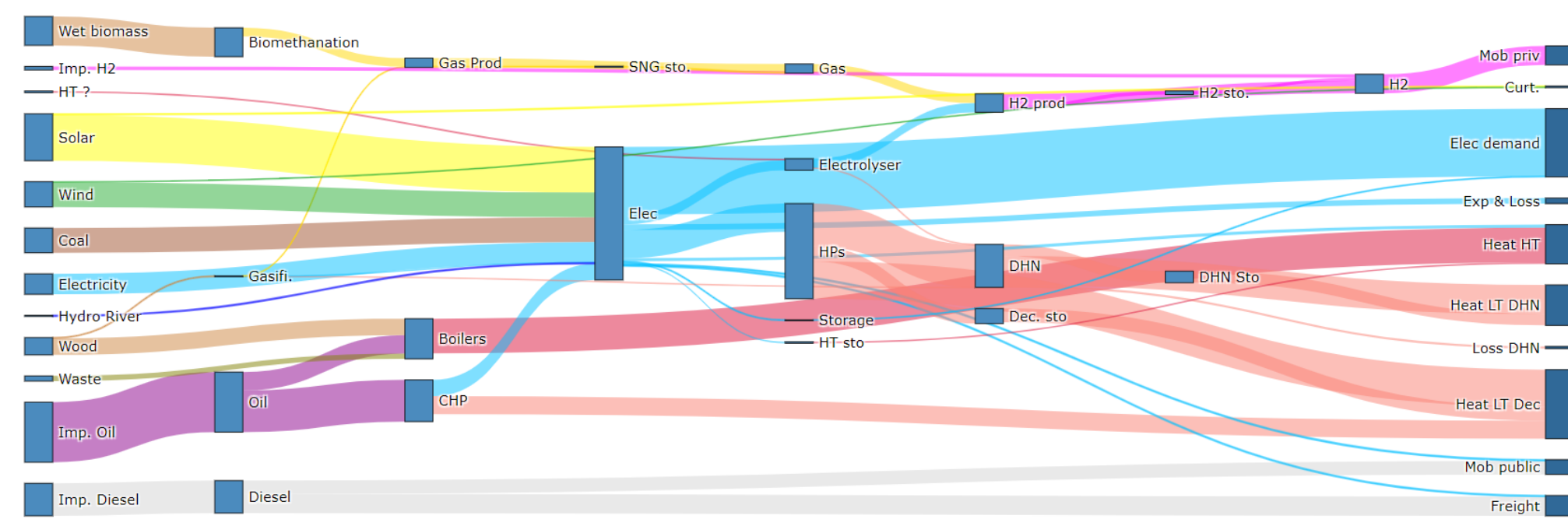


Figure A.13: Sankey diagram of the free natural gas energy system for Belgium in 2035

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consulted the 24/03/2021
- [35] https://fr.wikipedia.org/wiki/Distance_de_Manhattan
consulted the 13/04/2021

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