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Multi-regional energy systems: a multi-agent modelling approach

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Abstract

In the problem of energy transition and incorporation of renewable energies into an energy system, the interactions between neighbouring countries (imports/exports) play an essential role.

In order to study those, this master thesis develops a simplified multi-agent system on an energy system with two agents, primarily focusing on the exchanges of electricity. It relies on the existing energy system modelling tool, EnergyScope Typical Days.

Thanks to simple scenarios using two data sets of Belgium (years 2040 and 2050) as agents, the consistency of the model has been verified, along with some limitations and future perspectives.

Even if the system seems to be dependent on initial conditions, the simple cases (without storage) have converged to optimal solutions. They prefer exchanging electricity with each other rather than with the outside world. The obtained design and operation of each agent are convincing in that matter.

This gives room for future improvements.

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Introduction

In the world we live in today, more and more information is collected to help establish physical laws, mathematical models to help explain the underlying dynamics of complex problems. These complex problems can find solutions within the realm of mathematical optimisation. At an hour where everyone is looking to maximise their profit or minimise their costs, complex tools such as Multiple-Agent Systems (MAS) come in very handy in order to answer questions such as "When do I buy?", "When do I sell?", "When do I produce".

When adding a geopolitical constraint, one could be interested on knowing when a country (or region) will buy from another and when it will produce on its own. Let us say now that countries are dealing with energies, specifically electricity, the problem then becomes precise and solutions may be found, although somewhat complex.

Some countries, such as Belgium which has a high population density and thus intensive energy industry productions, do not possess enough renewable energy sources potential to reach a self-sufficient energy system. Hence, they will need to rely on the importation of these sources, as electricity and green synthetic fuels, for attaining the goal of a zero emission energy system. Therefore, the interactions (import-export) with neighbouring countries are a crucial topic for their energy transition. There is now a physical system to transcribe into equations to build a solvable mathematical model.

This thesis is inscribed within the possible plan to help Europe attain future low-carbon energy systems. It is of great interest to incorporate renewable energy sources to energy systems. In other words, the context in which this thesis lies is to simulate a competitive market between some actors who, in this case, will represent some countries. The number of agents in our work is two, but it would be a good idea to extend this possibility in the future. This gives rise to the following questions: **How to represent a consensus and the economic game between two countries through the concept of multi-agent systems ? How can such an approach be beneficial ?**

The idea developed in this thesis is to consider the agents independently while they can communicate iteratively, to see if a consensus is possible. Their first and foremost goal is to minimise their total costs. It may be achieved by modelling and simulating a market (with conditions): with the help of two agents, representing the market actors competing in order to fulfil their demand, minimise their costs and be able to exchange (import / export) with the other actor.

Contrary to the thesis of Paolo Thiran and Aurélia Hernandez [24], where they developed a multi-regional energy model which optimises one system with multiple regions inside, we optimise each system separately. We cut the problem to obtain two different agents, each of them optimising their own cost and try to resolve the sub-problem separately. Then we communicate certain variables/parameters in input to the other agent and observe the reaction of the other. It means that agents can interact with each other because their actions influence the environment with other agents in it. In the framework of multi-regional energy systems, these interactions are exchanges of energy carriers (such as electricity). We would expect that they arrive to a consensus that the quantities exchanged are logical (at some hours, one exports and the other imports, and inversely at other hours).

The added value of multi-agent systems is that they offer a better representation of reality: each country wants to find its groove. Moreover, they allow the communication between actors in order for them to fulfil their needs. As will be explained in the state of the art, multi-agent systems are complex to implement and apprehend. Combining MAS with energy systems with design and operation is thus a challenge. The road to implementing the proposed system was met with some dead-ends, but we managed to find what seems to be optimal solutions to some simple cases.

Hence, our version EnergyScope Multi-agent [1] is developed and modified in this work based on the existing model of EnergyScope TD [12].

This thesis will be conducted in the following manner:

- A state of the art is presented in Chapter 1, where both kinds of systems were reviewed in the literature,
- The mathematical base model of EnergyScope Typical Days is explained in Chapter 2,
- Chapter 3 explains the context, methodology and the idea of the implementation of the multi-agent system,
- Then, the results of the different runs are analysed in Chapter 4,
- Finally, it finishes by a conclusion including some future perspectives and the limitations of the model.

Throughout this thesis, the following conventions are used:

A left vertical bar indicates the paragraphs of what will be explained next to the reader.

The boxes contain the conclusion paragraphs.

[1] This version can be found on GitHub

CHAPTER 1

State of the art

In this chapter, a state of the art about multi-agent systems and energy systems has been carried out to understand how they have been studied in the literature. These systems are studied in the context where multi-regional energy systems get larger, inducing the need to discover and model new approaches to apprehend these energy systems correctly. On what type of problems are these techniques applied ? What has already been done in this field of research ? How can we approach this problem ?

1.1 Overview of multi-agent systems

1.1.1 Distributed control / optimisation

Firstly, distributed control is related to multi-agent systems because, as agents or actors are spread in a network, there is a need for control over their exchanged information. As it will be explained later, a multi-agent system comprises several interacting subsystems (agents). A distributed algorithm is best suited to respect such a connected nature of these systems, since its goal is to enable them to achieve a global objective through local coordination.

In the field of distributed optimisation, a possibility is that agents cooperate in order to minimise a global function being the sum of local objective functions. Many diverse distributed optimisation algorithms have been developed, where each agent performs a local computation based on its own information and that received from its neighbours through the underlying communication network, so that the global optimisation problem can be solved in a distributed manner. These algorithms are separated into two vast categories: discrete-time and continuous-time algorithms. [25]

Centralised management is based on a *top-down* approach, and requires the program to be exhaustive in terms of control flow. The program must be completely redesigned if the configuration has to be changed for a minor addition of an element. It is thus difficult to implement because these solutions are not open. [9]

On the contrary, distributed management solutions are generally based on the multi-agent system paradigm, which allows for a more natural design, based on a *bottom-up* approach, and a better system reliability than a centralised solution. They must present fault tolerance for certain elements (if there is one element's failure, the system must continue to work), openness and adaptability of the system, distribution of the control and easier design. A control system is considered distributed if it consists of independent and autonomous agents linked by a communication network.

1.1.2 Agents and their characteristics

Next, in order to be able to define a multi-agent system, it is essential to understand what an agent is. Depending on the area of research and application, the term agent can be defined differently.

An agent can be defined as "a software (or hardware) entity, located in a certain environment and capable of reacting autonomously to changes in this environment", the environment being everything external to the agent concerned. The term *autonomy* can be described as the ability to "plan an action based on observations of the environment", meaning that agents can exercise control over their own set of possible actions. [15]

A distinction between agents and intelligent agents can be made by extending the characteristic of autonomy to *flexible autonomy*. This would result in three properties: reactivity/responsiveness (agents can react to changes in the environment), proactivity (agents possess a goal-oriented behaviour) and social ability (intelligent agents can interact with each other by communicating and negotiating).

Concretely, the notion of autonomy distinguishes multi-agent systems from other software or hardware systems such as web services or grid computing. In fact, they support a more extensive set of interactions (such as negotiation).

An agent must be an entity disposing of the following features[9]:

- perception of its environment (to a limited extension) and having only a partial representation of it, and the ability to act in and on it ;
- direct communication with other agents ;
- possession of own resources, skills and services ;
- self-centred behaviour.

Another general definition for the term "agent" designates everything that can be considered as observing its environment with the help of sensors and taking actions on it through actuators.[7] A particularly important subject is, therefore, the agent's interaction with its environment.

First, by perceiving the environment via its sensors, the actor then takes some measures, influencing the environment. For this reason, an agent is also defined as an encapsulated computer system located in an environment that can act flexibly and autonomously in this environment in order to achieve its design objectives.

It should be noted that a computer system consists of hardware and intangible software. A software agent is just a virtual computer program requiring a hardware environment. Software agents can also be mobile because they can migrate to another hardware environment. Moreover, the computer system is an autonomous unit with an internal structure whose exact structure can remain hidden and whose elements are not directly accessible.

However, interfaces are available to allow interactions with the environment. This implies that the agent uses social skills to communicate with its environment. Usually, the agent is not omniscient, but only perceives part of its environment via its sensors. Limited knowledge and uncertainty determine its actions. In this respect, a certain flexibility of the agent is required.

1.1.3 Multi-agent systems

Multi-agent system **(MAS)** theory is the one that emerged from distributed artificial intelligence. There are many definitions of a multi-agent system. By definition, a MAS is a system composed of many autonomous entities, called agents, that behave commonly in such a way as to reach the desired goal. [15] According to this definition, there is no central unit controlling the system because all the agents act autonomously. [14]

Another definition of a MAS is that it is a system composed of the following elements[9]:

- an environment (with generally a specific volume) ;
- a set of passive objects (meaning that they can be perceived, created, destroyed and modified by the agents) ;
- a set of agents (i.e. specific objects representing the active entities of the system);
- a set of relations linking the objects (therefore agents) to each other ;
- a set of operations that agents can perform.

In addition to this definition, the author in [8] emphasises two fundamental points that allow us to say whether a system is a multi-agent system or not. The first point is that the system is composed of multiple autonomous agents with a goal or any other system giving its "reason to be" to the agent, and all the agents operate in parallel. The second point is that agents have a component allowing interactions with other agents, such as a communication protocol or manipulating the environment.

In general, a multi-agent system is designed for a specific purpose. Ultimately, the interaction of many agents provides the desired problem-solving outcome in the form of a feature or service.

Nevertheless, the agents do not behave entirely independently of each other, but rather exhibit a collective behaviour at the macroscopic level. For instance, they can compete with each other (competition) or work together in the same team (cooperation). Thus involving coordination and communication mechanisms. That is also based on the assumption that each agent has only limited skills and incomplete knowledge of the world.

Communication is a central aspect of a multi-agent system. Agents can communicate by exchanging messages mostly. This exchange can be synchronous, like a phone call, or asynchronous, like an e-mail. It can occur directly between the agents involved or indirectly using a shared component from which messages can be stored and retrieved. In practice, communication assumes that the agents have a common basic knowledge and speak a common language whose syntax and semantics must be defined.

A multi-agent system can be considered as Artificial Intelligence. On the one hand, each learning agent may already have an intelligence, and on the other hand, the interaction of reactive agents at some level may produce new structures that can be seen as a kind of "dark" intelligence. These ordered structures arising from self-organisation are also called emergence. Agent-based modelling deals with the computer-aided modelling and simulation of precisely these systems. The purpose of this modelling is to find explanations for the collective behaviour of agents.

Interaction is a fundamental notion in multi-agent systems, and this notion is the cause of many problems but also of many solutions. Agents have interaction mechanisms to enable them to accomplish their objectives. Interactions are thus expressed through a series of actions whose consequences, in turn, influence on the agents' future behaviour. [6]

The growing interest in multi-agent systems is mainly because they offer a flexible and scalable solution to the problems they face. The decomposition of a complex system into autonomous interacting subsystems makes it possible to focus on some part of these subsystems instead of being forced to consider the system as a whole. While it is easy to imagine that such a system is more flexible and scalable because it limits adaptation to new situations to the entities concerned, adaptation techniques must be developed.

The multi-agent paradigm offers a favourable framework for these developments, but does not yet offer standard solutions, because it depends on the case. In the context of the scalability of a MAS, we are particularly interested in its openness. An open system is a system in which new functionalities can be added or removed during execution. In a MAS, these functionalities are provided by the agents that compose it. Thus, an open MAS must be able to integrate new agents and allow the departure of existing agents.

1.1.4 Domains of application

Multi-agent systems can be exploited using two specific approaches that can explain how and why they may be applied in energy applications.

They can be used to construct flexible and extensible systems, thanks to their properties of autonomy (allowing them to respond appropriately to dynamic situations), their open architecture and fault tolerance.

The other approach used is the modelling one, consisting of the fact that the internal data structures and methods (or actions) that an agent can execute are hidden from other agents. Because MAS offer a way of seeing the world, it can intuitively represent a real-world situation of interacting entities and provide the means to test the emergence of complex behaviours. [15]

Many different fields of application are cited in the literature: diagnostics and condition monitoring, market simulation, economic dispatching, automation, distributed network control, power systems operation and control (as generators), modelling, problem-solving, kinetics and more.

Indeed, problem-solving in the broad sense is how we can distinguish several types of resolution:

- 1. There is distributed problem-solving, which consists of solving a single problem by calling on several specialists whose objective is to solve this single problem.

- 2. We recognise the resolution of distributed problems consisting of the distributed resolution as previously but of a problem which is not centralised, such as the energy management, communication or monitoring systems.
- 3. We find the resolution by coordination, which is quite a classic problem solving where the problem is not distributed and where no expertise skills are required.

It should be noted that in market simulation, the benefits of using the MAS paradigm to represent autonomous actors are clear: the actors or the market, represented by agents, have attributes (such as their desired price) and possible actions (that other agents cannot manipulate directly, such as bidding).

1.1.5 Limitations and recommendations of multi-agent systems

From [13], we can understand some problems existing in the application of MAS. For starters, the interactions between the agents of the system may cause some problems. Generally, agents need to be closer to each other to better function as they should and carry out their actions for the system application. That poses a relevant problem: the gap between the different elements of multi-agent systems.

Another limitation lies in the communication between agents. Indeed, the sharing and the flow of information are essential factors in the functioning of a system. Moreover, in this dynamic, languages have been designed for each domain so that agents can understand one another. When communication fails, the agents cannot act to reach a common goal in the multi-agent system. That would then lead to a coordination problem between them.

It is worth asking whether a MAS is necessary to solve our desired problem. It is, therefore, necessary to clearly express the general problem and the needs we have concerning this. In general, there are many situations where multi-agent systems are the first solution suggested, such as particle simulations, social behaviour simulations, or any other system whose solving requires only multiple software entities.

All in all, this distributed artificial intelligence field is remarkably vast, and many aspects are still under study. Therefore, this development aims to make affordable one of the aspects called multi-agent systems, and thus demystifying such systems' design. Certain areas of research and development for industrial or social cases have significantly pushed and motivated the development of multi-agent systems, and the theories surrounding them.

We now ask ourselves how they can be used in energy systems and cost minimisation.

1.2 Energy systems

1.2.1 Specifics of electrical networks

Electrical networks (or power grids) can be defined as the infrastructure allowing the connection between electricity production and end use demand. These networks consist of generating stations producing electricity, but also high-voltage transmission lines transporting electricity from distant sources to demand centres, as well as distribution lines connecting individual consumers. By creating this infrastructure, the networks not only ensure a physical link allowing the circulation of energy flows but also they allow economies of scale and the optimisation of production tools. [5]

It is worth mentioning that unlike traditional power grids, smart grids provide all electric utilities with digital intelligence for the energy system.

In practice, the smart system comes with many smart measurement techniques, smart control systems, and also various digital sensors with analytical tools. The system in question also makes it possible first to automate, then to monitor and finally to control the flow of energy from the power supply to the outlet.

The smart grid is usually based on adding a communication system and also a control network to a traditional electrical grid system. [17] According to the explanations of the US Department of Energy [20], this kind of network possesses many characteristics:

- on the one hand, it can detect system overloads, and then redirect the power in order to prevent or reduce the risk of failure ; and on the other hand, it can work autonomously when all conditions require a resolution faster than humans can react, and cooperate in order to align the objectives of the public services and also of the consumers ;
- it has the ability to meet consumer demand, even if it is significant, without adding infrastructures ;
- it can accept energy that comes from all fuel sources, be it wind or solar, etc. ;
- it allows real-time communication between the public service and consumers so that the latter can adapt their energy consumption according to their preferences, such as environmental concerns or price ;
- it provides the quality of power that is essential without disruption and interruption to power our increasingly digital economy.

1.2.2 Multi-agent systems in energy systems

Energy management covering all sectors is a prerequisite for the rapid development of renewable energies, which is one of the primary objectives of the energy transition. Indeed, the combination of heat, cold, electricity and mobility forms the basis of an ecological, reliable and economical energy supply, both in the context of residential and commercial use.

Artificial intelligence multi-agent systems are often required in the context of the control and management of distributed or complex electrical systems. [16] Moreover, it can be found in the literature that the MAS contributes greatly to the progress of large industrial installations. This has led to the promotion of commercial products currently available. [18]

As part of the studies conducted by the authors of [15], multi-agent systems have been shown to be able to integrate a complex system with improved agent design. [4] These authors argue that that points like degree of autonomy and control measures need to be verified through further engineering research to advance the practice of multi-agent design. In this area precisely, there are different types of approaches proposed by researchers.

Thus, the following examples were identified, among others:

- [16] proposes central concepts of multi-agent systems. This paper provides two types of applications for the analysis and control of data from distributed or heterogeneous sources in an electrical network ;

- [23] is implementing new methods, including the Virtual Power Cooperative (CVPP), which brings distributed producers together to form a single producer ;
- in [9], the authors had also planned a MAS intended for the management of an electrical network connecting storage units to production units within the framework of a direct current network which uses Matlab-Simulink to connect to an alternating current network of distribution, regardless of transmission networks.

In order to optimise the efficiency of a MAS in the context of electrical systems, it is important to understand that such a system can concretely include three types of loads[2]:

- **electric**: the electric load is provided by the potential agents grid, micro turbine and the photovoltaic agent ;
- **thermal**: the thermal load comes from the boiler and the micro turbine agent ;
- **cooling**: the cooling load is ensured by the cooling agent.

Ideally, a multi-energy electrical system is composed of seven local agents and one optimising agent. The local agents are therefore distributed among the three charges/loads. This is how we get the following agents: grid [19], photovoltaic [22], micro turbine, boiler, cooling, thermal load and electrical load.

The figure below shows the ideal structure.

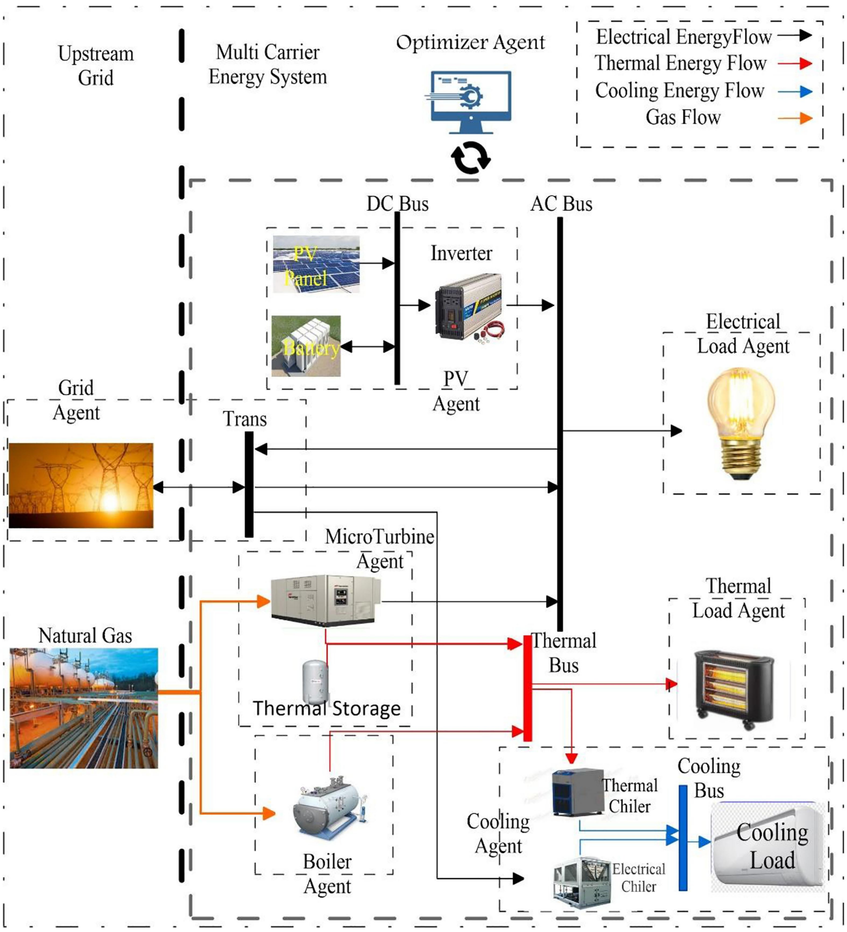

Figure 1.1: Multi-carrier energy system model [1]

1.2.3 Existing application: Agent-Based Simulation of Interconnected Wholesale Electricity Markets [3]

First thing to note, there is a difference between agent-based simulation/modelling (ABM) and multi-agent system (MAS). An agent-based model is a computer-based, often simplified, simulation model of a complex system, such as a MAS. Its goal is to create a simulation and to search for explanatory insight into the collective behaviour of agents (not necessarily *intelligent*) obeying simple rules, rather than to solve a specific problem. On the contrary, a multi-agent system is a complex system depicting a real-life situation where many independent agents simultaneously interact to reach a system-wide outcome within a set of predefined constraints. Its goal is to solve real-life (engineering) problems using various autonomous agents, often *intelligent*. The difference lies in the fact that a MAS (trying to model the system) can actually be implemented using an ABM (trying to model the phenomenon).

The simulation based on interconnected wholesale electricity market agents allows to find favourable ways to minimise costs and avoid excessive loads. It involves the inter-connectivity relationship between entities and wholesale electricity markets. First, the agents are connected to each other in a synergistic way to ensure a good relationship in the markets.

In addition, the production of interconnected electricity determines the level of consumption. Indeed, there are several wholesale market agents for interconnected electricity. In a wholesale market, electricity is sold and bought before it reaches the end customer, who may be a private individual or a company. All of this takes place within the application of a network system in which all agents develop a certain close relationship. Among the actors involved in this simulation, there are the electricity producers. They are the ones who negotiate and sell the production. Then there are the electricity suppliers. Their role is to negotiate and acquire the electricity and then sell it to the final customers. But this process is not obvious enough without the intervention of traders and shaving operators. In reality, this shows the effective application of ABMs (or even MAS) in the management of wholesale electricity markets. The agents have some autonomy in the network and with respect to selling and buying issues.

1.2.4 Cost minimisation in energy systems: the impact of the multi-agent approach

No concrete application about this subject has been found, but from our state of the art, it seems reasonable that it as an application that could be implemented. Multi-agent systems have become favourable solutions when optimising energy systems and minimising the costs. These systems are applied in the production processes of renewable and distributed energies. In fact, with the intervention of several entities, energy consumption is better managed.

Energy systems need to be restructured and modelled with new elements. This is where multi-agent systems come in. These systems involve a range of entities that allow the generation of energy while regulating the level of consumption. This is much more valid for renewable energies. Just as multi-agent systems have been applied in computer science, engineering and social science, this is how they have also been applied in the management of energy systems.

In addition, it is important to know that several reflections have been carried out in the literature concerning renewable energy production. The latter is the most concerned by the intervention of multi-agent systems, especially with multi-layer learning. This is the reason why energy systems are mainly looking to minimise their costs on the energy market. In fact, the analyses have given rise to several projects whose objectives and ideas are aimed at reducing costs. The most remarkable approach is the application of artificial intelligence from multi-agent systems.

To this end, an automated control system based on AI is then designed in order to optimise and control the behaviour of the agents in the system over time. [21] With this initiative, the energy system is no longer required to make quite remarkable investments to achieve controls. Its costs can then be minimised as much as possible. Furthermore, the implementation of multi-agent systems highlights the collective intelligence approach in the functioning of energy systems.

In reality, the costs become exorbitant for an energy system when there is less interaction and less automation. It is in this dynamic that the multi-agent systems approach has been implemented. With artificial intelligence, energy systems are in a much more advantageous condition and can develop their actions automatically. Moreover, the role of MAS gives so much interest to the systems on the energy markets because agents are required to collaborate in the system for its functioning (but they can also be on a competitive market). Each one of them plays a specific role and adapts by means of interactive communication. With this approach, it is obvious that an energy system can minimise its costs and optimise efficiently its management and that of its agents.

Summary of state of the art

In this state of the art, we can conclude that multi-agent systems are a powerful tool to model an energy system because it is a vast and complex domain, and one of its essential characteristic is that communication is possible between agents. Even though they have some limitations, we can manage to make the best use of MAS.

They are examples in the literature of MASs in energy systems, but we have not found an approach such as ours concerning cost minimisation of two countries. This may then be a start for a further exploration.

CHAPTER 2

EnergyScope Typical Days

> In this chapter, we present EnergyScope Typical Days (ESTD) [11], [12], on which we based ourselves to extend the version and program our implementation of a multi-agent system, and explain why we made that choice. We listed and explained the concepts that are necessary and used in this thesis.

EnergyScope Typical Days (ESTD) [1] is an energy system optimisation program (using both programming languages AMPL and Python) based on linear programming. It improves the system so that, in the end, it optimises the design (by computing the installed capacity of each conversion technology) and the system's operation. The solution found is the cheapest one it can achieve while complying with a set of constraints (hence the cost optimisation model).

In our thesis, its primordial objective, among others, is to satisfy the energy balance constraint (the supply has to meet the demand, counting on possible imports/exports). Multiple constraints are applied to the system, but in this thesis, the most important one is the one of layer balance. Concerning the system's parameters, they can be divided into three categories of inputs: technologies of energy conversion, resources and end-use demand (which will be briefly presented).

This modelling framework is a simplified representation of one energy system, considering the energy fluxes in the region/country and across borders. As it is a regional model, the optimisation takes place in one single region. It considers its neighbours as an external system, allowing imports or exports of electricity from the outside of the system at a fixed price. However, in our case, we will not allow the exports outside the system, but only to the other agents, as it will be explained later.

EnergyScope TD possesses thus the following features, which are useful for our thesis:

- Optimisation of the investment and operation costs,
- Hourly time resolution (using typical days, allowing seasonality and energy storage),
- Open source (on Github) and documented,

[1] it has been forked from GitHub

– Short computational time.

In fact, we want to use the feature of optimisation (and not simulation) through the operation and design of the system, and explore other possible fields, such as how it can be modelled thanks to multi-agent systems.

ESTD also has the advantage of being multi-sector and whole-energy (electricity, heat and mobility). However this feature will not be used in our thesis because exchanges of electricity are the main focus, for the sake of simplicity. Nonetheless, eventually, one could apply MAS to the whole-energy system to model the entire energetic transition problem.

Regarding the modelling of renewable energy sources, ESTD relies on the concept of typical days (depending on weather conditions and demand) to accurately model the entire year. For our work, it is assumed that 12 TDs are taken to represent a year, which reduces the number of time slots accounted for in the model (288 hours, which represents 12 days). This particular selection is explained in [11] and [24].

The concept of *layers* is defined as "all the elements in a system that need to be balanced in each time period, including resources and EUTs (end-use types)". Thus it is either a resource or an end-use demand, and it must be balanced at all times (hence the layer balance constraint). To cite an example, the electricity layer must be balanced at all hours, i.e. the production and storage of electricity must equal its consumption and losses. The conversion technologies connect the layers.

Let us first present the three categories of inputs, then the decision variables, the constraints, and the objective function.

2.1 Technologies parameters

There exist three types of technologies: technologies of end-use type (which can convert the energy, for example as a fuel resource, from one layer to an end-use type layer), storage technologies (converting energy from a layer to the same one) and infrastructure technologies.

Several parameters are needed to characterise a technology j. The ones we are interested in are listed below:

- **Specific investment cost** $c_{inv}(j)$ [M€/GW]: the investment cost of technology j for 1 GW of installed power ;
- **Specific yearly maintenance cost** $c_{maint}(i)$ [M€/GW/y]: the maintenance cost of technology j for 1 GW of installed power ;
- **Lifetime** *lifetime*(j) [years]: the lifetime that can be expected from technology j ;
- **Yearly capacity factor** $c_p(j)$ [-]: the maximum load factor that can be expected from technology j, representing a percentage, value lying between 0 and 1 ;
- **Minimum and maximum allowed capacity** $f_{min}(j)$ & $f_{max}(j)$ [GW]: the min/max power of technology j that the optimisation is allowed to put in the energy system.

The capacity factor of a technology is characterised by two components: a capacity factor for each period $c_{p,t}$ depending on resource availability (for example, renewables, such as the sun, are not available all the time) and a yearly capacity factor c_p considering maintenance of a technology and its downtime.

2.2 Resources parameters

The set of resources regroups the primary renewable energies (such as wind, solar, wood...) and the secondary energies (electricity, synthetic natural gas...). The difference between both these energies lies in their availability. Indeed, a primary energy possesses some availability depending on the quantity that can be extracted, on the contrary that a secondary energy is not available because it can not be found in nature and must be produced through a conversion technology.

To characterise a resource (such as electricity, gas, coal), several parameters are needed. The ones we are interested in are listed below:

- **Yearly total availability** $avail(i)$ [GWh/year]: the availability of resource i each year in terms of energy, representing the maximum quantity of resource that can be imported;
- **Specific operational costs** $c_{op}(i)$ [M€/GWh]: the specific cost of resources i per GWh that it can deliver.

2.3 Demand parameters

Demand is generally not constant over time, varying throughout days, weeks and seasons. For example, in Europe, the electricity demand is higher in winter than in summer because of the weather and daylight time. The end-use demand (EUD) corresponds thus to the requirements in energy services (in this thesis, only electricity, but there is also heating and mobility).

The hourly end-use demand (characterised by the variable **EndUses**) is computed based on the yearly end-use demand (the parameter *endUsesInput*), distributed according to a normalised time series.

The time series of the energy demand and the weather conditions represent respectively the hourly demand of the different sectors and the hourly potential production of the renewable energy technologies (with the technology PV as example, the entry of the time series during the night will be 0).

2.4 Decision variables

These variables, all continuous and non-negative, optimised by the solver, can be split into two categories:

- **independent** decision variables: they can be freely fixed, we can cite three of them that will be used:
  - **F**(j) [GW]: installed capacity of technology j (with respect to main output) ;
  - $\mathbf{F_t}(i, h, td)$ [GW]: quantity used of resource i or quantity produced of technology i in each period (operation) ;
  - $\mathbf{Sto_{in}}, \mathbf{Sto_{out}}(j, l, h, td)$ [GW]: input to/output from storage unit j entering layer l in each period.
- **dependent** decision variables: linked to the independent ones via equality constraints:
  - **EndUses**(l, h, td) [GW]: end-uses demand required (set to 0 if layer l does not belong to the set of end-uses types) ;

– $\mathbf{C_{tot}}$ [M€/y]: total annual cost of the energy system ;
– $\mathbf{C_{inv}}(j)$: [M€]: total investment cost of technology j ;
– $\mathbf{C_{maint}}(j)$ [M€/y]: yearly maintenance cost of technology j ;
– $\mathbf{C_{op}}(i)$ [M€/y]: total cost of resource i.

2.5 Minimisation of costs

As said before, the basic model optimises the choice of technologies while minimising the total annual cost of the system $\mathbf{C_{tot}}$ ([M€/year]), defined as follows:

$$\min \mathbf{C_{tot}} = \sum_{j \in \text{TECH}} (\tau(j) \cdot \mathbf{C_{inv}}(j) + \mathbf{C_{maint}}(j)) + \sum_{i \in \text{RES}} \mathbf{C_{op}}(i) \tag{2.1}$$

with the following explanations:

- $\tau(j)$ being the investment cost annualization factor of technology j: $\tau(j) = i_{rate} \cdot \frac{(1+i_{rate})^{lifetime(j)}}{(1+i_{rate})^{lifetime(j)} - 1}$, with *lifetime*$(j)$ being the lifetime of technology j and i_{rate} the interest rate ;
- for each technology j, there is an annualised investment cost $\tau(j) \cdot \mathbf{C_{inv}}(j)$;
- TECH and RES: sets of respectively all the different end-use type technologies and all the different resources in the model.

In the model, equations 2.2, 2.3 and 2.4 define the total costs of technologies and resources

$$\mathbf{C_{inv}}(j) = c_{inv}(j) \cdot \mathbf{F}(j) \qquad \forall j \in \text{TECH} \tag{2.2}$$

$$\mathbf{C_{maint}}(j) = c_{maint}(j) \cdot \mathbf{F}(j) \qquad \forall j \in \text{TECH} \tag{2.3}$$

$$\mathbf{C_{op}}(i) = \sum_{t \in \text{T} | \{h,td\} \in \text{T\_H\_TD}(t)} c_{op}(i) \cdot t_{op}(h,td) \cdot \mathbf{F_t}(i,h,td) \qquad \forall i \in \text{RES} \tag{2.4}$$

where, for remainder, parameters and variables are:

- $c_{inv}(j)$ and $c_{maint}(j)$ are respectively the specific investment and maintenance costs of technology j (as mentioned in 2.1) ;
- $\mathbf{F}(j)$ is the variable of installed capacity of technology j ;
- $t_{op}(h,td)$ is the operation time/time period duration ;
- sets T and T_H_TD: sets of respectively all periods of the year (8760 hours) and of typical day of period t ;
- $\mathbf{F_t}(i,h,td)$ is the actual end-use of the resource i in each time period.

It is good to note that in equation 2.4, summing over the typical days by using the set T_H_TD is doing the same as summing over all the hours of a year. To simplify the reading, we will only write $t \in \text{T}|\{h,td\} \in \text{T\_H\_TD}(t)$ (not possible to implement that directly in the code, because we need two more sets), which is equivalent in the code to $t \in \text{T}|h \in \text{HOUR\_OF\_PERIOD}(t), td \in \text{TYPICAL\_DAY\_OF\_PERIOD}(t)$.

2.6 Constraints

For the primordial layer balance equation, all outputs from the resources and conversion technologies, including storage if used, must equal the end-use demand and inputs to other resources or technologies. The following constraint represents this equality:

$$\sum_{i \in \mathsf{RES} \cup \mathsf{TECH} \setminus \mathsf{STO}} f(i,l) \cdot \mathbf{F_t}(i,h,td) + \sum_{j \in \mathsf{STO}} (\mathbf{Sto_{out}}(j,l,h,td) - \mathbf{Sto_{in}}(j,l,h,td) - \mathbf{EndUses}(l,h,td) = 0$$
$$\forall l \in \mathsf{LAYERS}, \forall h \in \mathsf{HOURS}, \forall td \in \mathsf{TD} \tag{2.5}$$

with the following parameter and variables being:

- set STO: set of all the different storage technologies in the model ;
- param $f(i,l)$ (or also sometimes referred as *layers_in_out(i,l)*): input from (negative value) or output to (positive value) layers (and $f(i,l) = 1$ if l is the main output layer for technology/resource i) (corresponding to data layers_in_out) ;
- sets LAYERS, HOURS and TD: sets of respectively all the different layers, all the hours of a day, and all the typical days.

There are also constraints in the base model on the global warming potential (GWP), but we will not explain them as they will not be changed in this thesis.

We can also mention that there are constraints on the system design and operation: bounds on the installed capacity, link between the installed capacity **F** and the actual use of this technology in each period $\mathbf{F_t}$ via the two capacity factors, or else the limitation of total use of resources.

Moreover, some constraints concerning the storage exist: about storage level (for storage systems that can only be used for daily application and the other ones for seasonal storage), or on power input/output.

CHAPTER 3

Implementation of the multi-agent system

In this chapter, different formulations (not all formulations are presented) for the multi-agent system are presented (based on the implementation of EnergyScope TD). Firstly, the context in which this work takes place is explained, as well as the methodology. To demonstrate the complexity of multi-agent systems in an energy system with design and operation, we will show some of the dead ends we have encountered, three propositions are explained.

3.1 Context and methodology

As explained before, the idea of this thesis is to simulate a competitive market between two actors by allowing communication between them, so that a "consensus" is achievable between them, while it is still possible for them to buy some electricity to the "outside world" in last resort (possibility already implemented in ESTD before). Therefore we consider these two actors independently and they can communicate in an iterative way, until reaching convergence. Their primal goal is to first minimise their own total cost, as we find ourselves in a decentralised competitive optimisation (as explained in the state of the art).

Thus a solution to this problematic is to create a multi-agent system with two agents, where each performs the optimisation on its own and then sends some information to the other one in order to exchange electricity. Our model is supposed to use a decentralised approach, where agents do not try to optimise the sum of the costs of everyone, but better only take care of their own minimisation of coststhe result is a competitive approach, rather than cooperative.

For this new implementation, the model of EnergyScope TD in AMPL, as explained in Chapter **??**, is taken as basis, and we remodelled it to only take into account all parameters, variables and demand linked to electricity (thus excluding the other sectors), for sake of simplicity.

As discussed, EnergyScope TD is an open source energy system model optimising the investment and operation costs of a defined area, based on linear programming. It is usually applied to a region or country, while its main objective is helping in the decision making of strategies relative to energy system. Consequently, we add parameters and variables in the AMPL model, and the communication part and iterations will take place in the Python file.

As preview, in order to implement the multi-agent system with communication, concerning the last working model, it has been decided to send the following features of one agent to the other:

- the marginal cost of each hour (taken as the dual variable of the constraint layer balance);
- the quantity to be imported from the other country ;
- the quantity that the agent can still produce in order to export it.

But before deciding to use this model, we tried some other ways that will be explained in the first two sections.

The acquisition of the results pursued the following methodology. To pursue the goal of this thesis, a first step was to document on multi-agent systems, which is a very broad subject, not easy to implement, and on energy systems, and to write the state of the art on these subjects (in Chapter 1).

A second step was to familiarise ourselves with EnergyScope, and to understand in which frame lies this thesis. In order to achieve this step, it was important to read the documentation at disposal to understand the model taken as basis.

Furthermore, a simplified multi-agent system was implemented, with only the sector electricity, accompanied with its parameters, variables and sets. From the model presented in section 2.5, new variables and parameters have been added in order to represent the communication between the two countries. The initial code had thus to be modified in order to only include this sector and adapt to technologies and resources required.

We ran our model on a simple case in order to get results (in Chapter 4) to analyse and assume the feasibility and aim of our problem. We also ran it on different initial conditions arrangements.

Before finding what seems to be the right multi-agent model, we present older versions and the reason of the failure/unsuitability. We do not present other dead ends that we encountered, only to focus on the main model.

3.2 Model with buying/selling quantities and costs

The first idea for the multi-agent system consisted in separating the exchange into a buying part and a selling part, and thus integrating those quantities and costs of each agent in the model.

A first agent would therefore have a variable of the quantity it wants to buy from a second agent, a parameter of the quantity the second agent wants to buy from the first, and the costs for buying and selling a certain quantity of electricity at a certain time.

The costs would be the marginal costs (at each period) of one of the agents. They can be retrieved by the dual variable of the constraint "layer balance". By definition, the marginal cost is the cost of producing one additional unit of output. We decided to exchange the marginal costs because it is an "obvious" cost that exhibits well the "threshold" at which an agent would be willing one unit of its production. Also, if producing one more unit and reselling it costs less, then the agent jumps on the occasion.

Although the following statement may seem logical to sum, let it be clear for the rest of this thesis: as we work on time slots of an hour each (on each typical day), the power installed on one slot (which is constant) is equivalent to the energy produced during that time. That is why we say that the quantities bought and sold are in GWh. This fact will remain untampered throughout the rest of this thesis.

Hence, we present in the following tables the variables and parameters that we thought adding to the base model.

Parameters	Units	Description
$c_{buy}(l,h,td)$	[M€/GWh]	Cost of buying one unit of a layer l on hour h of typical day td
$c_{sell}(l,h,td)$	[M€/GWh]	Cost of selling one unit of a layer l on hour h of typical day td
$q_{sell}(l,h,td)$	[GWh]	Quantity to be sold of layer l on hour h of typical day td

Table 3.1: List of additional parameters of buying/selling model with units and description

Variables	Units	Description
$\mathbf{C_{buy}}(l)$	[M€]	Total cost of buying the quantity of layer l
$\mathbf{C_{sell}}(l)$	[M€]	Total cost of selling the quantity of a layer l
$\mathbf{Q_{buy}}(l,h,td)$	[GWh]	Quantity to be bought of layer l on hour h of typical day td

Table 3.2: List of additional variables of buying/selling model with units and description

The objective function is thus changed in the base model by adding a final (red) term containing costs of selling and buying:

$$\min \quad \mathbf{TotalCost} = \sum_{j \in \mathsf{TECH}} (\tau(j) \cdot \mathbf{C_{inv}}(j) + \mathbf{C_{maint}}(j)) + \sum_{i \in \mathsf{RES}} \mathbf{C_{op}}(i) + \sum_{l \in \mathsf{LAYERS}} (\mathbf{C_{buy}}(l) - \mathbf{C_{sell}}(l))$$

Next are the constraints changed for this model:

- Total cost of buying a certain layer

$$\mathbf{C_{buy}}(l) = \sum_{t \in \mathsf{T} | \{h,td\} \in \mathsf{T\_H\_TD}(t)} c_{buy}(l,h,td) \cdot \mathbf{Q_{buy}}(l,h,td) \qquad \forall l \tag{3.1}$$

- Total cost of selling a certain layer

$$\mathbf{C_{sell}}(l) = \sum_{t \in \mathsf{T} | \{h,td\} \in \mathsf{T\_H\_TD}(t)} c_{sell}(l,h,td) \cdot q_{sell}(l,h,td) \qquad \forall l \tag{3.2}$$

- Layer balance

$$\begin{aligned} \sum_{i \in \mathrm{RES} \cup \mathsf{TECH} \setminus \mathsf{STO}} f(i,l) \cdot \mathbf{F_t}(i,h,td) + \sum_{j \in \mathsf{STO}} (\mathbf{Sto_{out}}(j,l,h,td) - \mathbf{Sto_{in}}(j,l,h,td)) \\ - \mathbf{EndUses}(l,h,td) - q_{sell}(l,h,td) + \mathbf{Q_{buy}}(l,h,td) = 0 \qquad \forall l,h,td \end{aligned} \tag{3.3}$$

As said in section 2.5, the initial subscript for the sum over the periods was $t \in \mathsf{T} | h \in \mathsf{HOUR\_OF\_PERIOD}(t)$, $td \in \mathsf{TYPICAL\_DAY\_OF\_PERIOD}(t)$, but it was not possible to implement it in the code, thus it is replaced by $t \in \mathsf{T} | \{h,td\} \in \mathsf{T\_H\_TD}(t)$, because in both cases we sum over all the hours of the year.

As for the exchange part of this model, we give to one model the variable of quantity that it wants to buy $\mathbf{Q_{buy}}(l, h, td)$ so that it becomes the parameter of the quantity the other model will have to sell $q_{sell}(l, h, td)$, which is logical in view that we want the quantities to match.

Concerning the exchange of costs, we give to each agent the other agent's marginal cost as its parameter c_{buy} (because it can buy some quantity at this price) and its own marginal cost as its parameter c_{sell} (because it is the price it is willing to receive by selling a unit of electricity).

These exchanges of information are performed in several iterations (the number is arbitrary) in order to find the most suitable set of parameters, so that it can be applied to real life. It thus means that it is an "imaginary" iterative loop, meaning that the exchanges inside it will not happen, they just exist to find the most suitable solution, hoping it will converge to some optimal solution. In one iteration, we perform the exchanges of all information and run on both countries, so they do not exchange their information at the same time because they use the information of the previous iteration. There is thus a lag between iterations, by doing two by two.

On Figure **??**, we can observe a diagram representing the exchange of information throughout iterations.

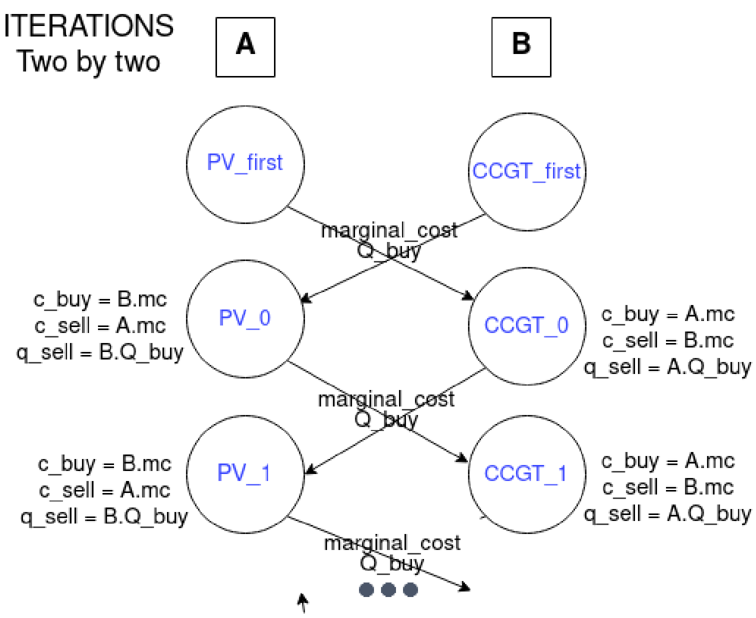

Figure 3.1: System of exchange with two by two iterations

Here after is the algorithm written in Python for the exchange of information, placed in a for-loop for a certain amount of iterations (the convergence criteria was not defined). The parameters $[l, h, td]$ are implied for all concerned parameters/variables.

Let us make a note: the obtained marginal cost (by taking the dual variable of the constraint of layer balance in the AMPL model) is for one hour of one typical day, thus to have the satisfying marginal cost, it has to be scaled according to the number of typical days out of all days of the year.

We initialise each selling quantity to 0 GWh, because we do not know how much quantity each agent would like to buy, thus it has to start new. The buying and selling costs are both initialised with the operational cost of electricity [M€/GWh].

Algorithm 1: Pseudo-code of the exchange of information

```
Initialisation & Run on both countries
for i in [1..?] do                    /* convergence criteria to be determined */
    agent1.c_buy[i] = agent2.mc_scaled[i − 1]
    agent1.c_sell[i] = agent1.mc_scaled[i − 1]
    agent1.q_sell[i] = agent2.Q_buy[i − 1]
    agent2.c_buy[i] = agent1.mc_scaled[i − 1]
    agent2.c_sell[i] = agent2.mc_scaled[i − 1]
    agent2.q_sell[i] = agent1.Q_buy[i − 1]
    run_es(agent1) & run_es(agent2)
    scale_marginal_cost(agent1) & scale_marginal_cost(agent2)
    i + +
```

3.2.1 Problems encountered

It turned out that undesirable effects appeared, such as quantities of a same layer being bought and sold at the same time, which was not possible in reality (either it has to be bought, or either it has to be sold). We tried in post-processing to take the sum of $\mathbf{Q_{buy}}$ and q_{sell} to obtain the "true" value bought or sold, but the model would not make sense otherwise because it would not erase the principal problem. Therefore, a constraint that would make sense at some point is that, if an agent decides to sell a certain layer, then it can not buy this layer to the other agent.

Another problem is having two different costs (one selling and another buying) for one country. Indeed, it would be strange because, for a same quantity, there should be a consensus over the global price. The case with two prices would suggest that an agent would be willing to pay a quantity a certain price, but to sell it at another one (and preferably for them higher to get some profit). Thus, a unique cost of exchange for each agent is the preferred solution.

At this stage, we hoped that, at the end of the run, both scaled marginal costs are equal, as well as the buying quantities and selling, such as in the following equations. That was what would make sense to obtain convergence in this arrangement, but that was not what we obtained, only big oscillations of the concerned variables and parameters.

$$country1.mc\_scaled = country2.mc\_scaled$$
$$country1.q\_sell = country2.Q\_buy$$
$$country1.Q\_buy = country2.q\_sell$$

Because of these problems, the model had to be rethought of and redesigned.

3.3 Model with import/export

This model is actually a sort of reformulation of the previous one in section 3.2, because, among other things, instead of buying and selling, it is export and import. But the major differences are that we only have now one cost of exchange (representing the cost of importing the quantity to the other agent) and that we added a constraint implying that there can not be import at the same time as export (as we had the problem of buying and selling electricity at the same time).

In that matter, we included to the base model of section 2.5 one parameter of the quantity to be exported q_{exp}, one variable of the quantity to be imported $\mathbf{Q_{imp}}$, both to be greater or equal to 0. The quantity q_{exp} given as parameter to one agent is seen as the quantity demanded by the other agent, and thus interpreted as an additional demand to cover by the production of the first agent.

Here are the variables and parameters that are joined to the base model of 2.5:

Parameters	Units	Description
$c_{imp}(l,h,td) \geq 0$	[M€/GWh]	Cost of importing one unit of a layer l from the other agent on hour h of typical day td
$q_{exp}(l,h,td) \geq 0$	[GWh]	Quantity to be exported of layer l on hour h of td

Table 3.3: List of additional parameters of import/export-model with units and description

Variables	Units	Description
$\mathbf{C_{imp}}(l) \geq 0$	[M€]	Total cost of importing layer l
$\mathbf{Q_{imp}}(l,h,td) \geq 0$	[GWh]	Quantity to be imported of layer l on hour h of typical day td

Table 3.4: List of additional variables of import/export-model with units and description

The objective function, which is the minimisation of the total cost, is the following, with the supplementary term written in red:

$$\min f = \sum_{j \in TECH} (\tau(j) \cdot \mathbf{C_{inv}}(j) + \mathbf{C_{maint}}(j)) + \sum_{i \in RES} \mathbf{C_{op}}(i) + \sum_{l \in LAYERS} \mathbf{C_{imp}}(l) \tag{3.4}$$

The new constraints to the model from section 2.5 are the following:

- Definition of total import cost:

$$\mathbf{C_{imp}}(l) = \sum_{t \in T | \{h,td\} \in T\_H\_TD(t)} c_{imp}(l,h,td) \cdot \mathbf{Q_{imp}}(l,h,td) \qquad \forall l \tag{3.5}$$

- There cannot be import if there is already export for this agent:

$$\begin{aligned} \mathbf{Q_{imp}}(l,h,td) = (&\text{if } q_{exp}(l,h,td) > 0 \text{ then } 0 \\ &\text{else } \mathbf{Q_{imp}}(l,h,td)) \qquad \forall l,h,td \end{aligned} \tag{3.6}$$

- The energy balance equation is also changed, $\forall l,h,td$:

$$\begin{aligned} &\sum_{i \in RES \cup TECH \setminus STO} (\text{layers\_in\_out}(i,l) \cdot \mathbf{F_t}(i,h,td)) + \sum_{j \in STO} (\mathbf{Sto_{out}}(j,l,h,td) \\ &- \mathbf{Sto_{in}}(j,l,h,td)) - \mathbf{EndUses}(l,h,td) + \mathbf{Q_{imp}}(l,h,td) - q_{exp}(l,h,td) = 0 \end{aligned} \tag{3.7}$$

In the previous model, we tried optimising the two agents simultaneously in one iteration, but as we can see on Figure 3.2, the 'double' of iterations have to be made for the same result in the end. At least, by doing one by one iteration, there will be less calculations to be made. Normally, the results by one by one should be the same as two by two. As we can see on the right diagram, none of the agents exchange information during a same iteration (PV_0 does not exchange with CCGT_0). The sequence [PV_first, CCGT_0, PV_1, ..] does not rely on the sequence [CCGT_first, PV_0, CCGT_1, ..] and thus, this second succession can be suppressed and we will only use the system of iteration of the left image.

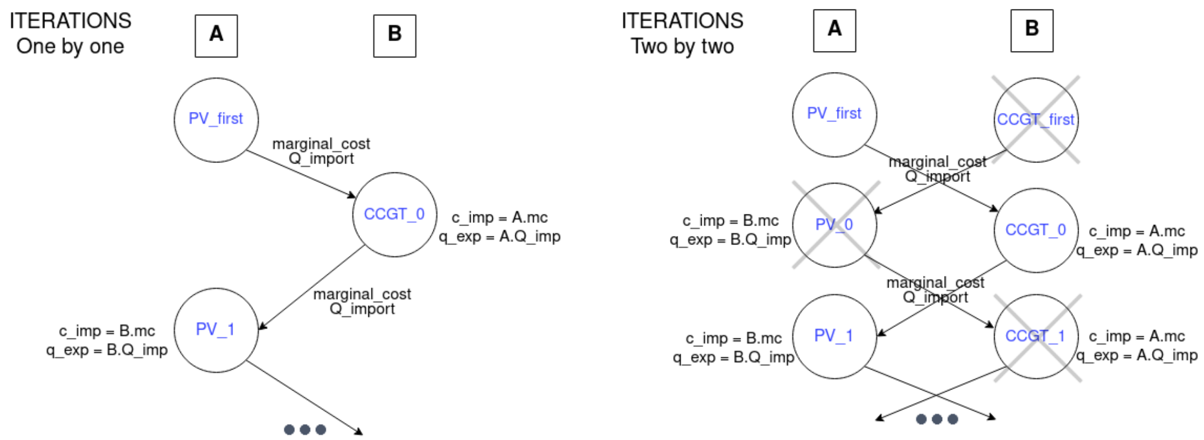

Figure 3.2: Comparison between one by one iterations and two by two

As explained just before, we now choose to iterate one agent at a time. The model intrinsic to AMPL was also presented, and the real exchange part happens in the Python code. First of all we initialise agent A, then we send its information (its marginal cost becoming the import cost of the other agent and its quantity to be imported becoming the parameter q_{exp} of the other agent) to agent B so that it optimises on its side. Then again agent B sends its information back to agent A and so on (as it can be seen on the following diagram 3.3).

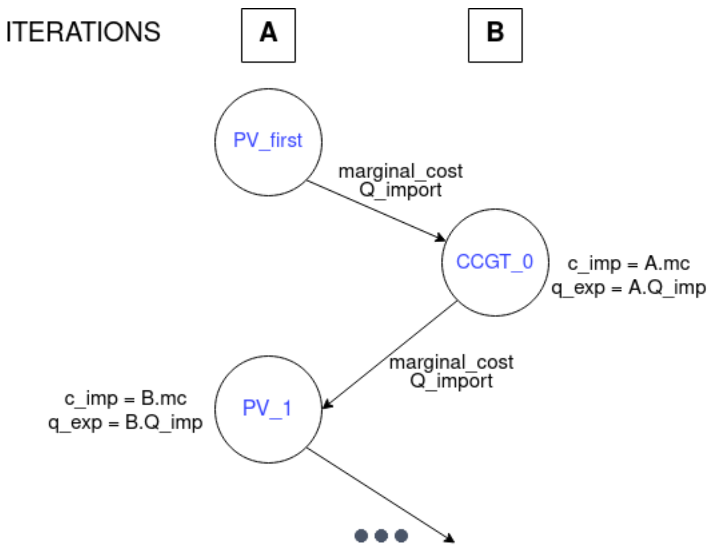

Figure 3.3: System of iterations and exchange between the two agents

We analyse one case with this model in section 4.1.1, showing that it is one step from being the right model.

3.4 Previous model with new bound on quantity to import

Here is the final model[1], with which we obtain the results from the next Chapter.

[1]For the case with possible storage, it would normally be the same approach with α, without other terms in the definition of the parameter.

From the short results (explained in section 4.1.1) obtained with the previous model, we understood that it is necessary to impose a maximum quantity to be imported, α, which represents what the country can produce in addition to what it already produces (and which can thus be exported to the other country). It is used therefore as the curtailment applied on a certain technology. This value is initialised for the first agent to a very large value, to avoid it being constrained and so that it can import all it needs.

Thus, there is only the parameter α to be added to the previous model from **??**, which represents the maximum quantity that the agent can import from the other agent:

Parameter	Units	Description
$\alpha(l,h,td) \geq 0$	[GWh]	Residual production of layer l on hour h of typical day td

Table 3.5: Additional parameter of alpha-model with units and description

Still from the previous model in section **??**, concerning the constraints, we keep them (the layer balance equation 3.7 stays identical) and we only added the following constraint:

$$\mathbf{Q_{imp}}(l,h,td) \leq \alpha(l,h,td) \qquad \forall l \in LAYERS, h \in HOURS, td \in TYPICAL\_DAYS \tag{3.8}$$

In post-processing, after running EnergyScope on an agent, we update the value of α by the following line, keeping in mind that j represents the technology used, and $\mathbf{F}(j)$ is the installed capacity:

$$\alpha(l,h,td) = \underbrace{c_{p,t}(j,h,td) \cdot \mathbf{F}(j)}_{\text{max production possible}} - \mathbf{EndUses}(l,h,td) \tag{3.9}$$

It is important not to include the terms $-q_{exp}(l,h,td) + \mathbf{Q_{imp}}(l,h,td)$, because if we did, the value would be too constrained, and it would mean that the agent would not be able to update well the value it wants to import (the alpha-value would be too small in that way).

In the cases where α would be negative (which would mean that the agent cannot export and would need to import), we apply in post-processing the following function, in order to put to 0 the negative terms:

Algorithm 2: Check alpha

```
for i in α.index do
    for j in α.columns do
        if α[i, j] < 0 then
            α[i, j] = 0
```

Here after is the pseudo-code for the exchange of information, based on the one by one iteration (thus, for case of simplicity, the indices are in the list [*first*,0,1,..] and so on). The convergence criteria still has to be defined, so for now, we were using an arbitrary number according to how fast the convergence was. The last algorithm for this model is the following:

Algorithm 3: Pseudo-code of the exchange of information

```
Initialisation of first agent A                              /* iteration first */
A.curtailment[first] = c_{p,t}(j) · F(j) − EndUses
Exchange of 3 information to the second agent B
Run on second agent                                          /* iteration 0 */
for i in [1..?] do                      /* convergence criteria to be determined */
    if odd iteration then                                    /* Runs of first agent A */
        A.c_imp[i] = B.mc_scaled[i − 1]
        A.q_imp[i] = B.Q_imp[i − 1]
        A.alpha[i] = B.curtailment[i − 1]
        run_es(A)
        scale_marginal_cost(A)
    else                                                     /* Runs of second agent B */
        B.c_imp[i] = A.mc_scaled[i − 1]
        B.q_imp[i] = A.Q_imp[i − 1]
        B.alpha[i] = A.curtailment[i − 1]
        run_es(B)
        scale_marginal_cost(B)
    i + +
```

Summary of the multi-agent modelling

In summary, the adaptation of the mathematical model of EnergyScope TD (by only taking the sector of electricity) to a multi-agent model with two agents is realised with some steps. First we added the parameters of import cost c_{imp}, quantity to be exported q_{exp} and curtailment α (calculated a posteriori), and the variables of quantity to be imported $\mathbf{Q_{imp}}$ and total cost of importing $\mathbf{C_{imp}}$. Then the definition of the total cost of importing and the constraints 3.7, 3.6 and 3.8 are changed or added to the model. The value of α is primordial, as it considers the quantity that can in reality be exported to the other agent.

Outside the AMPL model in the run file **run_energyscope.py**, the big part of the communication is implemented, where the quantity to be imported $\mathbf{Q_{imp}}$ and the marginal cost of one agent are informed to the other agent, and the process is iterative until a certain arbitrary number is reached (until convergence).

CHAPTER 4

Analysis of the results

In this chapter, we try to analyse the validity of our model. Results from models developed in the previous chapter are presented and analysed, most of them being the results of the last model. First, we present the results from the "faulty" models. Then all other simulations are variations of runs of the alpha model (section 3.4), with some ''simple" data. Finally, some discussion is set.

First of all, we lay some important hypothesises for our analyses. As said before, we investigated a simplified case with two agents, exchanging only information about electricity. Except when said otherwise, the case study is the following: the first agent with the only technology being photovoltaic (**PV**) and the other one produces electricity only through a combined cycle gas turbine (**CCGT**). We also did not allow storage of energy (because it would add to the complexity of interpretation), except when said otherwise.

We chose this configuration because we supposed it would be easy to apprehend if the solution was convenient. Indeed, at hours with no or insufficient sun, the PV agent would not be able to provide for itself and should thus import from the other (if it was more beneficial for it to buy there and not to the outside). On the contrary, when the production with PV is enough, the CCGT agent would jump on the occasion to import the maximum it can (as it would cost nothing to the PV agent to produce one more unit, if it is not at its maximum capacity).

In this configuration, it is still possible that an agent buys electricity from the outside and from the other agent simultaneously if the other agent cannot provide all its demand. As the export of electricity is initially implemented in ESTD, it is not desirable for our case. Consequently, the availability of the resource 'ELEC_EXPORT' has been put down to zero, because otherwise, we would have two quantities representing the export of electricity instead of just one.

For all the simulations, we used the model including the value α (section 3.4) and the data sets from 2040 and 2050 of Belgium, restricted to the electricity sector.

Other assumptions had to be made. Intending to obtain results making sense, it is primordial allow the technology PV to produce the amount of energy it wants without restrictions. In this optic, we have to augment the maximal possible installation of PV (passing from 59.2 GW to infinity) and declare to infinity the parameter of $solar\_area$ (available area for solar panels).

As a means to realise these tests, we make the initial importation cost c_{imp} vary depending on the case we want to observe, the cost of buying electricity to the outside is set to 0.5 [M€/GWh = €/kWh] and there is an infinite availability of electricity for both agents. It is thus essential to note that these initial prices are arbitrary. Taking higher values that we adopt for our actual cases will change drastically the result, and therefore it is crucial to stay in a certain range of possible. For the initialisation, the parameter α (for the PV agent only) is equal to a very high number in order to not restrain the first run, and the parameter q_{exp} is set to 0, as it does not know for now what it will have to export.

As outlined in Chapter 2, we chose to analyse our results with the typical days in order to understand the logic behind our system better. For having a view on the correspondence between a day in the year and a typical day, the following table presents that in addition to the number of days represented by one typical day.

TD_number	Day number in the year	Number of days
1	14	12
2	65	35
3	109	9
4	117	26
5	193	26
6	226	40
7	234	52
8	254	23
9	266	28
10	297	41
11	310	56
12	362	17

Table 4.1: For each typical day, corresponding day number in the year and number of days it represents

Another remainder from previous section is the way of iterating we are using. Figure 4.1 reminds that all odd iterations (and the *first* one) are linked to the PV agent, and all even iterations to the CCGT agent.

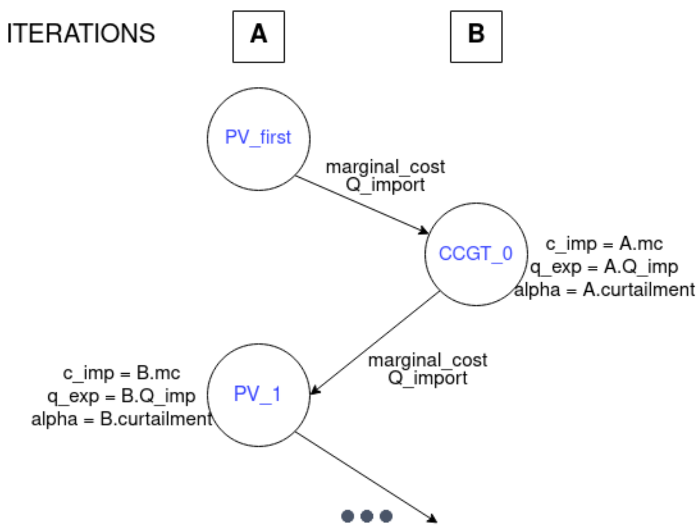

Figure 4.1: System of iterations and exchange of the three information between the two agents

4.1 Results from "faulty" models

4.1.1 Results from model with import/export (section ??)

We run the import/export model as explained before, with agent A only producing electricity through PV, and agent B only through CCGT. The initial import cost c_{imp} is 0.2 [M€/GWh], and the cost to import from the outside is 0.5 [M€/GWh], higher than the import cost because we want the exchanges happening between the two agents instead than with the outside.

Let us first analyse the response to some input import cost. The figure on the right can be explained with the following reasoning. When agent B is run for the first time with the first exchange, it is given agent A's marginal cost as its import cost. The values of the import cost are therefore supposed to be 0 or x (the initial chosen value, here 0.2, when agent A need to import). The first column with the sequence [0,0,EUD] is the following case: 0 is agent A's marginal cost when it can produce all its demand with PV and therefore it does not need to import, thus agent A's variable $\mathbf{Q_{imp}}$ being 0, it is passed on as agent B's parameter q_{exp}. As agent B receives an import cost of 0, it would be profitable for B to import all it can, so B's $\mathbf{Q_{imp}}$ is positive, equal even to its demand. In the second column, if the import cost was x, it means that agent A needs to import, so agent B's q_{exp} is positive, and because of the constraint 3.6, agent B cannot import, thus $\mathbf{Q_{imp}}$ must be 0.

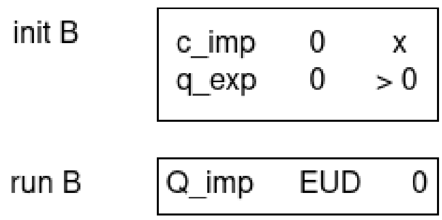

Figure 4.2: Two scenarios for the import costs at the first exchange

Not setting an upper bound on the quantity that can be imported makes the model wrong. In fact, sometimes we enter in some sort of cycle: first, the agent PV can produce enough electricity for it, thus its marginal cost is 0 and agent CCGT wants to import all its end-use demand from agent PV. However, as for the next iteration, agent PV is always restricted to its production by the capacity factor $c_{p,t}$, it is thus possible that it cannot produce enough electricity for its own demand and the one of the other agent, and thus would have to buy from the outside. Then its marginal cost would be at least the cost of buying to the outside. Hence, at the next iteration, agent CCGT will want to produce only its own demand. We will show in the next section that by adding this upper bound will correct this phenomenon.

Let us show an example of this kind of cycle in Table 4.2, where the CCGT agent does not take into account the possible curtailment of the PV agent. This is a big inconsistency of this model. At the first exchange, the PV agent needs to import part of its demand because it cannot produce everything on its own (because of the lack of sunshine). Thus the CCGT agent provides it what it needs. At the next iteration, the PV agent produces enough (because it has augmented its installed capacity, as can be seen on the bottom Figure 4.3), but we do not know its current curtailment. Then, as the CCGT agent receives an import cost of 0, it wants to import all its demand. However at the next exchange, the PV agent receives the quantity to be exported, but it is too big for its production and thus needs to import the residual to the outside, which highers its marginal cost. Consequently, the CCGT agent will prefer next to only produce its demand of electricity. It will continue then in this kind of cycle.

	ELEC	PV	CCGT	Q_{imp}	q_{exp}	END_USES	mc ELEC
PV_first	0	9.28	/	4.72	0	-14	0.2
CCGT_0	0	/	20.74	0	-4.72	-16.02	0.087
PV_1	0	14.23	/	0	0	-14.23	0
CCGT_2	0	/	0	15.04	0	-15.04	0
PV_3	5.47	24.54	/	0	-15.04	-14.97	0.52
CCGT_4	0	/	15.78	0	0	-15.78	0.087

Table 4.2: Values of layer "ELECTRICITY" and marginal cost of period TD 1 H 15

On Figure 4.3, we can see that there is a sort of convergence, but a cyclic one, as it seems that both agents respond in the same way to the other. However, the installed quantity of PV at *convergence* seems to be too high to be realistic: indeed, the true maximum that is possible in Belgium is 59.2 GW. Thus, there can be the second problem of this formulation.

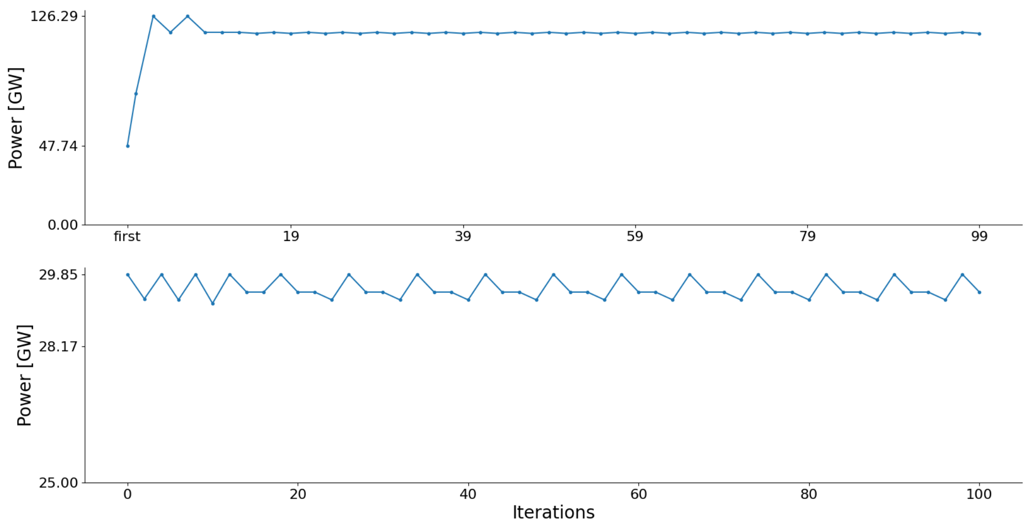

Figure 4.3: Evolution of installed quantity: top figure is the PV agent with its installed PV quantity, and bottom is the CCGT agent with its installed CCGT quantity

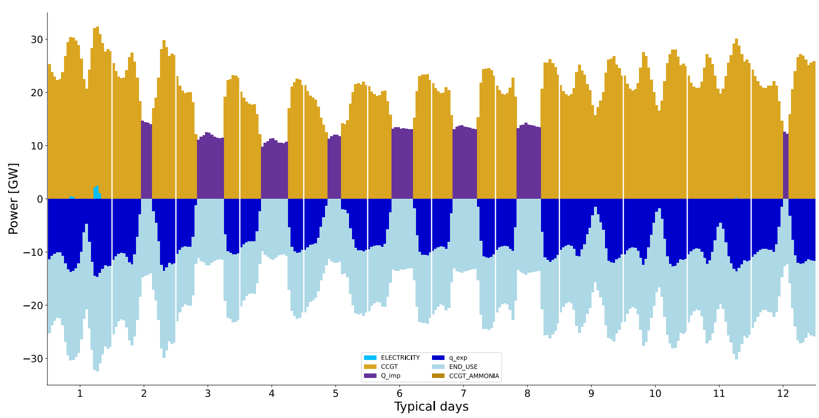

Figure 4.4: Layer "ELECTRICITY" at the iteration $CCGT_0$

When only looking at the situation after the first exchange, we can see that there is no middle ground, as the CCGT agent imports to the PV agent all its demand, without paying attention if the first agent possesses enough electricity to sell to it, without being obliged to buy to the outside. It is however in accordance with the marginal cost of PV (which thus becomes the import cost of the CCGT agent): when it is 0, the agent takes advantage of it and buys all its demand, and otherwise, it produces the sum of its demand and the quantity to be exported to the PV agent at the next iteration.

4.2 Comparison of cases with different initial import cost

4.2.1 Initial $c_{imp} = 0.2$

A number of 400 iterations in total have been realised (meaning half of it by the PV agent and the other half by the CCGT agent), and the total values of installed quantity of a technology (of PV and CCGT) seem to have converged (as it can be seen for PV on Figure 4.17). The optimal solution is found and it seems to stabilise itself, as it will be seen later. Therefore we can conclude that the method seems stable.

In general the purchase of electricity from the outside by an agent was hardly ever done, except as a last resort when it could not do anything else, which is logical since the price was higher than producing on its own or importing from the other agent.

An remainder to take into account is that the used values for the layer balance are considered in terms of power (which is constant for each hour), thus in units [GW]. But, as the modelisation happens on time slots of one hour each, each stick of the next graphs represents the equivalent energy.

Figure 4.5 represents the energy balance during the initialisation (PV_first). We can clearly see the peaks of PV production according to the sunshine (generally in the middle of the day), and during the nights the agent is obliged to import from the other agent.

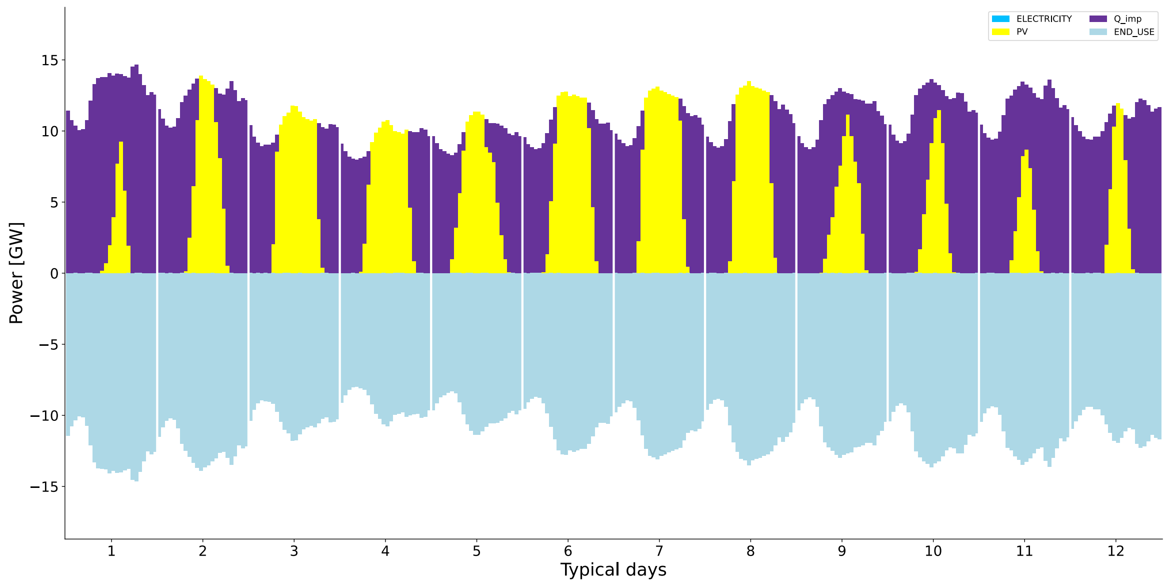

Figure 4.5: Layer "ELECTRICITY" of iteration PV_first

Figure 4.6 represents the same layer balance as the previous one, with the addition of the representation of the curtailment operated on the PV production. It represents a percentage of 32% of the total production, which is quite fair.

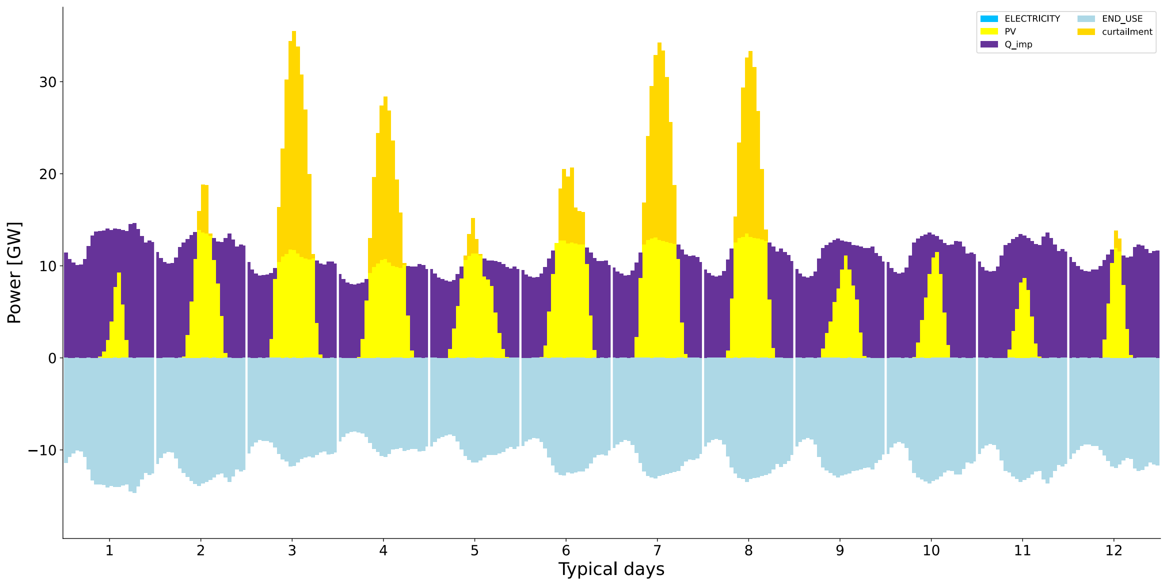

Figure 4.6: Layer "ELECTRICITY" of iteration PV_first with curtailment

In both cases of the layer balance, we can observe that the graphs are symmetrical with respect to the x-axis.

Figure 4.7 represents the marginal cost of the iteration PV_first, which is therefore given as the import cost at CCGT_0. We can observe a strange value in TD6, which is not 0 or the import cost, as mentioned in the table 4.5. Its presence can be explained by the fact that the PV agent is at the limit of what it can produce, given its capacity factor at this hour and its installed capacity. We can therefore understand that, when the cost is 0, the CCGT agent chooses to import, as confirmed on the graph 4.8.

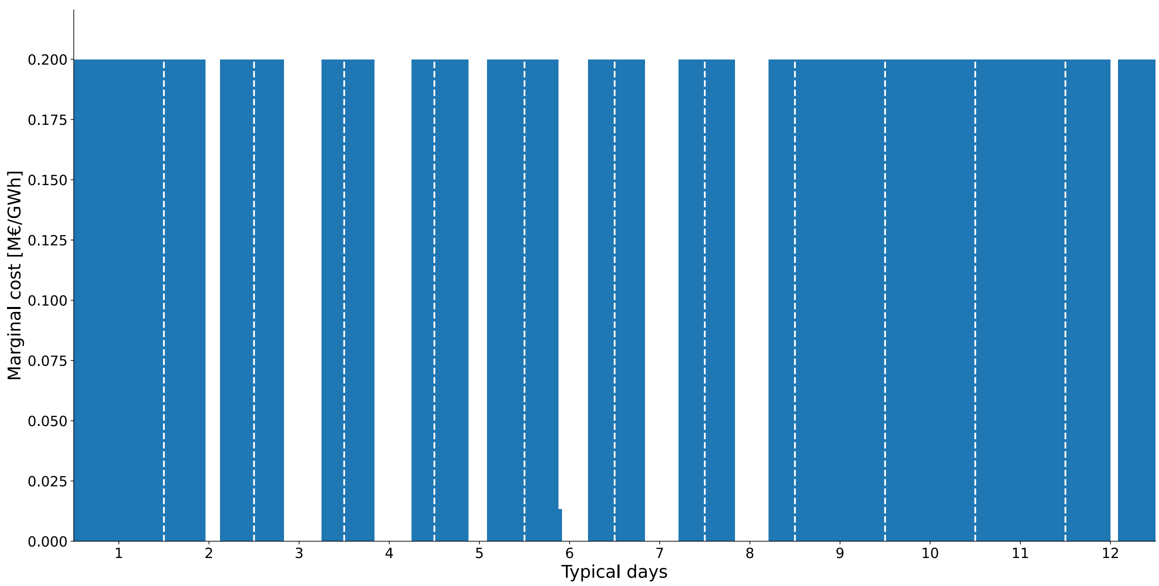

Figure 4.7: Marginal cost of agent PV over the typical days

Figure 4.8 shows the energy balance after the first exchange (CCGT_0). We can see that the quantity to be imported in the first graph 4.5 is the opposite of the quantity to be exported in the other, which was a prerequisite. We can also see that when the agent has to meet the needs of both demands (i.e. the quantity to be exported and its own demand), it is obliged to produce more thanks to its technology CCGT. We can also observe that, when the other agent PV satisfies its demand entirely thanks to its production, the CCGT agent takes advantage of this to import what it needs according to what is available with the α parameter/curtailment (which can be seen by the brown bar, CCGT production, surmounted by the purple bar, quantity to be imported available). Another observation is that the CCGT agent is obliged to buy electricity to the outside world, as it is already at its maximal production.

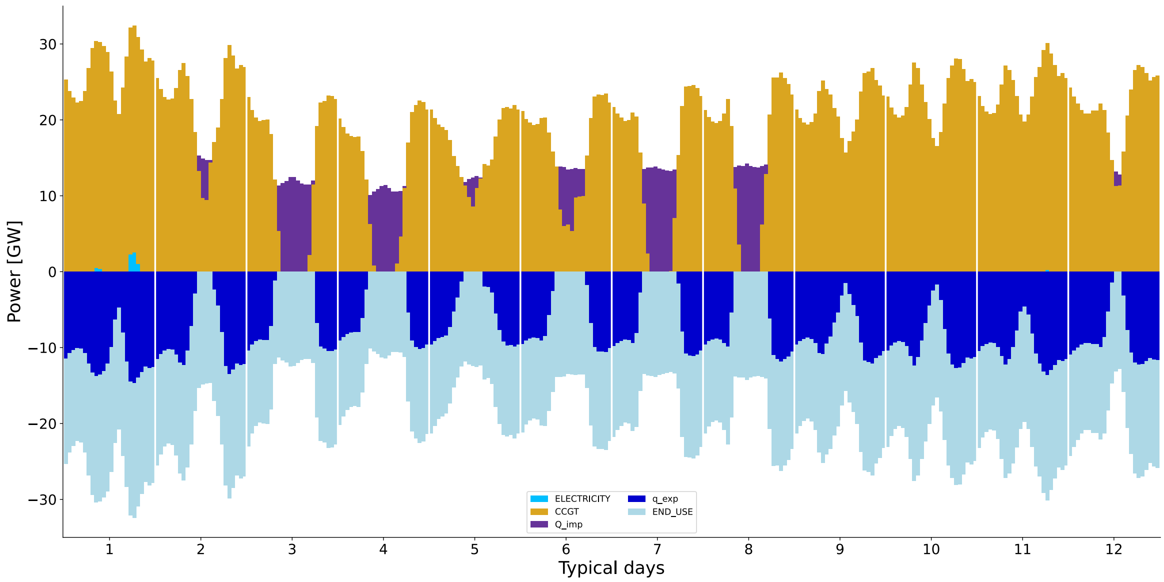

Figure 4.8: Layer "ELECTRICITY" of iteration CCGT_0

We could have shown a graph of the balance of exchanges, but as there are only two agents, it would only be seen that on one side of the horizontal axis there is positive input and on the other side negative output, so no useful purpose.

Concerning the convergence of the algorithm, we can see that it takes a lot of iterations before attaining what seems to be the optimal solution. A possible problem is that the agent realises that it is not at the place where it can converge, but we do not let him enough space to develop (maybe because of the parameter α which only grows or lowers little by little). In fact, it is from iteration 283 that the solution only begins to differ by some numbers behind the comma. Thus,

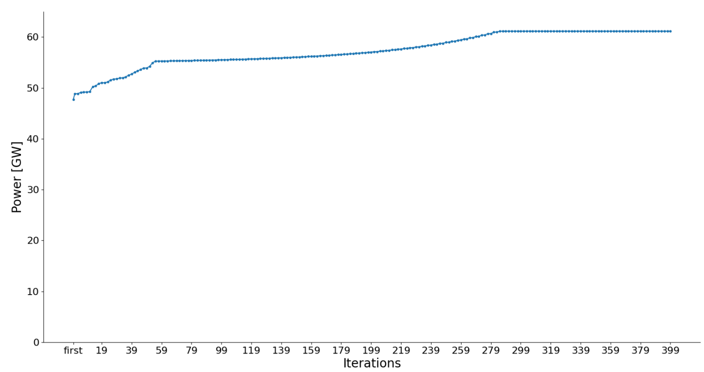

Figure 4.9: Evolution of the installed quantity of PV over the 200 iterations of the PV agent

in this configuration of initial conditions, the optimal installed quantity by the PV agent is very close to 61 GW. It is a rather reasonable solution, as, initially, the upper bound on the installation of PV was 59.2 GW. Also, the installed quantity only goes higher because it is as if the CCGT agent pushed it to produce more and more until it reaches the quantity just before it is no more profitable.

Concerning the convergence of the installed quantity of CCGT for the CCGT agent, it converges almost immediately to the value of 29.4 GW.

About convergence of the total costs, Figure 4.10 presents this. We can see a cyclic convergence, that oscillates between two values (close to each other) for each of the agents.

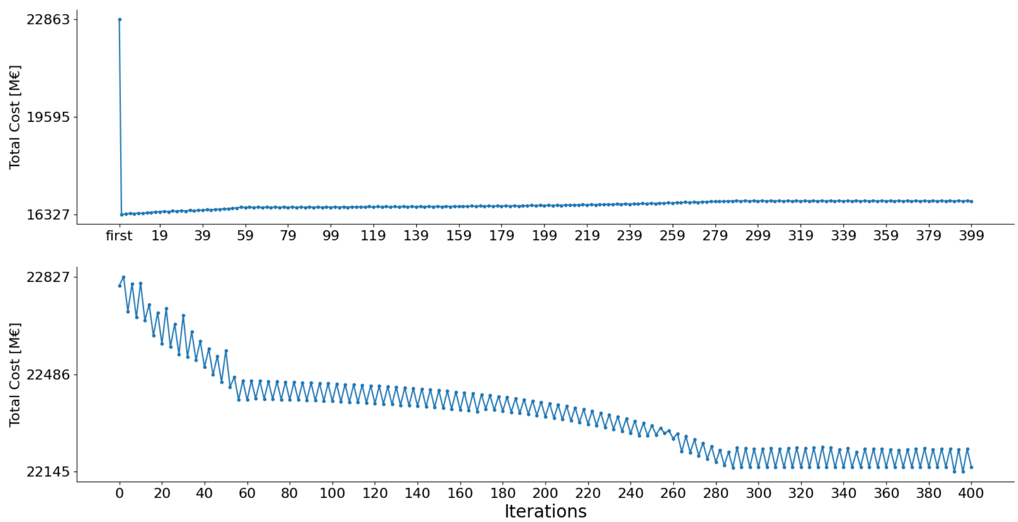

Figure 4.10: Evolution of both total costs (case $c_{imp} = 0.2$): top figure is for the PV agent, bottom figure is from the CCGT agent

In order to understand furthermore the situation and the exchanges happening within this case, we analyse the following tables, representing the values of the layer electricity, the parameter α and the marginal cost at a same hour from a same typical day: we can thus observe that the energetic balance is well respected (the sum of the energies equal to 0). We only show some general cases in the exchanges: exchange from CCGT to PV, or vice versa (or no exchange, or else really small).

In this first table, we can observe a "normal" exchange where the CCGT agent prefers to import electricity from the PV agent because it will cost nothing (marginal costs of PV agent are 0). It can indeed be seen on Figure 4.6 that the third typical day is the one with the biggest curtailment, meaning that it will be able to provide electricity to the other agent.

It can also happen partially, meaning that there is some curtailment, but it will not be sufficient for the CCGT agent and it will thus have to also produce the rest of its demand.

	ELEC	PV	CCGT	Q_{imp}	q_{exp}	END_USES	α	mc ELEC
PV_first	0	11.78	/	0	0	-11.78	1000000	0
CCGT_0	0	/	0	12.48	0	-12.48	22.6	0
PV_1	0	24.87	/	0	-12.48	-12.39	17.37	0
CCGT_2	0	/	0	142.48	0	-12.48	22.78	0

Table 4.3: Values of layer "ELECTRICITY" and marginal cost of period TD 3 H 12

The following table also represents a normal exchange, where the PV agent does not produce enough electricity to meet its needs and thus have to import from the other agent, given that the price is more favourable than to buy some from the outside. That can in particular be verified on the graph 4.5 where, on the 14th hour of the first TD, we can see a yellow bar (energy produced by PV) with a little purple bar above (which represents the quantity to be imported).

	ELEC	PV	CCGT	Q_{imp}	q_{exp}	END_USES	α	mc ELEC
PV_first	0	7.72	/	6.31	0	-14.03	1000000	0.2
CCGT_0	0	/	22.52	0	-6.31	-16.21	0	0.087
PV_1	0	7.90	/	6.14	0	-14.04	13.64	0.087
CCGT_2	0	/	22.34	0	-6.14	-16.20	0	0.087

Table 4.4: Values of layer "ELECTRICITY" and marginal cost of period TD 1 H 14

In the following table, the strange value of marginal cost appearing in Figure 4.7 can be understood. In fact, the amount of energy produced (12.47 GWh) is at the limit of production (multiplying the installed quantity by the capacity factor at this hour). This would mean that, for producing one more unit of electricity, the marginal cost would not be 0 as the agent would have to install more capacity and pay more. We can also see that the installed quantity of PV grows a little bigger, as the CCGT agent can at its second iteration import a little bit of curtailment.

	ELEC	PV	CCGT	Q_{imp}	q_{exp}	END_USES	α	mc ELEC
PV_first	0	12.47	/	0	0	-12.47	1000000	0.013
CCGT_0	0	/	13.85	0	0	-13.85	0	0.087
PV_1	0	12.47	/	0	0	-12.47	16.00	0
CCGT_2	0	/	13.55	0.29	0	-13.83	0.29	0.087

Table 4.5: Values of layer "ELECTRICITY" and marginal cost of period TD 6 H 10

In the next table, we can also observe another "normal" exchange where the PV agent needs entirely its electricity (because it cannot produce it itself in the middle of the night) and thus it imports from the CCGT agent which possesses enough in order to sell to agent PV. The marginal cost is in each case the one of the production of CCGT.

	ELEC	PV	CCGT	Q_{imp}	q_{exp}	END_USES	α	mc ELEC
PV_first	0	0	/	9.14	0	-9.14	1000000	0.2
CCGT_0	0	/	20.28	0	-9.14	-11.14	0	0.087
PV_1	0	0	/	9.14	0	-9.14	18.71	0.087
CCGT_2	0	/	20.28	0	-9.14	-111.14	0	0.087

Table 4.6: Values of layer "ELECTRICITY" and marginal cost of period TD 10 H 4

4.2.2 Initial $c_{imp} = 0.1$

As for the previous case, we inspect the same concepts. In Figure 4.11, it is obvious that there is less production of PV than in the previous case. It can be explained by the fact that the import cost is lower, so it is more beneficial for the agent to buy than to produce more.

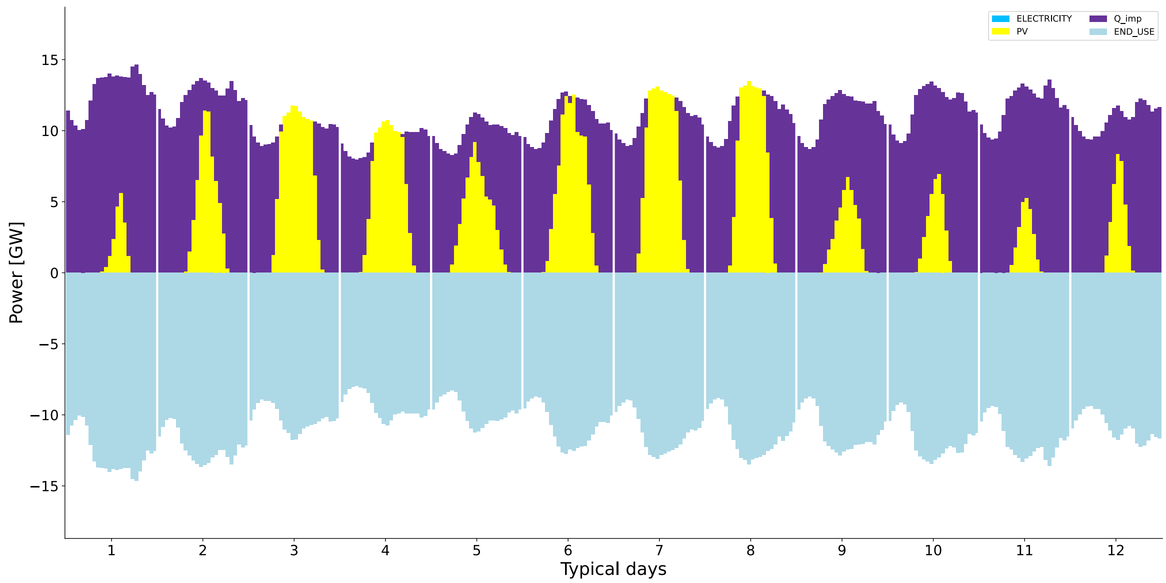

Figure 4.11: Layer "ELECTRICITY" of iteration PV_first

As previously said, less production happens, meaning that a smaller quantity of PV is installed, and comparatively, the curtailment is even smaller than before. We can see on Figure 4.12 that there are only 4 days with curtailment, in comparison to the previous case where there were 7 typical days with curtailment.

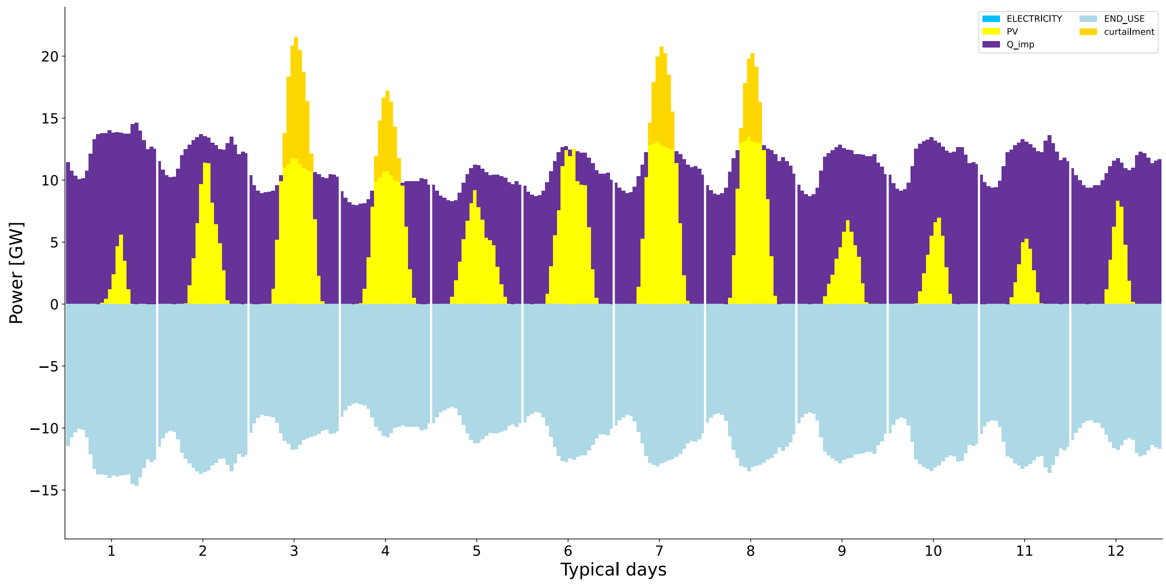

Figure 4.12: Layer "ELECTRICITY" of iteration PV_first with curtailment

Here also, there is a strange value of marginal cost in TD6, as it can be seen on Figure 4.13, that can be attributed to the fact that at this hour, the agent PV is at the limit of its production, which will thus cost more to produce one more unit.

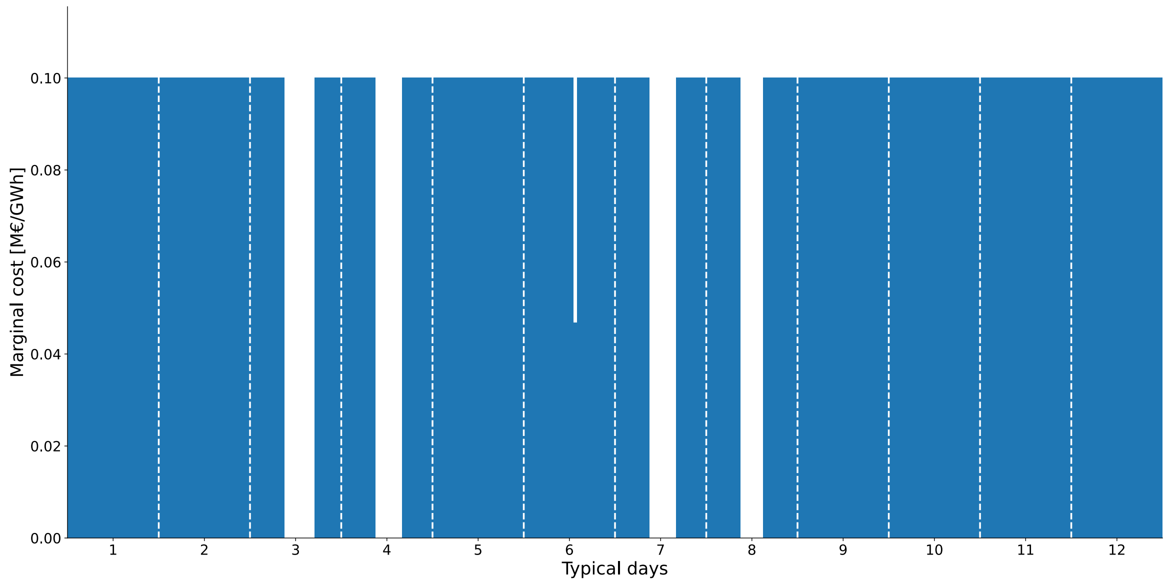

Figure 4.13: Marginal cost of agent PV over the typical days

Because there are less hours with curtailment, there are thus less moments where the CCGT agent can import electricity from the other agent. This can be verified on Figure 4.14, where the agent imports on the same four days as the figure with curtailment. As before, it must import a little quantity of electricity from the outside in order to meet its demand. It is however a really minimal part of the system.

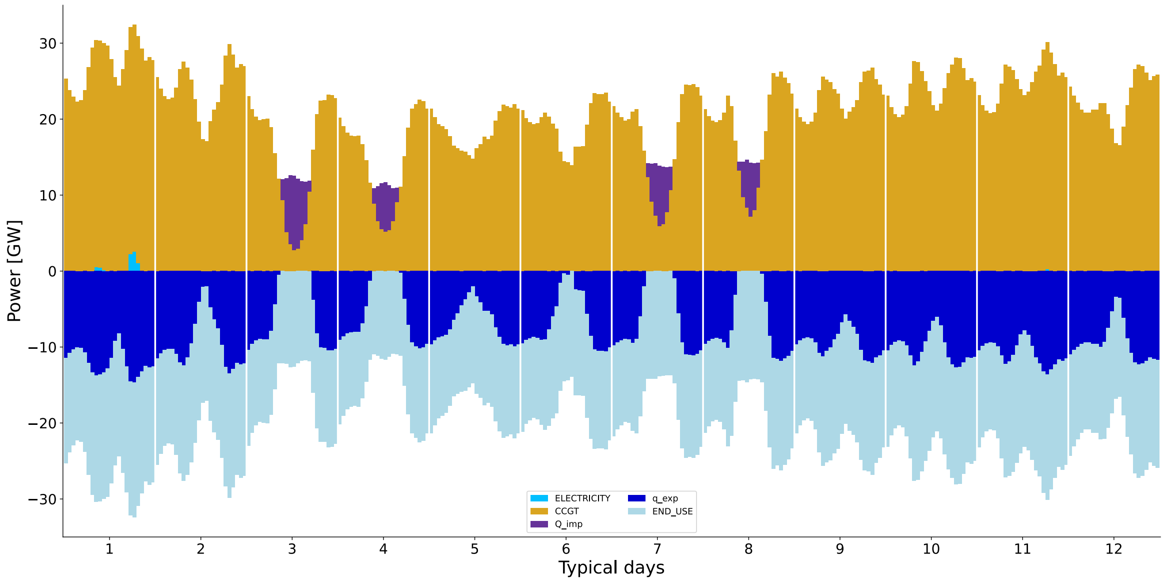

Figure 4.14: Layer "ELECTRICITY" of iteration CCGT_0

Concerning the convergence of the installed quantity of PV, we can see that it takes also a lot of iterations before attaining what seems to be the optimal solution. In fact, it is from iteration 123 that the solution seems to have attained its maximal value of 33 GW. It is a reasonable solution, because it is in the initial range of [0;59.2].

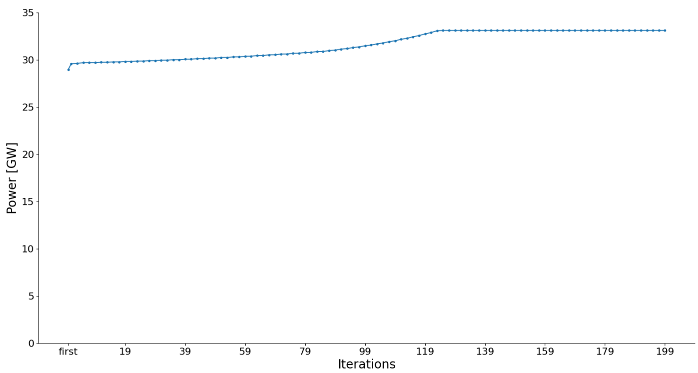

Figure 4.15: Evolution of the installed quantity of PV over the 100 iterations of the PV agent

This time, concerning the convergence of the installed quantity of CCGT for the CCGT agent, it converges almost immediately to the value of 29.8 GW.

Concerning the convergence of the total costs of both agents, Figure 4.16 shows the (cyclic) convergence of both costs, but comparatively to the number, it is not really significant.

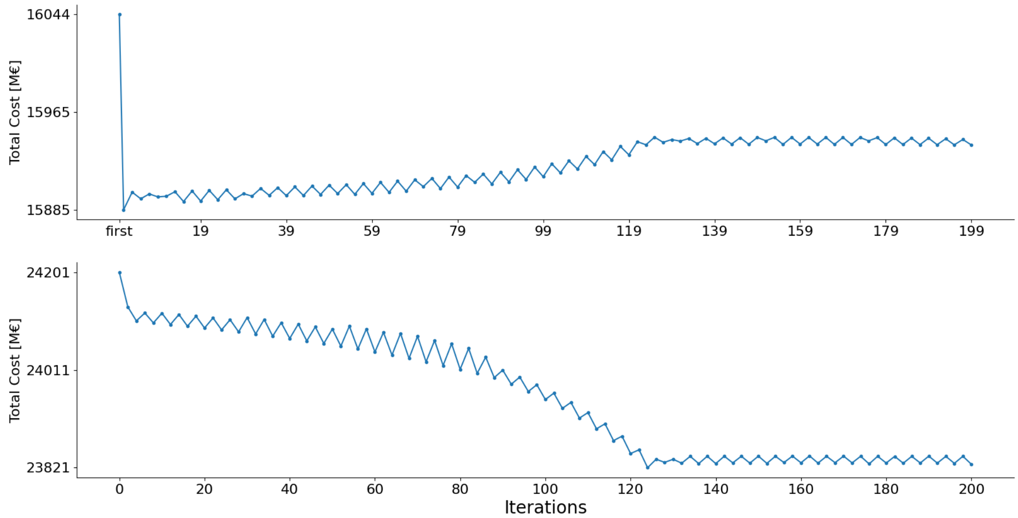

Figure 4.16: Evolution of both total costs (case $c_{imp} = 0.1$): top figure is for the PV agent, bottom figure is from the CCGT agent

4.2.3 Initial $c_{imp} = 0.05$

In the case of this initial import cost, we observe in the results that the PV agent chooses not to produce anything, and only import from the CCGT agent. When running more tests to conclude what is the threshold value from which the PV agent begins to produce electricity, we find a value around 0.056 (at this moment, the PV agent produces but do not curtail anything). This thus means that for a number smaller than this, its LCOE is bigger than the import cost, and therefore chooses to only import and not install anything.

What we do not understand is that, when calculating the LCOE apriori with the parameters given, with the formula $\frac{c_{inv}(PV) \cdot \tau(PV) + c_{maint}(PV)}{c_{p,expected}(PV) \cdot 8760}$ taken from [10], we obtain a value of approximately 0.045, which is less than 0.05, meaning thus that the PV agent should produce what it can and then import the rest. Maybe that we do not take into account everything into this LCOE, such as some values that could be taken as taxes (that for producing they need to pay and inversely). One of these could be the cost of the efficiency measures in the energy system, or the electrical grid cost, or else the parameter $c_{grid,extra}$ (cost to reinforce the grid per GW of intermittent renewable). When integrating only this last contribution times its annualisation factor into the LCOE, we obtain a value around 0.052, which is close to the threshold value. And when adding the two other, the number becomes much bigger than 0.056, which means that this would still not be the good way to calculate that. Perhaps the way the optimiser calculates the moment when it becomes profitable to produce is not how we just did it.

However, in spite of this initialisation, we still obtain results of convergence. This is normal, as the import cost changes at each iteration and does not keep the value of 0.05.

As explained, the initialisation gives an installed capacity of 0 GW. However, after that, the import cost changes (with the previous iteration's marginal cost of the CCGT agent) and thus the PV agent can in turn produce electricity (as its LCOE must be lower than the import cost). The value of convergence, obtained quite quickly in the iterations, is around 27 GW.

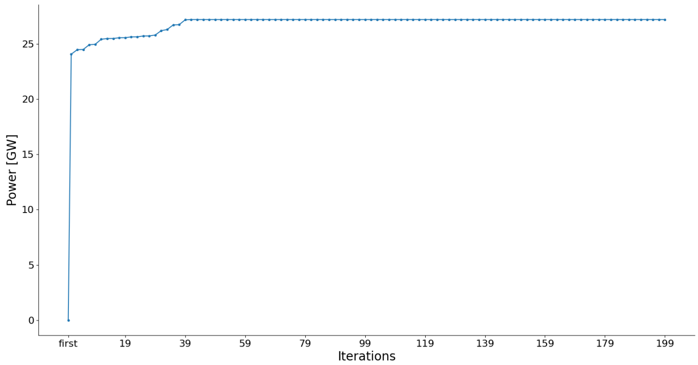

Figure 4.17: Evolution of the installed quantity of PV over the 100 iterations of the PV agent

The convergence of the installed quantity of the CCGT agent, as for the two previous cases, is attained after one iteration, at the value of 29.18 GW.

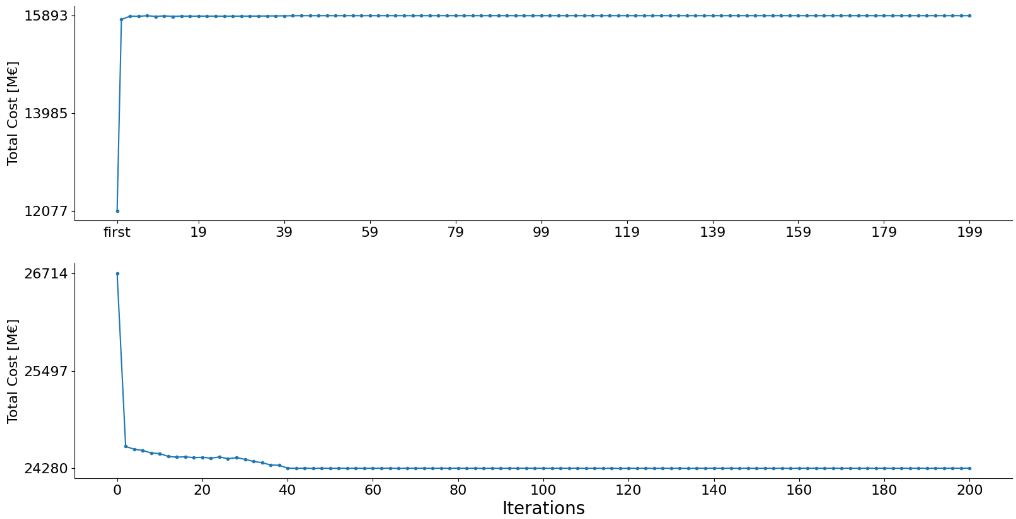

Figure 4.18: Evolution of both total costs (case $c_{imp} = 0.05$): top figure is for the PV agent, bottom figure is from the CCGT agent

We can see on Figure 4.19 that the yearly imported quantity of the CCGT agent is first 0 (logical because the PV agent does not produce) but then it increases. On bottom Figure 4.18, we observe that the total cost decreases consequently, because the CCGT agent al-

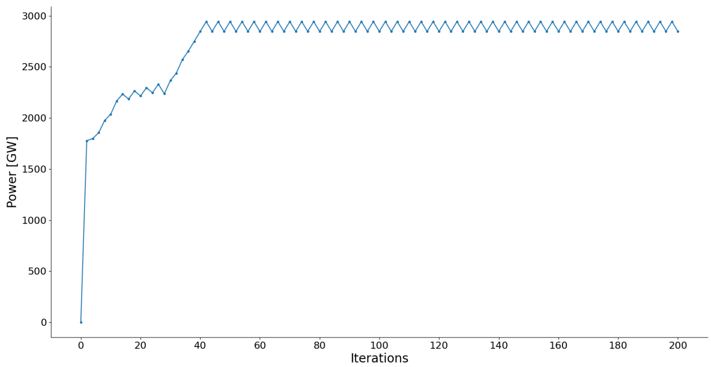

Figure 4.19: Evolution of the yearly imported quantity of the CCGT agent over its 100 iterations

ways imports to the PV agent at the cost of 0 (as it is the latter's marginal cost).

4.2.4 Comparison of these cases

In the following table 4.7, some information mentioned in the previous subsections are gathered.

Initialisation	c_{imp}=	c_{imp}= **0.1**	c_{imp}= **0.2**
F_PV [GW]	0	29	48
Curtailment [-]	0	13%	32%
Yearly $\mathbf{Q_{imp}}$ [GWh]	97 270	72 300	65 057
$\mathbf{C_{imp}}$ [M€/GWh]	4863	7230	13 011
TotalCost [M€]	12 078	16 045	22 863
LCOE [M€/GWh]	/	0.05232	0.0668
LCOE (with grid cost) [M€/GWh]	/	0.1227	0.12579

Table 4.7: Comparison between initialisations PV_first according to the initial import cost of the other agent

Thus, from this table, it can be noted the following: if the PV agent receives a signal of a higher import cost, it will install more of its technology, and on the contrary, if it receives a lower import cost, it will install less. As the PV's production is higher, so is the curtailment. Another logical concept that can be seen is that, if the PV agent produces more, it does not need to import a large quantity. The total import cost is thus proportional, and so is the total cost.

We can also compare the convergence we obtain for each case:

At convergence	c_{imp} = **0.05**	c_{imp} = **0.1**	c_{imp} = **0.2**
F_PV [GW]	27.18	33.10	61.14
Curtailment [-]	10%	15%	32%
Yearly $\mathbf{Q_{imp}}$ [GWh]	Around 73 100	Around 70 100	Around 61 500
Yearly production PV [GWh]	Around 28 200	Around 34 000	Around 54 000
Total cost [M€]	Around 15 900	Around 15 940	Around 16 780
LCOE (without grid) [M€/GWh]	0.0456	0.046	0.0537
LCOE (with grid cost) [M€/GWh]	0.111	0.101	0.092

Table 4.8: Comparison between convergence iterations for PV agent according to the initial import cost of the other agent

From Table 4.8, we can observe the same behaviour as for the initialisation for some quantities. Now, there is some capacity installed for the case $c_{imp} = 0.05$, and it is, as expected, lower than the other ones. The curtailment is the same as the initialisation, except the first case, which is normal.

Depending on the initial conditions (import cost from the other agent or outside), the results will be completely different. Also, it seems that the first exchange fixes the rest of the problem, so that the solution stays in a certain range by growing a little, but not lowering. This will be explained in more detail in section 4.6.

4.3 Cases with storage

In theory, storage used in the system with the technology PV could be beneficial: the energy that would be produced in excess during the hours of sunshine could be stored in the batteries to be released when the agent needs it during the night. Nevertheless, adding storage adds to the complexity of interpretation, but could also be beneficial to diminish its own costs.

By first running by allowing batteries, there were problems because there was energy coming in and out of a battery at the same hour of the same typical day, which was too weird because normally not allowed ..see..

The lithium battery possesses a round-trip efficiency of 10%, so if it charges and discharges at the same time, it loses 10% of its energy produces. It is thus quite surprising that the system would choose to accept this loss, while it could avoid it.

It is also bizarre regarding the marginal costs (they should be influenced by the batteries, because if some surplus is produced, it must be stocked, which changes the costs).

In page 19 of [12], they say that "we systematically verify during the post treatment that a storage technology is not charging and discharging at the same time, which removes the need of using a binary variables", but during our tries of code, that thing they prevented happened as just explained.

However the results seem to obtain convergence of, for example, the quantity of installed PV (or CCGT). We also need to accept some tolerance in relation to said convergence, depending on the range of variation (in the case there is no "strict" convergence and it oscillates a bit). For example, on Figure 4.20 the variations are not very big, so we can guess that the optimal solution lies in this range.

4.3.1 Only lithium batteries

When allowing only lithium batteries to the PV agent, we also obtain some convergence of installed quantity of PV. It is important to note that the maximum

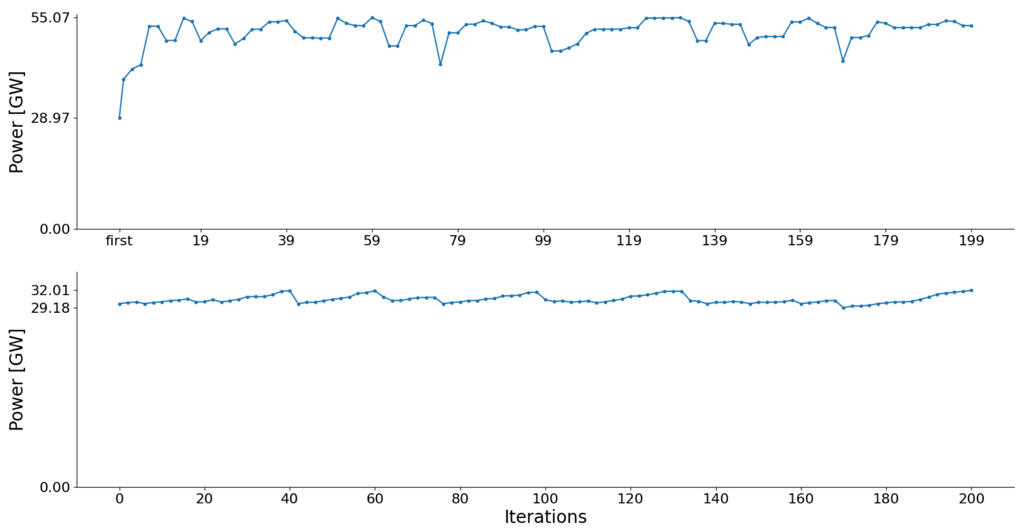

Figure 4.20: Evolution of both total costs (case $c_{imp} = 0.1$ and BATT_LI): top figure is for the PV agent, bottom figure is from the CCGT agent

We could do the same for the case with the battery PHS (but its range of possible installed quantity is quite restrictive [5;6.5]) or else with a combination of both batteries.

4.4 Comparison with scenario without exchanges

In the case without exchanges, it is easy to run a version of the old model without all the new parameters and variables for exchange. In order to keep the same spirit as before, we keep the outside import cost to 0.5 [€/kWh] (arbitrary value taken for all our examples).

4.4.1 PV agent

Its total cost (sum of the annualised investment, maintenance and operational costs) is equal to 42 472.35 [M€/GWh], which is way higher than the total costs obtained with the exchanges (for the three cases).

Its installed capacity of PV is 85.98 GW, which is bigger than the installations of the first three different cases.

Obviously, it produces what it can depending on the capacity factors of each hour of the typical days (representing the amount of sunshine). What misses to meet the demand is thus imported from the outside, which is why the price is high.

4.4.2 CCGT agent

The total cost of agent CCGT without exchanges is 17 479.10 [M€/GWh], which is in general way lower than the ones of the cases with exchanges possible. Its installed capacity is only 15.84 GW, which is way less that the one with exchanges in general (because in these cases, it has to cover the other demand).

The agent produces at each hour the amount of its demand of energy, and at very few hours it needs to import from the outside. This is why the total cost is the lowest of the cases, since here it does not have to take into account the demand of the other agent, and it can almost suffice by itself, because of the choice of the technologies.

Thus, the multi-agent model system as we designed can be beneficial to some agent, and detrimental to the other, depending on the choice of technologies implemented.

4.5 Case with more technologies allowed

In order to add more depth to the analysis of the proposed multi-agent system, we added the possibility to incorporate more technologies for both agents: more renewable technologies (wind on and off-shore, and hydro-river) for the PV agent, and the use of ammonia in another unit of CCGT for the CCGT agent.

There are more "constrained", in the sense that the maximal capacity to be installed is quite low (5 for wind offshore, 10 for wind onshore). Concerning the convergence of installed capacities of each technologies, the technology wind onshore stays at all iterations at level 10 GW, wind offshore also stays at its maximum possible (5 GW), and hydro river stays constant at the value 0.115 GW (which is also its maximum capacity to be installed). On the following figure, we can see that the installed quantity of PV converges at a reasonable capacity, and that the one of CCGT converges already after the first iteration.

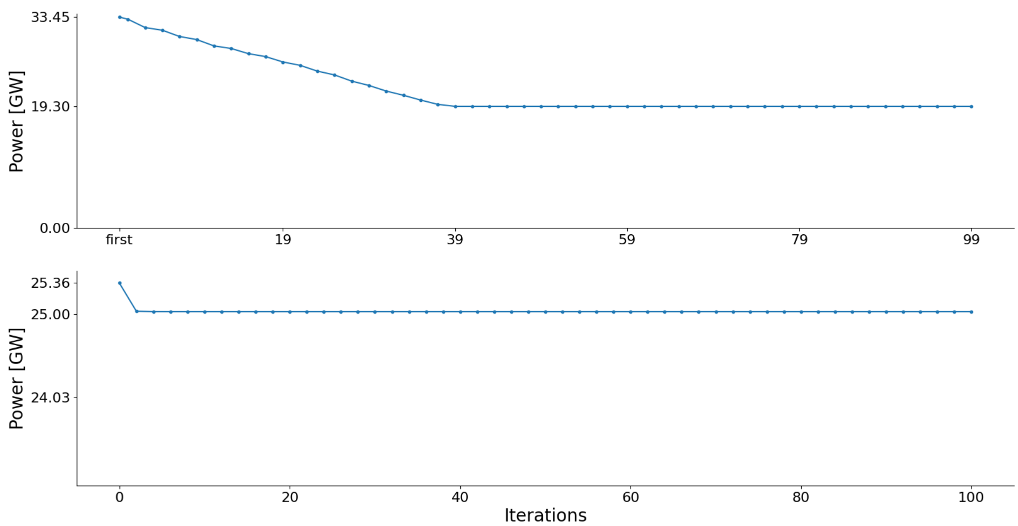

Figure 4.21: Evolution of installed quantity: top figure is the PV agent with its installed PV quantity, and bottom is the CCGT agent with its installed CCGT quantity

On Figure 4.22, we can observe the layer electricity at the initialisation, along with the curtailment. The latter here regroups the curtailments for all the technologies involved in the producing of electricity. We can mention that the curtailment of PV is the bigger one, as it is the only one happening in TDs 3, 7 and 8, and on the others it is the sum of all of them.

We can also see that, there is already less needs to import from the other agent, because with more technologies at disposal, more electricity can be produced for the own demand of the PV agent.

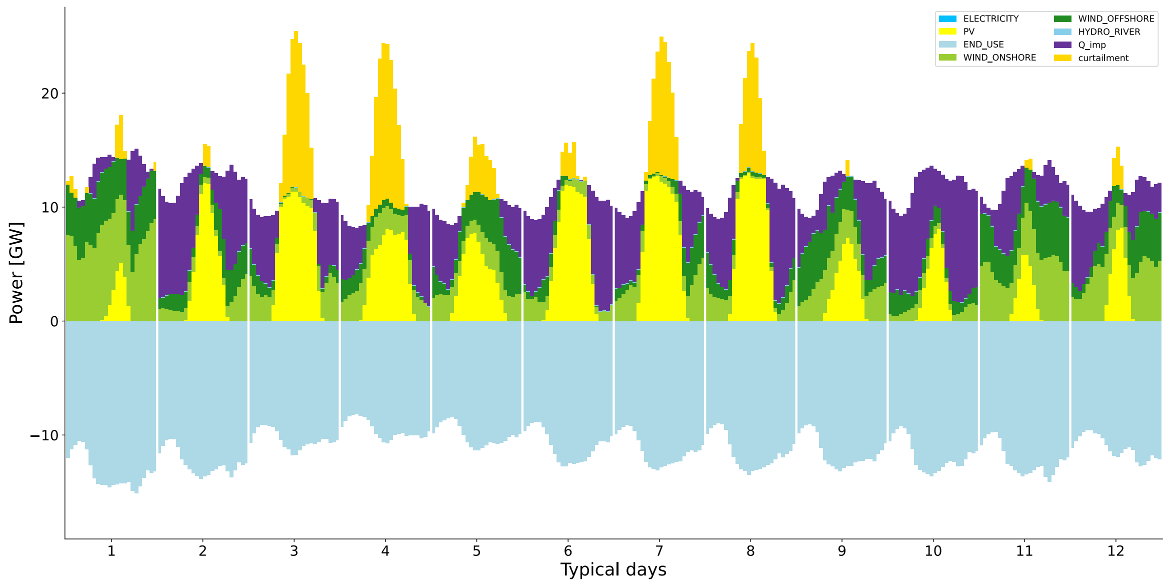

Figure 4.22: Layer "ELECTRICITY" with curtailment of iteration PV_first

As for the CCGT agent, after the first exchange, as the curtailment is not that big, the agent takes the curtailment available and then has to produce as well on its own.

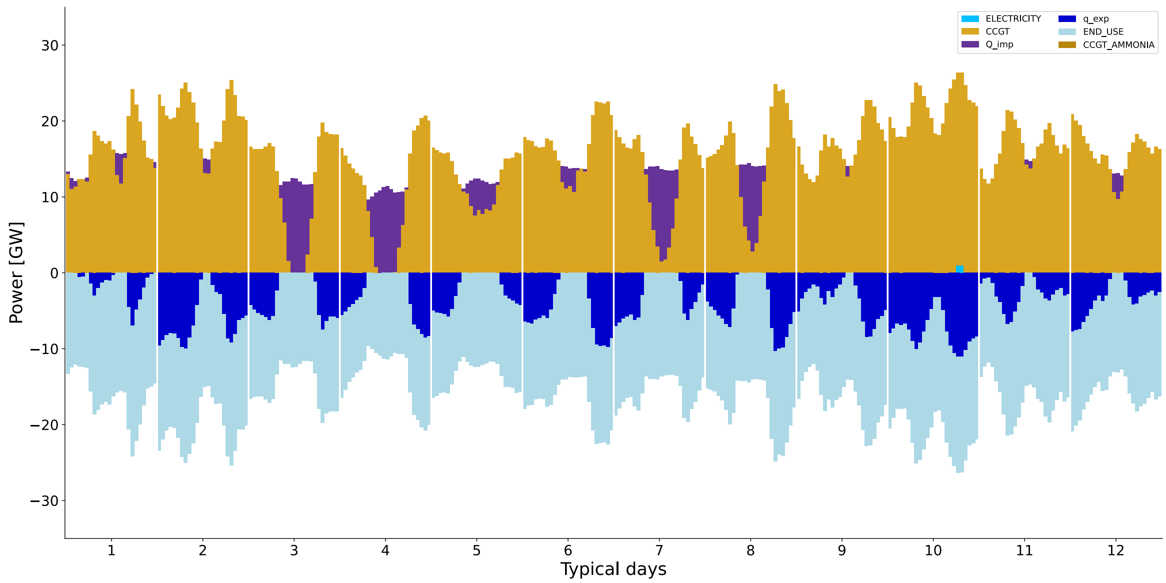

Figure 4.23: Layer "ELECTRICITY" of iteration CCGT_0

The analysis of the case with more technologies involved is thus a good assumption that the system is well designed for larger possibilities of technologies, as it seems that the factors observed converge all to some values.

4.6 Discussion

From the analyses, our initial objective is achieved. We want to obtain the design and operation of each agent, while at the same time attaining an optimal solution where the two agents only exchange with the outside when it is necessary. Typical case is when one of them cannot meet the two demands. The aim is to have a closed system where the agents are forced to make arrangements with each other.

However, the cases do not converge towards the same solution for an identical system but with only the initial import cost differing. This is weird because, at first thinking, the initial condition of the import cost should not be determinant since the initial cost is only valid for the initialisation, and should not matter for the successive iterations. However, after some observations, it is logical that it is determinant. Indeed, the initialisation and the first exchange fix the rest of the problem: if the PV agent can produce a lot, and thus curtail more, the CCGT agent will import more, augmenting its variable of quantity to be imported. As it is passed on as the parameter q_{exp} to the PV agent, it acts as an *obligation* to produce for the PV agent, and it will have to continue to install at least the same capacity. We can understand that CCGT agent's import potential is fixed from the beginning and then it is hard for the PV agent to lower its capacity.

Thus, we do not converge towards a same solution with different initial import costs because the convergence does not happen the same way. If we begin with a low import cost, the PV agent would prefer to import more and thus produce less, and after some iterations, the solution will generally stay on a same range (and not be able to descend a lot). On the contrary, if the import cost is high, then it will prefer to install more, thus the initial installed quantity of PV will be higher, and after some iterations it will stay in the same range, but higher than the previous situation.

The results are radically different when initialising with other values for the import cost to the other agent and the outside. For instance, when $c_{imp} = 2$ and $c_{ext} = 5$, the initialisation gives an installed capacity of 174 GW for the PV agent, which is too huge to be feasible. We can explain this by the fact that, as explained, the model seems to be dependent on initial conditions.

In addition to the fact that the system depends on the initial conditions, these are arbitrary. We did not include a case where the cost for importing electricity from the outside would be smaller than the one for importing to the other agent, as we would lose the interest of our model. We want to avoid as much as possible to make imports from the outside, as our goal is to create a multi-agent system between two agents, that would provide for themselves in that way.

We also made the following tests: augmentation of the PV price or diminution of the CCGT price. However, we did not have the time to analyse them in depth. We can only say that globally, their behaviour is the same as the ones we already analysed. We also hoped that the first case would install less PV (and it did).

Another small incoherence is that the marginal costs (taken as the dual variables) rarely perform erratically. For example, the following situation happened when the initial costs were higher than the ones we use in the analyses. When there was some curtailment for the PV agent, the marginal cost was nonzero, which was nonsense, since it would not cost anything more to produce one more unit of electricity using PV and thus should be 0. Instead, we could maybe use the global real marginal cost, but it would not be correct. In that case, it would not show that some hours are sometimes better than others (distinction between 0 or importation).

A further limitation is that we do not take into account the export to the other agent in the total cost, there is thus no profit for an agent to sell to the other. As the CCGT agent "buys for free" some electricity to the PV agent (as its marginal cost is 0), the PV agent gains no profit of sending its curtailment. We could incorporate in the total cost a negative term representing the profit made, but we thus would have to come up with a cost term (which would represent the marginal cost, but not 0 for when PV produces). The other problem to implement this is that we do not have access to the dual variables during optimisation (only after), thus we would also have to impose values to these costs.

One other thought we had while analysing results is that we force an agent to export the other agent's requested import quantity. We might introduce a variable for the exportation and border on the upper limit by the parameter q_{exp}. However it would be not helpful because it would not be used elsewhere in the model, as we only take costs into account in the total cost, and not the selling profit (as explained in the previous paragraph). Nevertheless, even if we wanted to implement this method, it would be complicated because we would have to agree on a specific selling cost.

We also tried to integrate one agent's quantity to be imported from the outside in the export demand of the other agent: $A.q_{exp} = B.Q_{imp} + B.outside$. However, this induced some repetitive behaviour (each 60 iterations, the installed quantity of PV would be put down to 0) because the external import would be too tremendous (as it would just add up at each iteration because the agent would not be able to produce this amount).

Conclusion

In the context of studying interactions between a country and its neighbours, multi-agent systems are a valuable tool to model these in a multi-regional energy system because of the communication made possible between agents. Although no concrete application about the integration of minimisation of costs into a multi-agent system had been found in the literature, we were able to reach our goal on a simplified case.

Throughout this work, we have built a simplified multi-agent model on a multi-regional energy system to extend to the already established optimisation program EnergyScope TD. We only studied the exchanges between two countries because it suffices to cover the research question. Our research question was answered by explaining the model in Section 3.4 and analysing different cases to verify our multi-agent system's reliability.

After a quick review of state of the art multi-agent systems, energy systems and how to apply them in actual physical problems seen in Chapter 1, a linear programming model, ESTD, was thoroughly described in Chapter 2. Basing our work on this model, we implemented multiple models (same of them were fruitless) that we presented along with our final working model 3. Thanks to this implementation, we obtained some conclusive results, analysed in Chapter 4.

In the modelling of each agent's system, it considers its own demand plus, if it exists, the other agent's quantity to import (which acts as a second demand). In this prospect, this model has been applied on fictive cases, which were analysed and proved that exchanges are possible and lead to a consensus after a fictive iterative process.

However, the model possesses some limits. First, we based our cases on arbitrary initial costs that can change all the results. The problem is sensitive to initial conditions as the first exchange fixes the quantity to be exported, thus the other agent's production.

Another drawback is that the computation time is too high when running a considerable number of iterations (around 20 to 30 minutes sometimes).

Some improvements could thus be implemented in the future. The first step would be to pass from a fictive case (the data sets of 2040 and 2050 used for Belgium) to a more realistic case. At the same time, allowing all technologies for both agents would be helpful, as the introductory example did in section 4.5.

Then including more sectors in order to get a multi-sector energy system would be another option. One further step would be to allow more agents into the MAS, as in reality energy systems can be composed of more countries. Indeed, it is known that in reality exchanges are made between more countries (for an exact "environment"), such that the European Union allows an easy "access" and exchange of information.

Another thing to implement is the convergence criteria: for all the performed iterations, only a for-loop was designed, with a fixed number of iterations. We could not develop a reasonable criteria that would embrace all the possible cases. It would be wise to automatise the process (because, for now, the code is not significantly optimised).

To conclude, the developed model can be taken as a basis to extend in the future the multi-agent system with two agents to one with more agents. The results were relatively consistent, but not all cases have been studied, and there is certainly room for improvement.

APPENDIX A

Different models used

A.1 Model with exchanged quantity and cost

The idea here is to replace the buying and selling costs with only one exchanging cost, in order to simplify the model. As for the quantities, we also reduce the number from two to one, so only a quantity to be exchanged.

Parameter	Units	Description
$c_{exch}(l,h,td)$	[M€/GWh]	Cost of exchanging one unit of a layer l on hour h of typical day td

Table A.1: List of additional parameters of ESMA with units and description

Variables	Units	Description
$\mathbf{C_{exch}}(l)$	[M€]	Total cost of exchanging one unit of a layer l
$\mathbf{Q_{exch}}(l,h,td)$	[GWh]	Quantity exchanged at the border for layer l on hour h of typical day td

Table A.2: List of additional variables of ESMA with units and description

Objective:

$$\min \ \mathbf{C_{tot}} += \sum_{l \in LAYERS} \mathbf{C_{exch}}(l) \tag{A.1}$$

Changed constraints:

- Total cost of exchanging a certain layer

$$\mathbf{C_{exch}}(l) = \sum_{t \in T | \{h,td\} \in T\_H\_TD(t)} (c_{exch}(l,h,td) \cdot \mathbf{Q_{exch}}(l,h,td)) \qquad \forall l$$

- Layer balance

$$\sum_{i \in \mathrm{RES} \cup \mathrm{TECH} \setminus \mathrm{STO}} f(i,l) \cdot \mathbf{F_t}(i,h,td) + \sum_{j \in \mathrm{STO}} (\mathbf{Sto_{out}}(j,l,h,td) - \mathbf{Sto_{in}}(j,l,h,td))$$
$$- \mathbf{EndUses}(l,h,td) + \mathbf{Q_{exch}}(l,h,td) = 0 \qquad \forall l,h,td$$

In that matter we can understand it that way: if there is no storage, the difference existing between what is produced (**F_t**) and the end-use demand is absorbed either in the parameter q_{exp} (which is fixed, thus it will be the variable **F_t** which will augment/decrease), or either in the variable of import, meaning that if one more unit is produced, it will therefore have to be exchanged and sold at the price cexch.

We thought of adding a parameter of exchanged quantity $q_{exch}(l, h, td)$ of the other country and write the line "country1.q_exch[i] = country2.Q_exch[$i-1$]" in the for-loop in order to exchange the information, and not putting any constraint on both the parameter and variable of exchanged quantity, then the problem would be over constrained. It would not be possible to get results because the variable would already be set to a value.

We tried two approaches for the exchange cost: one is to give as exchange cost the marginal cost of the other (and vice versa), the other is to give the mean of the marginal cost of the other countries over all previous iterations (in order to maybe reduce the oscillations that we could see in the costs).

Algorithm 4: Pseudo-code of the exchange of information

Initialisation & Run on both countries
for i *in [1..5]* **do** /* convergence criteria to be determined */
  country1.mc_scaled[i] = $\frac{i}{i+1}$ country1.mc_scaled[$i-1$] + $\frac{1}{i+1}$ country1.mc_scaled[i]
  country2.mc_scaled[i] = $\frac{i}{i+1}$ country2.mc_scaled[$i-1$] + $\frac{1}{i+1}$ country2.mc_scaled[i]
  country1.$c_{\text{exch}}[i]$ = country2.mc_scaled[$mean$]
  country2.$c_{\text{exch}}[i]$ = country1.mc_scaled[$mean$]
  run_es(country1) & run_es(country2)
  scale_marginal_cost(country1) & scale_marginal_cost(country2)
  $i++$

where, contrary to the first algorithm, the scaled marginal costs are taken over all previous iterations, in order to soften the jumps over them.

By taking a higher initial exchange cost, same for both cases, in the end, the exchange costs converge to the same values over all the table. Thus, in our last attempt, there is no need of taking the average of previous marginal costs.

A.2 Notions to analyse

A.2.1 Curtailment analysis

In order to realise it, we calculate a posteriori the value of α which is exactly the value of operated curtailment, which also can indeed be seen on the different graphs.

We would like to know the percentage of curtailment operated on the whole year. In order to do so, we need to compare the total potential production of PV of the year and the production unused because curtailed: we thus compare energies.

As we know the energy PV really used (A) and the one curtailed (B, or α in the model), the percentage of curtailment is $\frac{B}{A+B}$.

A.2.2 Calculation of LCOE

The Levelised Cost of Energy (LCOE) is an indicator quantifying the price of produced electricity and allowing to compare different production means. It has been developed to find out which electricity source is the cheapest over its lifetime. But because it relies on multiple predictions, it is sometimes difficult to quantify. Normally, we would not rely only on this indicator to decide if a technology should be installed or not, but we use it in our case to compare our different scenarios.

The obtained value of total cost of investment from the model $\mathbf{C_{inv}}$ is already annualised, so no need of doing that in our formula. In our case, the LCOE takes into account the annualised cost of a facility construction and the maintenance cost per year. By adding these terms and then dividing them by the produced electricity during one year, we obtain a result in [€/kWh]. The "real" equation is given by:

$$\mathrm{LCOE} = \frac{\sum_{t=1}^{n} \frac{I_t+M_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}}$$

where:

- n: lifetime of the facility ;
- I_t: annualised investment cost in year t ;
- M_t: maintenance cost in year t ;
- r: discount rate ;
- E_t: electricity generation in year t.

Thus, it is mostly preferred to choose a lower LCOE over a higher one because it minimises in general the generated energy.

Thus the theoretical (minimal) LCOE we can hope to obtain, if the installation produces energy at maximum power, with the total production as the denominator (taking into account the curtailment in this production):

$$\frac{\mathbf{C_{inv}} + \mathbf{C_{maint}}}{\mathbf{F} \cdot c_p \cdot 8760}$$

The capacity factor c_p can be obtained (as said in section **??** *estd*) by summing all the $c_{p,t}$ of the Time series given as input to the model, and dividing by the 8760 hours taken into account. Thus this is given by the mean of the series, which is 0.118708.

If we want to calculate the "real" LCOE, we take as denominator the total capacity produced for the end-use demand:

$$\frac{\mathbf{C_{inv}} + \mathbf{C_{maint}}}{\mathrm{Total\,prod\,end\_use}}$$

It would actually be wiser to include the cost of the grid into the calculation of the LCOE.

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