FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Carbon Market Multi-Agent Simulation Metamodel: a Testbed for Coordination Mechanisms in Sociotechnical Systems

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Abstract

Sustainable development has today a very high priority as a factor in the majority of public policy decisions in all kinds of public institutions. However, goals and regulations in a worldwide and international context - like the Sustainable Development Goals (SDGs) established by the United Nations and the Paris Agreement - clash with national, local and individual objectives. Furthermore, the implementation of regulations in the macro level is many times not efficient nor effective, failing to address requirements on the micro level. This context is typical of competitive sociotechnical systems in which appropriate mechanisms should be implemented to allow a correct coordination of resources, having into consideration global performance measurements of the system like equity and sustainability.

The creation of a multi-agent reference social simulation model, mobilizing concepts of dynamic game theory, has the purpose of decision-making and public policy planning support and the design of mechanisms that conduct to the fulfillment of the SDGs and that are able to align priorities and preferences of the agents. This model should have into consideration policies of alignment of global and local utilities of the system, and should also be parametric, scalable and hierarchical.

For validation of the metamodel, and as a proof of concept, topic of carbon markets was selected. This dissertation focuses on the study of mechanisms that are currently being used or have the potential to be used in the context of carbon emissions regulation and instantiates a model that mobilizes those concepts and is intended to simulate the functioning of various types of carbon markets.

Keywords: Socio-technical systems, Social simulation, Artificial societies, Agent-based modelling, Decision support systems, Algorithmic mechanism design, Game theory

Resumo

O desenvolvimento sustentável tem hoje uma muiito alta prioridade como faotr na maioria das decisões sobre políticas públicas em todos os tipos de instituições públicas. No entanto, objetivos e regulações num contexto mundial e internacional - como os Objetivos de Desenvolvimento sustentável (ODS) estabelecidos pela ONU e o Acordo de Paris - entram em conflito com metas nacionais, locais e individuais. Para além disso, a implementação de regulações num nivel macro é muitas vezes pouco eficiente e eficaz, falhando na resposta a requisitos num nível mais micro. Este contexto é tipico de sistemas sociotécnicos competitivos nos quais devem ser implementados os mecanismos apropriados que permitam uma correta coordenação de recursos, tendo em consideração medidas globais de desempenho do sistema tal como equidade e sustentabilidade.

A criação de um modelo de simulação social multi-agente de referência, mobilizando conceitos de teoria dinâmica dos jogos, tem o propósito de apoiar à aos processos de tomada de decsão e de planeamento de politicas publicas, e ao desenho de mecanismos que conduzam ao cumprimento dos ODS através do alinhamento de prioridades e preferências dos agentes. Este modelo terá em consideração politicas de alinhamento de utilidades globais e locais do sistema, e deverá também ser paramétrico, escalável e hierárquico.

Para validação do metamodelo, e como prova de conceito, foi selecionado o tema dos mercados de carbono. Esta dissertação foca-se no estudo de mecanismos que estão a ser utilizados atualmente, ou têm o potencial de ser utilizados no contexto da regulação das emissões de carbono, e instancia um modelo que mobiliza esses conceitos e tem como objetivo simular o funcionamento de vários tipos de mercados de carbono.

Keywords: Sistemas sociotécnicos, Simulação social, Sociedades artificiais, Modelação baseada em agentes, Sistemas de apoio à decisão, Desenho algorítmico de mecanismos, Teoria dos jogos

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Author

*"If you assume that there is no hope, you guarantee that there will be no hope.
If you assume that there is an instinct for freedom, that there are opportunities to change things,
then there is a possibility that you can contribute to making a better world."*

Noam Chomsky

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Abbreviations

ABM	Agent Based Model
CGE	Computable General Equilibrium
CPR	Common-pool Resources
EU	European Union
EU ETS	European Union Emission Trading System
ETS	Emission Trading Scheme
GDP	Gross Domestic Product
GHG	Greenhouse Gas
IIA	Independence of Irrelevant Alternatives
IPD	Iterated Prisoner's Dilemma
PD	Prisoner's Dilemma
PG	Public Goods

Chapter 1

Introduction

1.1 Context

The world of today faces many humanitarian and climate crises. According to the United Nations, one in ten people in developing regions still lives on less than US$ 1.90 a day, and 2.2 billion people lack access to safely managed drinking water services [67]. Those issues are aggravated by the climate crisis we currently live in, as global warming causes droughts and rising sea levels responsible for more famines and forced migrations[66].

In an attempt to respond to those and other pressing issues, and because of their global nature that makes them impossible to be solved by independent and uncoordinated action, there has been a call for international partnership and common response. The United Nations have been a catalyst of those actions, promoting global summits to develop action plans and establish goals and objectives to tackle the issues mentioned above. After Agenda 21, established in 1992, and the Millennium Development Goals (MDGs), established in 2000 and due in 2015, there was the need to revamp those strategies. That is how the 2030 Agenda for Sustainable Development, adopted by all United Nations Member States, came to light. The 2030 Agenda is a shared plan for peace and prosperity with a better future in mind. In its core are the 17 Sustainable Development Goals (Figure 1.1) [68]. The Paris Agreement, signed by 196 states, is a global commitment establishing emission targets and several mechanisms to limit the global average temperature increase well below 2ºC and pursue efforts to keep it below 1.5ºC. [65] This agreement is another international cooperation mechanism that represents the perception of common risks and the need for global decision making.

1.2 Problem and Motivation

The initiatives to establish common goals mentioned in the previous section can be seen as attempts to formalize global utilities and create plans of action. The accomplishment of those goals

Figure 1.1: United Nations' Sustainable Development Goals

would benefit in the long-term the entire humanity. However, pursuing those goals and the regulations that result from the aforementioned international initiatives frequently clash with the interests of groups of or individual nations, corporations and individuals, each having their own interests that are often short or medium-term based. For example, climate action benefits us all in the long run - for a principle of survival - but it goes against the immediate interests of companies and countries that have their sources of revenue dependent on oil. Those individual or local interests and the seeking of instant results or profit frequently overlap global interests in terms of importance in the decision-making process of all kinds of entities. Therefore, it is necessary to develop mechanisms that align as much as possible the constellations of local and global utilities in an effort to maximise both of them.

This dissertation aims to propose a carbon market multi-agent metamodel for social simulation that is parametric, scalable and hierarchical. The purpose of this metamodel is to be a tool of support on decision-making and public policy planning on the design of utility alignment mechanisms. The users should be able to extract insights on how different policies may result in the real world. The model is evaluated with the basis of instances of real-world problems concerning emissions regulation mechanisms like carbon auctions.

1.3 Document Structure

The remaining document is organized into the following chapters: Chapter 2 - Literature Review is the review of the literature on the state of the art of topics of this dissertation, with a focus o common pool resources and social dilemmas, social choice theory, multi-agent-based social simulation and complex systems, and carbon market. This chapter is concluded by presenting relevant related work in the fields of game theory and simulation applied to climate policy. Chapter 3 - Methodology is the explanation of the steps that were carried in order to reach the designated goals of this dissertation and to come up with a metamodel and an instantiation of it that makes it possible to extract results. Chapter 4 - Experiments and Results is the section where results of experimentation with the model, utilizing different parameters, are presented and discussed. Finally, chapter 5 develops a general overview of the dissertation by presenting the main contributions of this work and builds on potential future work.

Chapter 2

Literature Review

2.1 Background

2.1.1 Common Pool Resources and Social Dilemmas

Game theory is the study of mathematical and logical models of conflict and cooperation between rational agents who perform decisions to maximize their utility [41]. However, rationality alone is hardly enough to explain human behaviour in a complex system. Thus, evolutionary game theory activates the Darwinian notion of evolution, assuming that agents adjust their strategies over time so that, consciously or not, may not be necessarily rational [27, 44]. In this context, it is possible to find many valuable metaphors for the problems intended to be approached in this dissertation. Understanding the metaphors that we will be present in this chapter is essential to clarify some concepts regarding the type of dilemmas and problems addressed in this dissertation.

In Economics, goods, services and resources can be classified according to two fundamental characteristics: exclusivity and competitiveness. They can either be excludable or non-excludable, and rivalrous or non-rivalrous [47, 69]. Excludable goods can be limited to paying customers only or have their free consumption limited in some way. On the other hand, a good is rivalrous if its consumption by one consumer prevents or reduces another agent's ability to consume it. Private goods are both rivalrous and excludable. Club goods are excludable but non-rivalrous. Common-pool resources are rivalrous but non-excludable. Public goods are both non-rivalrous and non-excludable. A visualization matrix of that characterization is presented in figure 2.1 [47].

In the context of this dissertation, **common-pool resources** (CPR) and **public goods** (PG) will have the focus. Starting with the first, examples of CPRs are forests, pastures, fishing grounds and the atmosphere. Those kinds of resources are harmed when faced with over-exploitation and pollution and risk destruction if their usage is not coordinated or restricted somehow. The situation when individual agents act independently to maximize their utilities, in an uncoordinated way and against the common good, causing the depletion of an open-access resource is called **tragedy of the commons**, in reference to an essay written by the economist William Forster Lloyd in 1833

	Excludable	Non-excludable
Rivalrous	Private goods	Common-pool resources
Non-rivalrous	Club goods	Public goods

Figure 2.1: Resource classification matrix

about the hypothetical example of overgrazing and subsequent destruction of common land, typically used as pasture in English villages. That could happen if herders put more than their allocated number of cattle on the common land [31]. That originated the concept of a **commons dilemma**, referring to the social dilemma in which short-term individual interests conflict with long-term group interests. Common property protocols are mechanisms that regulate the consumption of common pool resources in order to ensure their maintenance. Elinor Ostrom, a political scientist and winner of the 2009 Economics Nobel Prize, analyzed long-enduring, self-organized and self-governed CPRs and came up with eight design principles that are requisites for stable maintenance of the resources: [48]

1. Clearly defined boundaries of the CPR;
2. Congruence between appropriation and provision rules and local conditions
3. Collective-choice arrangements, that guarantee the participation of most affected individuals in the definition and modification of operational rules;
4. Monitoring, by having monitors who audit CPR conditions and appropriators' behaviours;
5. Graduated sanctions, for appropriators who violate the established rules;
6. Conflict-resolution mechanisms, to resolve conflicts between appropriators;
7. Minimal recognition of rights to organize, guaranteeing that external governmental authorities do not challenge the rights of appropriators established in the CPR agreement rules;
8. Nested enterprises (In the case of larger CPRs).

Collective action problems or **social dilemmas** are a class of situations in which all participants would be better off if everyone cooperates, but the payoff to be selfish is higher than the one to be cooperative if not everybody does so [1]. In the following paragraphs, some game theory metaphors that apply to the context of this dissertation and belong to the class of collective action problems will be presented.

The **Prisoner's Dilemma** is a game very frequently used to represent the problem of social cooperation. In this metaphor, there are two agents who both committed a crime. When the police interrogate them, they can either cooperate by staying silent or defect and betray the other agent. They will have different serving times, depending on their decisions. Figure 2.2 shows a possible payoff matrix.

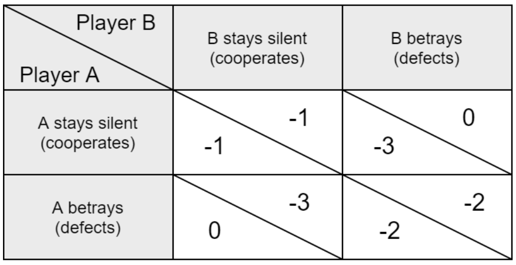

Figure 2.2: Prisoner's Dilemma example

This game is an example that two rational agents may not cooperate even if that guarantees the best outcome. Betrayal is the dominant strategy because it results in a better payoff independently of the other agent's chosen strategy. Mutual betrayal is the only strict Nash equilibrium, meaning that no player can improve its gain by unilaterally changing his strategy. Even though mutual cooperation is **Pareto efficient**, as it results in a better payoff for both agents, it is irrational from an individual perspective. Another version of this game called the **Iterated Prisoner's Dilemma** (IPD) or **Peace-War game**, opens the possibility for more than two players to participate in the game by playing a match of Prisoner's Dilemma with each other iteratively, evolving their strategies over time. This problem was deeply studied in Robert Axelrod's book The Evolution of Cooperation, from 1984 [6]. In that context, Axelrod organized an IPD tournament inviting several academic colleagues to develop a computer algorithm that remembered previous decisions and their results and would have to choose again and again to cooperate or defect. The winner strategy was called **Tit for tat**. Following that strategy, an agent would always cooperate on the first iteration and then do what the previous opponent did in the last round. By analyzing the best scoring strategies, Axelrod found out that altruistic strategies tended to do better than greedy ones and came up with four rules for a strategy to be successful in an IPD:

1. Do not be envious, meaning not ambitioning to score more than the opponent as PD, like most situations in life, is not a zero-sum game - both players can be better off than before the game (a win-win situation);

2. Do not be the first to defect, as this attitude is likely to set off retaliation by the other player that can extend over time;

3. Reciprocate both cooperation and defect. It is hard to guess an optimal level of forgiveness as it depends on the environment. By always reciprocating, the player avoids being explored by greedy strategies while at the same time avoiding unending mutual recriminations;

4. Do not be too clever. In PD, players benefit from cooperation and a good way to encourage it is for them to be clear on their intentions.

Another meaningful metaphor is the **Stag Hunt**, also called trust dilemma or assurance game. Stag hunt is a story by Jean-Jacques Rousseau, where two individuals go on a hunt. Each of them can choose to hunt a stag or a hare. To hunt a stag, the cooperation of both agents is necessary. On the other hand, an agent can catch a hare by itself. A hare is worth less than a stag. An example payoff matrix can be seen in figure 2.3. Stag Hunt differs from the Prisoner's Dilemma because it has two Nash equilibria, when both agents choose to cooperate and when both choose to defect.

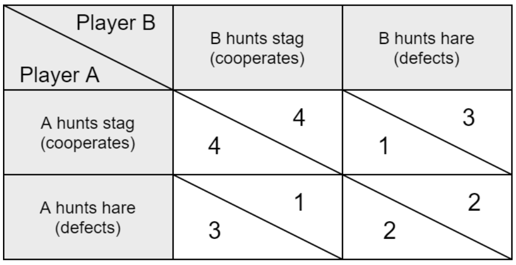

Figure 2.3: Stag Hunt example

Finally, a **Public Goods Game** is another widespread metaphor for the study of social cooperation. It is based on the idea that each participant chooses independently how many tokens to put into a public pot. The pot's total value is then multiplied by a factor greater than one and divided equally between all participants of the game, independently of how much or if it participated in the pot. An example can be found in figure 2.4. The global payoff is maximized if everyone contributes to the pot. However, the Nash equilibrium is when no one contributes to it. This situation leads us to the **free-rider problem**. It can be defined as the burden created by agents who benefit from a public good but under-pay for it or do not contribute at all for its maintenance.

2.1.1.1 Mechanism Design

The concept of mechanism design is central to the work of this dissertation. It is the development of policies, rules or incentives with the objective of achieving certain desired outcomes [42], having strategic agents that act according to their own self-interest. It is sometimes referred to as *reverse game theory*. A famous metaphor that exemplifies in a simple way this kind of mechanism is the fair cake-cutting problem. In this problem, a mother - who takes the role of a social planner or mechanism designer - has a daughter and a son - taking the roles of strategic agents. There is a cake that should be shared equally between daughter and son; however, if the mother slices the cake in two equal pieces and distributes them, this solution may not be acceptable because each kid will have the perception that they got the smaller of the two pieces. On the other hand, a mechanism that implements a desirable outcome would let one kid slice the cake and the other choose the piece he/she wants. The kid who cut the cake will have the impression that the two halves are exactly equal, and the kid who chose the slice will always select the one that, in his/her

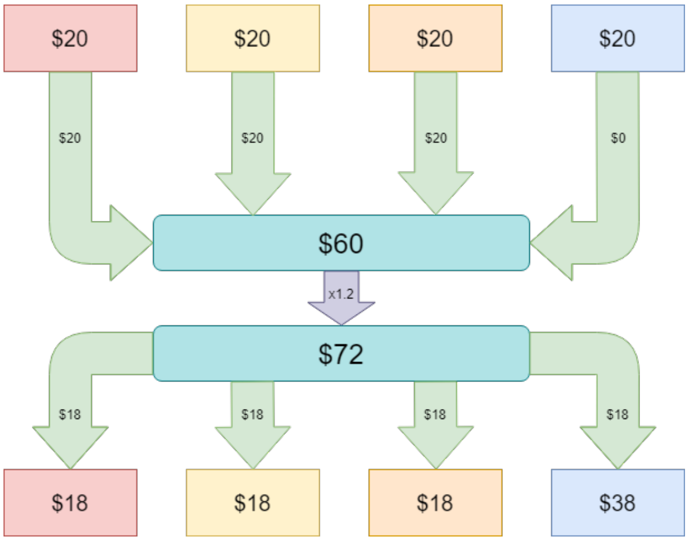

Figure 2.4: Public goods game example (by Wikipedia contributor Jcheming)

eyes, is the biggest one. In conclusion, both kids have reasons to be happy with this mechanism [42]. More formally, a mechanism design problem can be defined by an output specification and by a set of agents' utilities, as follows [45]:

1. There are n agents and each agent i has a certain private input $t_i \in T_i$ (its type);
2. The output specification maps to each type vector $t = (t_1 ... t_n)$ a set of allowed outputs o;
3. Each agent i's preferences are given by a value function $v_i(t_i, o)$ called its valuation. It quantifies the output o when its type is t^i. This agent aims to optimize this utility.

A mechanism is composed of two elements. An output function $o()$ and a tuple of payments $p^1()...p^n()$. The mechanism defines for each agent a set of strategies that it can perform. It also provides an output function and a payment function that takes as input the strategy chosen by each agent [45].

The **Vickrey-Clarke-Groves mechanism** is one of the most important results of mechanism design theory. It is a generalized form of the VCG auction model, and it is used to motivate agents to choose the most globally most efficient allocation of a public good, even if each agent has different private valuations of it. It can solve the **"tragedy of the commons"** under certain conditions. Assuming that the utility of the agents is given by a quasilinear function so that $u_i = P_i + v_i(t_i, o)$, being p_i a payment that can be either positive or negative, and assuming also that the goal is to select an outcome that maximizes the sum of valuations, so that $o(t) \in \text{argmax}_o \sum_{i=1}^{n} v_i(t_i, o)$, the payment for each agent under the VCG mechanism is given by: $p_i(t) = \sum_{j \neq i} v_j(t_j, o(t)) + h_i(v_{-i})$ where $h_i()$ is an arbitrary function. The VCG is a **truthful mechanism** because the dominant strategy for each agent is to bid their true valuations, and it is also proved to provide a solution to almost all utilitarian maximization problems, in other words, problems whose objective function is the sum of the utilities of the agents.

The function h_i is a parameter of the mechanism. One common possibility is for it to be $h_i(v_{-i}) = -\max_o \sum_{j \neq i} v_j(t_j, o)$, called the **Clarke pivot rule**. With this rule, the total amount paid by an agent i is exactly its **externality cost**, or in other words, the social welfare of the others if i were absent minus the social welfare of the others when i is present.

2.1.2 Social Choice Theory

Social choice theory is the field of study that analyses the aggregation of interests or preferences to reach a collective decision [59]. Social welfare functions rank social states from more desirable to less desirable [58]. There are several possible social welfare functions and voting methods used in different circumstances, and that let electors express different degrees of information. Those functions can be used not only to elect people but also, for example, new policies or regulations. There are also methods used to elect more than one entity, like the D'hondt method. However, the focus of this section will be on "single-seat" election methods. Examples of some of the most common are:

1. **Plurality voting:** The simplest of the voting methods. Each voter casts a single vote, and the candidate with the most votes is selected.

2. **Cumulative voting:** Each voter casts k votes that can be distributed as it wishes among candidates. The candidate with the most votes is selected.

3. **Approval voting:** Each voter can cast a single vote for as many candidates as he or she wishes. The candidate with the most votes is selected.

The last three methods do not allow for a voter to express its full preference ordering. Voting methods that enable that are **ranking voting** methods. Some examples:

1. **Borda voting:** Each voter submits a full ordering of the candidates, with the highest-ranked candidate being given the number of candidates (n) minus one point, the second-highest ranked n - 2 points and so on. The candidate with the most points is elected.

2. **Nanson's method:** Variant of Borda voting. Iteratively eliminates candidate with the lowest Borda score and recalculates remaining candidates' scores.

3. **Two-round system:** Each elector casts a single vote. If a candidate has the majority of the votes, it is elected. If not, a second-round is held with only the two candidates who had the most votes in the previous round.

4. **Instant-runoff voting / Alternative vote:** Each voter orders candidates from the most to the least preferred. If more than half of the electors choose a certain candidate as their first choice, it is elected. If not, the candidate with fewer first-choice votes is eliminated. The electors who selected the now eliminated candidate have their votes transferred to their second choices. This process is repeated until there is a candidate with more than half of the votes.

There are several criteria that can be used to evaluate voting systems, and some of them will be presented here. The **majority condition** states that if more than half of the electors rank first a certain candidate, then it must win. The **Condorcet condition** implies the majority condition states that if more than half of the participants prefer a when compared to b, then a must be above b in the final result [30]. **Condorcet loser** states the opposite: a candidate that loses when compared to every other candidate should never win. **Mutual-majority** states that if there is a set of candidates such that more than half of the voters prefer all of those candidates to every candidate that is not in the set, the winner must come from that set. **Monotonicity** states that no winner candidate can be harmed by being ranked higher on some ballots, and not loser candidate can be helped by being ranked lower on some ballots. **Non-dictatorship** states that a social choice function must always take into account the preferences of multiple voters or, in other words, in no situation can the output be defined by a single elector. **Independence of irrelevant alternatives (IIA)** states that the outcome between two candidates should depend only on their relative orderings and not on the positions of all other *irrelevant alternatives*. **Non-imposition** states that every outcome of a social choice function should be achievable by some set of individual choices. Finally, **universality** states that all electors are allowed to express all preferences, and the social function should provide the same results each time the electors' preferences are presented in the same way.

There is no social choice function that fits every criterion, as shown by **Arrow's impossibility theorem**, an impossibility theorem proposed by Kenneth Arrow that demonstrates that it is impossible to design a social welfare function that satisfies the criteria of non-dictatorship, universality, independence of irrelevant alternatives, monotonicity and non-imposition (the last two combined are equivalent to Pareto efficiency) all at the same time [2]. Figure 2.5 compares the different voting methods social choice functions in terms of the criteria presented.

	Majority	Condorcet	Condorcet loser	Mutual majority	Monotonicity	IIA
Plurality	Yes	No	No	No	Yes	No
Approval	No	No	No	No	Yes	Yes
Borda	No	No	Yes	No	Yes	No
Nanson's	Yes	Yes	Yes	Yes	No	No
Two-round	Yes	No	Yes	No	No	No
Instant-Runoff	Yes	No	Yes	Yes	No	No

Figure 2.5: Voting methods comparison

2.1.3 Social Simulation and Complex Systems

Social simulation is the application of computational simulation methods in the context of social sciences, in another words, in the study of societies and relationships between individuals in a complex system. Robert Axelrod described **social simulation** as "a third way of doing science, in contrast to both induction and deduction" by explicating that while both deductive approaches and simulation start with a set of assumptions, the latter does not prove theorems and instead generates data that can be analyzed inductively [5]. A complex adaptive system can be described as a set of agents who interact in interdependent ways to produce system-wide patterns, such that those patterns then influence the behaviour of the agents by, for example, adaptation or learning [19, 32]. Another way to define it is as a system that has the following general characteristics: [24, 26]

1. The system includes several agents who operate in and are influenced by a certain environment;

2. There is no global control over the system;

3. Each agent is driven by simple mechanisms that dictate their actions.

Sociologists and researchers of distributed artificial intelligence both face the questions raised by the relationship between local and global properties of complex systems and, in a more general way, the problem of emergence [26]. **Emergence** is the process by which macro properties "emerge" from behaviours of individuals in the micro-level. The products of emergence are the result of the interaction of the components of the system but are more than the sum of the parts, being instead structures, patterns or properties that are radically novel [15]. One of the most prominent approaches to the problem of the relationship between macro and micro levels in the field of sociology is the theory of structuration, proposed by Anthony Giddens. This theory mobilizes the concept of **"duality of structure"**. Structure in this context is a set of rules and resources, or "structuring properties" that allow social practices to be reproduced over time and space. Agents rely on structures to perform social actions. At the same time, those same structures are also the product of those social practices. In conclusion, "structure is both the medium and the outcome of reproduction of practices" [25]. Another concept worth mentioning is the one of **autopoiesis**. It refers to the capacity of a system to reproduce and maintain itself [38]. It was originated in the field of biology, and it was first mobilized in the context of sociology by Niklas Luhmann in the paradigm of Systems Theory [57].

According to Axelrod, the value of simulation resides in a number of purposes: prediction, performance, training, entertainment, education, proof and discovery [5]:

1. **Prediction** is the generation of consequences from complex inputs by means of hypothesized mechanisms.

2. **Performance** is related to the execution of tasks that require the mimicking of the techniques humans utilize to solve those tasks. It is usually the domain of artificial intelligence.

3. **Training** people is another common application. It is used in situations it is expensive or dangerous, or even impossible for humans receiving training to face certain real-life situations. For example, flight simulators are extensively used for the training of new pilots.

4. **Entertainment**, for example, in video games or other interactive experiences.

5. **Education**. By combining training and entertainment, simulation can also be used as an educational tool, allowing people to tinker and experiment with hypothetical scenarios. A good example is Democracy [17], a video game in which the player takes the role of a leader of a country. The gameplay is based on passing and revoking policies and allocating budgets to different sectors and programs. Those actions, like in real life, may result in intricate chain reactions. For example, as shown in figure 2.6, an increase in agriculture subsidies may result in a decrease in unemployment which causes in its turn a decrease in crime levels.

6. **Proof**. Simulations can prove certain theoretical hypotheses.

7. **Discovery**. Even though it is way easier to create more accurate simulations in the fields of exact sciences, simulation methods can still be used for the discovery of principles, relationships and intuitions in social complex systems.

In the context of this dissertation, the proposed hierarchical simulation metamodel has the goals of serving as a **predictive** tool as a way to test different mechanisms and understand their possible results and also as a **discovery** tool.

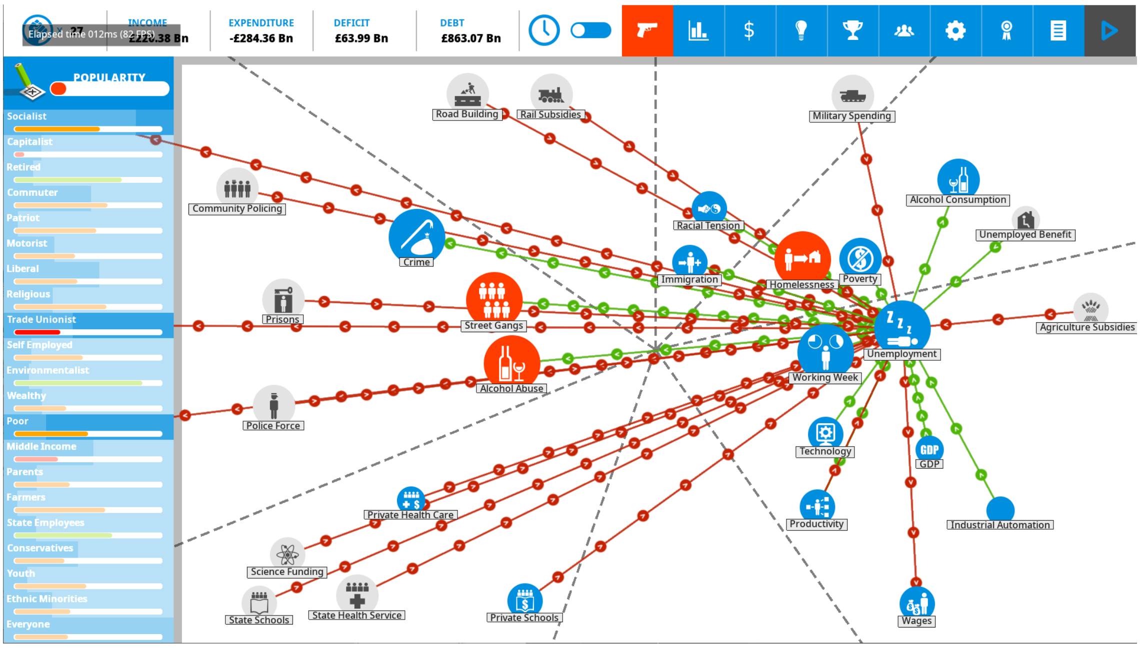

Figure 2.6: Democracy 4 screenshot

2.1.3.1 Multi-agent based development methodologies and simulation frameworks

To implement a social simulation model, many possible frameworks specifically designed for multi-agent based simulations can be used. Those frameworks have built-in template components to easily create agents, their behaviours, and the environment where they will be interacting. A visualization tool is also a key feature to be able to see how the agents interact with each other and the progress of the simulation in real-time. In our research, we tried three frameworks that, among others, fit our criteria: NetLogo, Repast, and Mesa.

NetLogo is the oldest framework on our list. It was developed in 1999 by Uri Wilensky for the need to design agent-based models [70]. Its programming language is based on Logo, an educational language created for students to learn how to code, being very easy to learn since humans can easily read its programs. This language can be an excellent starting point for coders that are unfamiliar with agent-based models not only because there is a wide array of tutorials available online that go along with very straightforward and extensive documentation on NetLogo's website, but also because its modelling environment, as well as its extensive model library, make it really easy to use. The default library comes with basic functions that help develop a simulation with various agent behaviours and interaction protocols between them. When writing the model, the developer can piece together different components depending on its needs, making the resulting script fairly readable to a beginner. However, because NetLogo is built on a language that is so simple, it may be hard to express concepts in the way that more experienced programmers may express in other languages of the object-oriented paradigm. For example, the way of accessing and manipulating variables of different objects is not very straightforward. Another downside is the rigidness of the environment and of the visualization tools. For example, unlike other more general purposed tools, the user can not simply decide to use a different set of visualization tools, having to rely on the ones provided by the NetLogo's environment.

Repast is also a very famous framework design for agent-based modelling. It is a Java-based modelling system [46] with a library of pre-defined classes with all kinds of functions, including ones for simulation visualization. This one has a steeper learning curve than NetLogo, making it harder for beginners but a great choice for developers familiar with the Java language. It is a robust framework with advanced data population and visualization tools. However, its documentation is minimal, and it is very hard to find more information and resources about it and use-case examples other than the ones that already come with the framework. Also, being built on Java, it requires many times for the user to be worried about software engineering questions like performance issues and what kinds of data structures to use even when creating simple simulations. This creates the risk of the process of implementing models being much more time consuming without a real clear advantage to make up for that.

Mesa is a Python-based counterpart to NetLogo and Repast [37]. Contrary to its competitors, it excels by having modular components imported into a project as necessities show up, and it can run directly on a web browser. Being a Python-based framework, Mesa also benefits from its integrated data analysis tools. Python is one of the most popular languages in the world, especially when it comes to data analysis in various domains like economics and social sciences, so it is also possible to take advantage of the many packages related to various aspects of processes to simulate. It is also popular because it is very straightforward, as it is not required for the user to be worried about types of variables or data structures. In terms of visualization, Mesa even allows the user to create their own modules using *JavaScript*.

2.1.4 Carbon Markets

Carbon markets are market-based tools that provide incentives for economic agents - like corporations or individuals - to reduce their pollutant emissions by incorporating the environmental costs of their operations as a factor to consider in their decisions. They are an example of a mechanism that intends to align individual goals- being those profit or other kinds of economic advantage - with a global utility (reduction on emissions to tackle climate change). They are based on the allocation and trading of allowances (also called credits or permits - those two terms will be used interchangeably from now on) that enable the holder to emit a certain amount of emissions proportional to their volume. One carbon credit is usually equivalent to one metric ton of carbon dioxide. Economic actors may have an obligation to hold the needed allowances to cover their emissions, otherwise facing some kind of penalty for the excess of emissions that the owned credits not cover. The rationale behind this kind of scheme is that companies will be encouraged to reduce their emissions in the most efficient, least-costly fashion. A carbon market can be implemented on very different scales, as there are examples of local, regional, national and even global markets. They can cover only a certain economic sector or the entire economy of their jurisdiction. Carbon markets can either be mandatory or voluntary. One example of a mandatory and supranational carbon market is the case of the European Union Emission Trading Scheme (EU ETS) [12]. Voluntary carbon markets, on the other hand, allow corporations to lower their emissions by investing in carbon credits generated by certified projects that avoid, reduce or remove emissions from the atmosphere.

2.1.4.1 Emission Trading Schemes

In this subsection, we will explore how cap and trade emission trading schemes, the most common type of carbon markets, can be configured.

Emissions Cap Emission trading schemes are based on the **'cap and trade'** principle, meaning that there is a predetermined cap of the total number of allowances in the economy at a given point in time. A central authority or regulator is responsible for introducing those allowances, and the cap value is set according to its goals. For example, a cap "equal to the covered sectors' business as usual emission levels mean that the system is not inducing emissions reductions beyond reductions in the emissions intensity of its economy" [43]. This mechanism allows for an accurate target level of emissions, and the cap usually descends over time, promoting an emission decline. For example, during Phase 3 (2013-2020) of the EU ETS, the cap was reduced annually by a linear factor of 1.74%. [11]. Emission caps are set according to reliable estimates on current and potential future emissions, so it is necessary for the regulator to have reliable information regarding emission levels of firms and their reduction potential. It is possible to observe that necessity by looking at the example of Phase 1 of EU ETS. In that case, the regulator did not accurately assess the capability of firms to reduce their emission, and they decided to reduce their emissions to their allocated allowance quantity without paying for additional permits. The European Commission published a report on verified emissions indicating that the emissions cap had resulted in an overestimation of 125 million allowances. A few days after that publication, the price of the credits fell by almost 50%, and within two years, they were reduced to almost zero [33, 43]. Emission trading schemes may cover only emissions of a few industry sectors and a few GHGs emissions. For example, EU ETS currently covers around 40% of the EU's GHGs[12], covering CO_2, N_2O and $PFCs$, while the South Korean ETS also covers CH_4, $HFCs$ and $SF6$ [43]. To improve the system's resilience to major shocks, the EU implemented a Market Stability Reserve (MSR), a program that reserves a certain number of allowances in case of an oversupply and releases allowances in case of shortage.

Credit Allocation and Acquisition There are two main ways through which carbon credits are introduced in the economy. The first one is through **free allocation**. The regulator in charge of the scheme defines the number of free credits to give to each polluter according to factors like industry sector, the dimension of the polluter, emission history and risk of carbon leakage, in other words, the risk that companies transfer their production to other jurisdictions with more lenient emission regulations, ultimately reducing costs but not reducing emissions. Taking into account those possible factors, there are two main ways by which the credits can be allocated. One of them is **grandfathering**, where credits are allocated according to a company's emission history. This type of allocation raises the problem of potentially penalizing companies that started the transition to more eco-friendly processes earlier, as they would receive fewer credits than companies who had historically put less effort in reducing their emissions [3]. The other way of allocating credits is through **benchmarking**. This way, companies receive credits based on a reference value relative to their industry sector. It is usually set on an output basis. In the case of EU ETS, benchmarks are based on the average greenhouse gas performance of the 10% best performing installations in the EU inserted on each specific production sector [11]. The number of freely allocated credits may be higher at the beginning of the scheme to decrease its implementation shock on the economy and then reduce over time.

Another way to introduce allowances in the market is by selling them in an auction market. Most schemes adopt an auction mechanism for central authorities to sell carbon permits in combination with or instead of a free allocation mechanism, although there are examples that rely exclusively on free allocation for the introduction of allowances in the economy. That is the case, for example, of the South Korean Emission Trading Scheme - the credits on its first phase came 100% from free allocation, while on its second phase, they came 97% from free allocation and 3% from auctioning. [49]. Carbon permit auctions are an instance of multi-unit auctions, meaning that they are auctions that sell multiple homogeneous items. They can take several forms. In the case of EU ETS, its carbon auctions follow a single-round, sealed-bid and uniform-price format. This means that bidders who want to buy credits can submit privately any number of bids during a single bidding window, and each bid must specify the number of allowances to buy and the price the bidder is willing to pay for them. When the bidding window closes, the auction platform orders the bids by price in decreasing order and determines the clearing price, in other words, the price at which the sum of volumes bid matches or exceeds the volume of allowances up for auction. All bids priced higher than the clearing price are successful, and successful bidders have to pay only the clearing price. Instead of having a uniform-price format, the auction can take a discriminatory-price format, meaning that successful bidders pay different prices for the allowances according to the price designated by their bid instead of the clearing price. There is also the possibility for regulators to establish ceiling or floor prices, meaning that allowances can not be sold for more than or less than a specified value.

Penalties Polluters who do not have enough credits to cover their emissions may have to pay a fine or have some kind of punishment. In the case of the EU ETS, during Phase 2 and 3, there was a fine of 100€ per ton of GHG not covered by a permit. There are schemes, however, that do not apply fines. It is the case of both Tianjin and Chongqing's pilot carbon markets. In those cases, companies that do not comply are disqualified from finance subsidies and government support. In other cases, like the carbon markets of Guangdong and Hubei, the regulator not only charges fines but also deducts the double of the excessive emissions from the freely allocated allowance of the next year [71].

2.1.4.2 Personal Carbon Trading

Emission trading schemes are more commonly used for regulating emissions of big corporations on an international (EU ETS), national (Korean ETS, New Zealand ETS) or regional (Chinese pilot schemes, Quebec ETS) level, but the principle can also be applied on a more personal basis - called personal carbon trading (PCT) [23] even though examples of its application are very scarce and limited [22]. In PCTs, individuals receive an equal volume of allowances and hold them electronically, surrendering them when buying carbon-intensive goods like electricity, gas, fuel and travelling. There are several proposals for personal carbon trading implementations, but two of the most known are Tradable Energy Quotas (TEQs) and Personal Carbon Allowances (PCA). The main difference between them is the scope. On PCA, only individuals are included, and the economic sectors impacted on the scheme are mostly household energy and personal transport, while on TEQs, the whole economy is within the scope of the scheme, as other sectors of society like industry and government would also have to participate on it. One frequent criticism of the approach proposed by personal carbon trading schemes is related to the role of the individual. Transferring the cost of climate transition to individuals is not only very complex and expensive, but it also may fail to encourage structural economic changes in the industry sector.

2.1.4.3 Voluntary Local Carbon Markets

Voluntary local carbon markets are a specific kind of mechanism that is applied in the context of cities, municipalities, or small regions with the goal of reducing emissions and improve the environment of the area. This type of market is yet not very common, although there are some examples in different stages of development and application. The Bologna carbon market [51] are an example of a local scheme that is already being applied. Citizens of the industrial city of Bologna, Italy, generate credits by riding bicycles instead of commuting by car, and then those credits are sold by the city council, the institution that oversees this scheme, to industrial corporations for the sake of offsetting their emissions. The revenue generated by the sale of the carbon credits is then invested in green projects like the construction of new bike lanes, providing positive impacts for the entire city. Another example voluntary local carbon market is the case of the AYR platform [9]. This platform is still being developed, and if applied as intended, will contribute to the improvement of the environment in the city of Matosinhos, Portugal. It is based on the concept of rewarding people by their avoidance of potential emissions instead of penalizing them for the emissions effectuated. The technology is blockchain-based and is centred on an app that monitors eco-friendly decisions, like riding a bike or taking a bus, quantifies the quantity of saved CO2 emissions and values it turning it into tokens. Those tokens can then be exchanged for useful rewards or be donated.

2.1.4.4 Comparison with Carbon Taxation

Carbon taxes are another tool that can be used in alternative to or alongside a carbon market. It is simply based on a fixed value that polluters have to pay for each pollution unit. This lack of complexity is one of its advantages as it becomes easier to legislate and to implement and enforce. Another advantage over cap and trade schemes that are based on free-allocation and not on auction is that it generates revenue for the regulator, as the tax has to be paid directly to the regulator instead of having allowances given for free that are then sold and bought between corporations. One other advantage is related to the signalling it provides to the economy. A carbon tax is clear: it sends a signal that pollution imposes a negative externality on society, so that cost should be internalized by the payment of a tax. Even if the polluter is willing to pay the price to pollute, it is still a tax, while on a carbon market system with free allocation, polluters may receive permits to "pollute for free", and even if that does not happen, the polluters are still able to purchase the "right to pollute". That clearly does not send the same signals as having to pay an additional cost for every activity that damages the environment. Another important comparison that can be made between these two tools is related to uncertainty. Cap and trade schemes may produce high levels of uncertainty when it comes to costs for polluters, as the price of allowances freely floats in the market while with a carbon tax, companies know exactly how much they will have to pay if they know how much they will emit. On the other hand, cap and trade schemes can limit precisely the total number of allowances (the cap), while with a carbon tax, even though it can be adjusted, it is not possible to know beforehand how much impact it will have in terms of limiting pollution. This precision that cap and trade schemes provide may also be a disadvantage when the cost of CO2 abatement for firms is unknown or uncertain. [4]

2.2 Related Work

2.2.1 Game Theory and Simulation Applied to Climate Policy

There are several examples of game theory concepts and simulation methods being applied to the study and design of climate policy. In the study of green consumption, some authors proposed a duopoly game model dividing consumers into two categories (aware and not-aware) to understand how environmental awareness affects business practices and social welfare [14, 53]. Cohen et al. proposed a Stackelberg game to model interactions between government and producers of green technology to study government subsidizing and understand possible industry's responses [10]. Several of those game theory approaches are based on several assumptions. One of them is that players are perfectly rational and capable of choosing the best action from several possibilities. However, as some authors proved [61], that assumption is not visible in reality because rationality is limited by several constraints, like limited time to act and limited information. To overcome the perfect rationality paradigm, evolutionary game theory was mobilized. Zhao et al. proposed an evolutionary game simulation for the study of carbon reduction labelling policies and possible enterprises' responses to incentive policies such as subsidies and preferential taxation rates [72]. Another interesting study is the simulation of a collective-risk social dilemma when there is a high risk of dangerous climate change [39]. Tradable token mechanisms, similar in concept to carbon markets, have been applied to a variety of contexts. Brands et al. studied the phenomena of road congestion and provided the design of an efficient market mechanism where commuters can trade permits that allow users to travel through certain paths. Their study focused on the design of rules that should govern trading behaving in the market so as to avoid undesirable speculation and trading, and yet ensure efficiency [8]. Azevedo et al. also worked on trading schemes applied to multi-modal urban mobility and proposed a blockchain-based trading system called *carbon Blockchain framework for Smart Mobility Data-market* (cBSMD), applying it to a case-study [20]. The study of the regulation of blockchain smart contracts within agent-based markets also relates with our research on regulation [55]. Finally, Multi-agent simulation has also been applied to resource-based integrated markets [54], and to electricity markets [56, 60].

2.2.2 Carbon Market Models

Over the years, a number of carbon market models have been proposed, with most of them focusing on the Chinese context. Computable General Equilibrium (CGE) models are economic models that receive real economic data as input in order to simulate, as close to reality as possible, economic structures and behavioural response of economic agents, with the goal of studying possible impacts of different policies and other shocks in the economy. CGE and dynamic CGE models have been used extensively in the study of climate policies in general and the carbon market in particular [21, 62]. Bi et al. proposed a dynamic CGE model to study the impact of the carbon market and carbon tax in China [7]. Multi-agent based models have also been used to simulate the behaviour of different industries on a national level [63]. Zhou et al. proposed a multi-agent simulation model to simulate regional emissions trading systems and try a different set of regulatory policies and carbon auction rules.[73]. Other multi-agent-based models have been used to study more particular aspects of emission trading schemes, like possible carbon auction rules [13] or international traffic flows [40]. Rafieisakhaei et al. proposed two models, one for the EU ETS and another for the global oil market and investigated the connection between them. The models were trained with historical data, and their work provides meaningful simulation results [52]. Many other models, however, do not use multiple agents, instead preferring other statistical methods. Koop et al. proposed a model to forecast the state of the EU ETS using dynamic model averaging [35]. Finally, in the context of this dissertation we devised a possible carbon market multi-agent simulation model [18].

2.3 Summary

In this section, we designated several topics that are the building blocks of the body of knowledge required to pursue the goals of this dissertation. We started by providing an overview of the areas of evolutionary game theory, and more specifically, mechanism design and social choice theory. We described common-pool resources, the tragedy of the commons, several games used as metaphors in the context of game theory and the Vickrey-Clarke-Groves mechanism. In the subsection regarding social choice theory, we presented several social choice methods and a set of conditions to evaluate them and concluded with a table with a comparison of voting methods. Then, we introduced the topic of social simulation and complex systems. In this section, we provided a definition for social simulation and presented several aspects present in simulations and examples of those, and finalized it with a comparison of three simulation frameworks. After that, there was a discussion on the topic of carbon markets, explaining in detail how different market mechanisms may operate in the real world. Finally, we developed on existing related work on simulation applied to climate policy and, more specifically on carbon markets, areas that have not been very explored, resulting in fewer publications worth mentioning.

Chapter 3

Methodology

3.1 Devising a Hierarchical Reference Metamodel

In this section, I will describe all the steps that were followed with the goal of designing a multi-agent metamodel capable of generalizing sociotechnical systems with the intent of studying regulatory and utility aligning mechanisms. This metamodel, following a similar modelling approach to [16], should be parametric, scalable, hierarchical, and appliable to a varied set of contexts of social dilemmas. The instantiation of this metamodel in the context of the study of carbon markets and emissions regulation will also be presented in this section.

3.1.1 Conceptualization

From the intended use cases for the metamodel, it is possible to identify a set of concepts and their relationships, summarized in the diagram of figure 3.1.

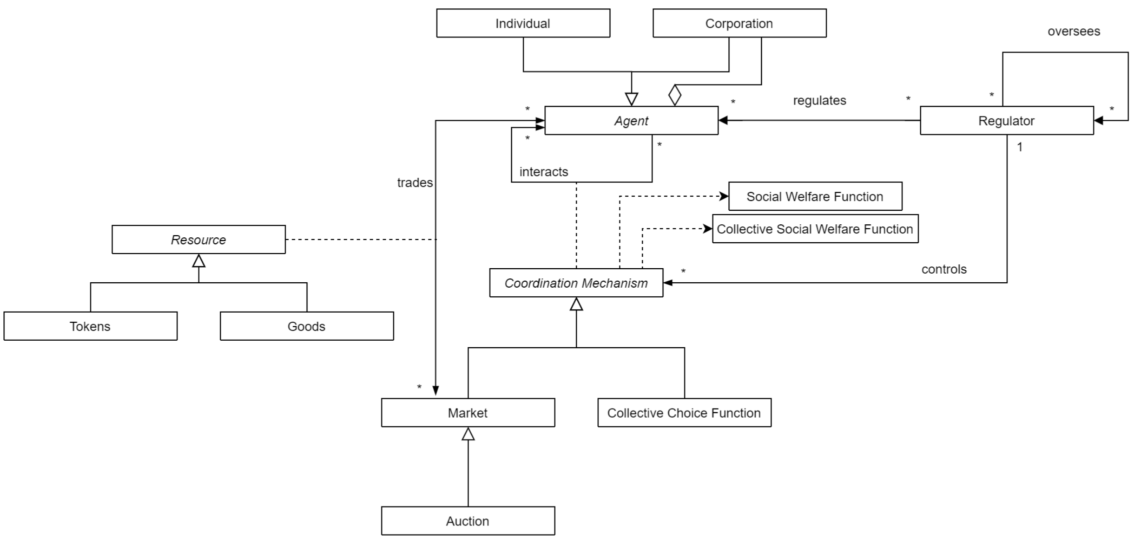

Figure 3.1: Metamodel conceptual class diagram

Starting with the **agent**, it is the main entity of the model. It can either be an **individual** or a **corporation**. Corporations have the special characteristic of being able to aggregate multiple agents, allowing for the possibility of having a group of multiple agents acting together as a single entity. Agents can be regulated by a variable number of **regulators**. Regulators are the authorities of the system and can influence the behaviour of the agents in several ways, directly or indirectly, by dictating the "rules of the game". They can directly intervene by issuing incentives or penalties based on goals or conditions that the agent has to oblige to, or by establishing constraints to the possible set of actions of the agent, to give some examples. They can oversee other regulators, thus maintaining the hierarchical feature of this metamodel, meaning that according to their position in relation with one another, a regulator higher in the hierarchical tree can override an action made by its lower counterpart. Regulators control the **coordination mechanisms** of the model, establishing their rules and parameters. Coordination mechanisms are the way agents interact between themselves. They can take the shape of a **collective choice function**, for example, in the case of an election or a collective decision, or the shape of a **market**. Through a market, agents can trade resources that can either be **tokens**, like carbon credits, or **goods**. Another possible type of mechanism is the **auction**, which is a specific kind of market where agents place bids and then those bids are ordered and processed according to a set of rules specific to the chosen auction mechanism. Through the coordination mechanisms, the agents incorporate a **social welfare function** and a **collective social welfare function** which are utility functions that determine the desirability of a certain social state according to the interests of the individual agent and of the entire group where it is inserted, respectively.

3.1.2 Metamodel Implementation and Operators

In this subsection, we present how the conceptual metamodel was translated into code. We used Python and the MESA package to implement this framework. We decided on those technologies because of the high modularity that enables the potential of this framework to be used in a variety of scenarios. Being Python a programming language of the object-oriented paradigm, the capability of dividing our agents and mechanisms into different classes make it much easier to develop complex models. This language is also known for having a vast selection of libraries; some of those can be used to implement a variety of mechanisms and agent behaviours. For example, more complex agent's reasoning can be enforced by the usage of machine learning modules like Scikit-learn [50], and market mechanisms can be implemented with the help of packages like PyMarket [34]. On the other hand, MESA was the package chosen to work as the backbone of the model because, as explained in chapter 2, it is the most advanced multi-agent simulation framework in Python, and at the same time, is easy to use and heavily modular.

The UML class diagram of the metamodel is present in figure 3.2.

First, we have the main class of the model, *MainModel*. This class includes general information of the model, global variables, references to the agents and other objects that are necessary for the entire set of features of this artefact to function appropriately, as seen in table 3.1. It also

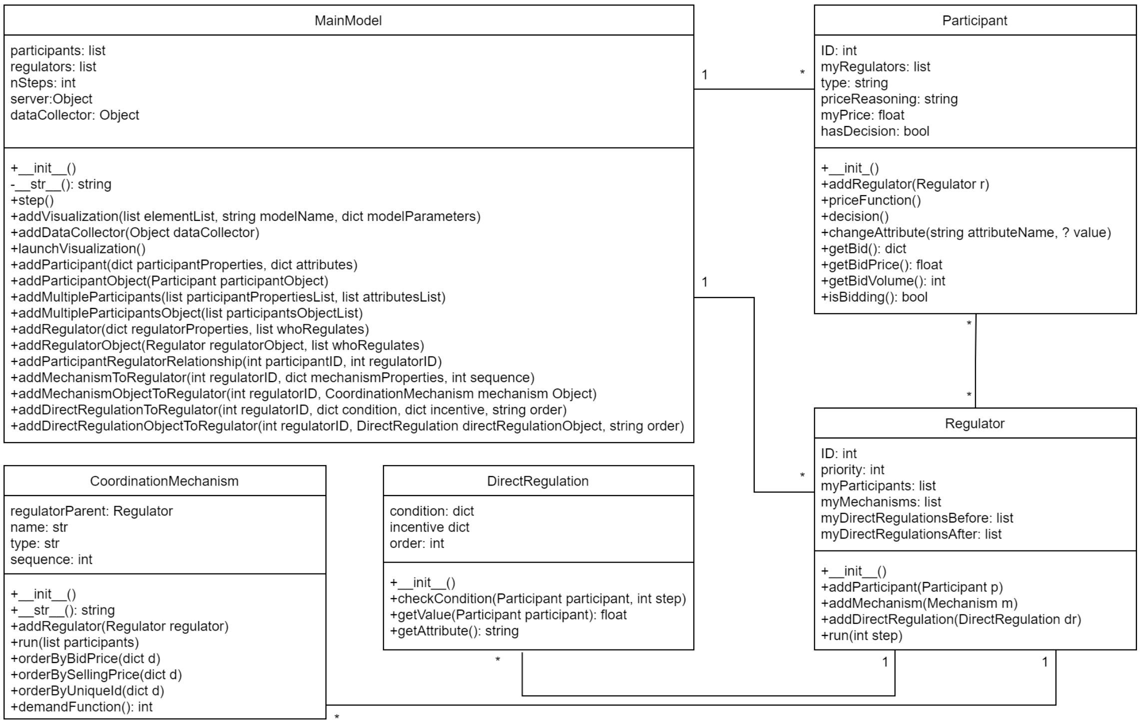

Figure 3.2: Metamodel class diagram

includes methods that are used to manipulate the model by changing its properties, adding features and agents and customize features. An extensive description of those operators is presented in table 3.2.

Then, we have the Participant class. This class is our main agent class, including both Corporations and Individuals in it. Its variables are described in table 3.3. Its methods are described in table 3.4.

The Regulator class is, obviously, the class of the regulator agent. Its variables are described in table 3.5. Its methods are described in table 3.6.

The CoordinationMechanism class contains in it all kinds of coordination mechanisms, being markets, auctions or collective choice functions. Its variables are described in table 3.7. Its methods are described in table 3.8.

Variables	**Description**
participants	List of references of agent objects of the type Corporation or Individual
regulators	List of references of agent objects of the type Regulator
nSteps	Number of time steps executed by the model. Starts at zero
server	ModularServer object from the MESA package. Used to launch a web server for visualization and interactive parameterization of the model.
dataCollector	DataCollector object from the MESA package. Used for generation and collection of data from simulations

Table 3.1: MainModel variables

Methods	Description
__init__()	Model constructor
__str__()	Prints information about the model and its agents.
step()	Advances the simulation by one time step.
addVisualization()	Adds a visualization component to the model, by creating a ModularServer object. Receives a visualization elements list, the name of the model, and a dictionary of model parameters.
addDataCollector()	Adds a DataCollector object to the model. Receives a previously created DataCollector object.
launchVisualization()	Launches a ModularServer web server for visualization and interactive parameterization.
addParticipant()	Adds participant agent to the model. Receives a dictionary of participant properties and a dictionary of agent variables.
addParticipantObject()	Adds a previously created agent object to the model.
addMultipleParticipants()	Adds multiple participant agents to the model. Receives a list of participant properties and a list of agent variables.
addMultipleParticipantsObject()	Adds multiple agent objects to the model. Receives a list of participant objects.
addRegulator()	Adds a regulator agent to the model. Receives a dictionary of regulatorproperties and a list of IDs of agents be regulated by the agent.
addRegulatorObject()	Adds a regulator agent to the model. Receives a Regulator object.
addParticipantRegulatorRelationship()	Adds a regulatory relationship between a participant agent and a regulator agent. Receives the ID of a participant agent and of a regulator agent.
addMechanismToRegulator()	Adds a coordination mechanism to a regulator. Receives the ID of the regulator, a dictionary of mechanism properties and the order by which the mechanisms of a regulator should be executed.
addMechanismObjectToRegulator()	Adds a CoordinationMechanism object to a regulator.
addDirectRegulationToRegulator()	Adds a direct regulation to a regulator. Receives the ID of the regulator, a dictionary with information on the triggering condition of the direct regulation, a dictionary with information on the incentive to be given if the condition is true and a string representing if the direct regulation should be run in the first direct regulation phase or in the second (see section 3.1.3).

Table 3.2: MainModel methods

Variables	Description
ID	agent unique identifier.
myRegulators	List of references of the regulators in charge of this participant agent.
type	String describing if the agent is a Corporation or an Individual.
priceReasoning	Type of price determination method of the agent.
myPrice	current price as determined by the agent.
hasDecision	Boolean. True if the agent has an action to perform in the participants' decision phase (see section 3.1.3).

Table 3.3: Participant variables

Variables	Description
__init__()	Participant agent constructor.
addRegulator()	Adds reference to a regulator that is overseeing this agent. Receives a Regulator object reference.
priceFunction()	Function that returns the value that the agents gives to a certain token or good at a certain moment.
decision()	Action of the agent in the participants' decision phase.
getBid()	Function that returns a dictionary with information on a bid to be used in an auction mechanism.
getBidPrice()	Function that returns price of a bid to be used in an auction mechanism.
getBidVolume()	Function that returns volume of a bid to be used in an auction mechanism.
isBidding()	Function that returns a boolean,telling if the agent is placing a bid on a auction mechanism or not.

Table 3.4: Participant methods

Variables	Description
ID	Regulator agent unique identifier.
priority	Integer that gives the priority by which the regulator should be run in regards to other regulators.
myParticipants	List of references of the participants the regulator is in charge of.
myMechanisms	List of references to CoordinationMechanisms controlled by this regulator.
myDirectRegulationsBefore	List of references to DirectRegulations controlled by this regulator and to be run in the first direct regulations phase.
myDirectRegulationsAfter	List of references to DirectRegulations controlled by this regulator and to be run in the second direct regulations phase.

Table 3.5: Regulator variables

Variables	Description
__init__()	Regulator agent constructor.
addParticipant()	Adds reference to a participant that is being regulated by this agent. Receives a Participant object reference.
addParticipant()	Adds reference to a coordination mechanism that is being controlled by this agent. Receives a CoordinationMechanism object reference.
addDirectRegulation()	Adds reference to a direct regulation mechanism that is being controlled by this agent. Receives a CoordinationMechanism object reference.
run()	Function that runs all the phases of a regulator, starting sequentialy all of its mechanisms. (see section 3.1.3

Table 3.6: Regulator methods

Variables	Description
regulatorParent	Regulator agent unique identifier.
name	Name of the coordination mechanism.
type	Type of the coordination mechanism. Can either be an auction, a market, or a collective choice function.
sequence	Integer that establishes the order by which this mechanism should be run in regards to other mechanisms of the same regulator.

Table 3.7: CoordinationMechanism variables

Variables	Description
__init__()	CoordinationMechanism object constructor.
__str__()	Returns a string with the current status of the coordination mechanism.
addRegulator()	Adds reference to a regulator that controlls this coordination mechanism. Receives a Regulator object reference.
run()	Executes the mechanism. Receives a list of Participant agents that are participating in this mechanism.
orderByBidPrice()	Auxiliar function to order bids by bid price.
orderBySellingPrice()	Auxiliar function to order selling orders in a market by bid price.
orderByUniqueId()	Auxiliar function to order agents by their ID.
demandFunction()	Function that returns the demand of a goods market.

Table 3.8: CoordinationMechanism methods

Variables	Description
condition	Condition that enables the application of the direct regulation on the agents that satisfy it.
incentive	Dictionary containing information on what incentive/penalty to give to the agent if the condition is satisfied.
order	Order by which the direct regulation should be applied in regards to other direct regulations.

Table 3.9: DirectRegulation variables

Finally, there's the class DirectRegulation. While the other classes derive mostly directly from singular concepts presented in section 3.1.1, this class represents a different kind of relationship. Direct regulations in this context are to be intended as ways that regulators influence the behaviours of other agents by the usage of incentives or penalties depending on certain conditions. For example, if an agent does something that maximizes the global utility of the system, it may receive an incentive, while if the opposite happens, it may receive a penalty that internalizes the externality costs of its actions. The variables of the DirectRegulation class are described in table 3.9. Its methods are described in table 3.10.

3.1.3 Execution Flow

The basic building blocks of the execution flow of the models implemented within the presented framework are the regulators. The execution of the model starts by ordering the regulators according to their priority values. Then, each of the regulators is executed. Regulators are the ones who call for the execution of their direct regulations, coordination mechanisms, and other decisions of their participants. For each regulator, four phases are executed sequentially. In the beginning, there is a first Direct Regulation Phase. This phase can contain multiple direct regulations that are then ordered according to their sequence number. Then, there is a Participants' Decision Phase. In this phase, the list of participants that are being regulated by the regulator in question is shuffled for the decisions of the agents to be executed in random order. Next, there is the coordination mechanisms phase. Multiple coordination mechanisms can be contained in this phase, and they

Variables	Description
__init__()	DirectRegulation object constructor.
checkCondition()	Checks if the agent satisfies a condition. Receives a reference for the agent to check and the time step number, as some conditions are triggered by periodicity.
getAttribute()	Returns the name of the attribute of the agent to be modified by the regulation (i.e. money, in case of a fine).
getValue()	Returns the value to be added or to be removed from the designated attribute of the agent to which the regulation is being applied.

Table 3.10: DirectRegulation methods

are executed according to their order. Participants involved in the mechanisms are activated randomly to dissuade a possible bias of the model. Finally, there is the second direct regulations phase, and again, multiple direct regulations can belong to it. This flow is described visually by figure 3.3.

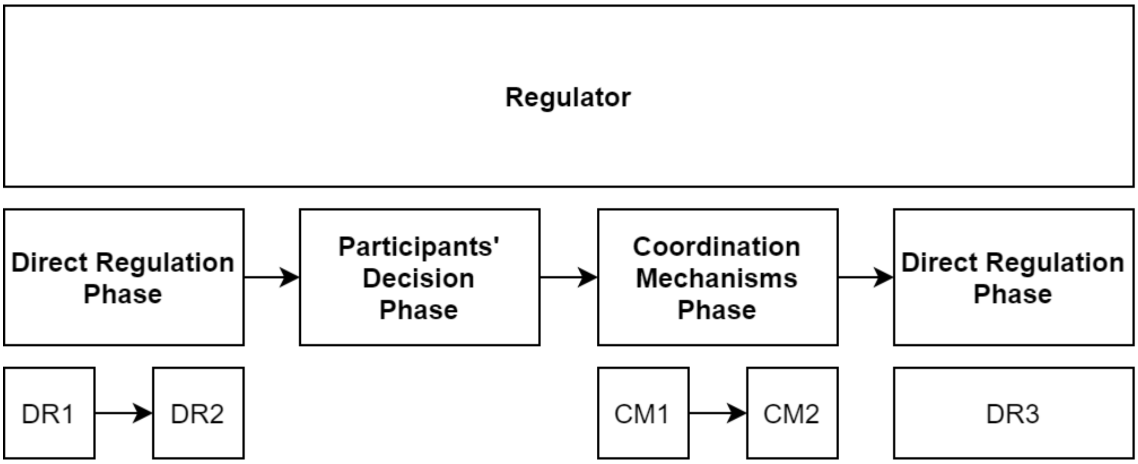

Figure 3.3: Metamodel flow diagram

3.2 Model Instantiation

To materialize the metamodel into a simulation that can be run and provide meaningful results, I decided to instantiate it in the context of carbon emissions regulation. As explained in Chapter 2, market-based tools for emission mitigation like cap and trade schemes in combination with carbon taxes are complex and contain multiple "moving parts". There are many possible ways to implement those kinds of regulations, and how all the different economic agents will respond to them is often impossible to predict. The uncertainty involved in this problem makes it a good candidate for applying a Multi-Agent-Based Simulation, where agents perform reasoning and make production and market decisions. This instantiation should be able to replicate the interactions of different agents through regulatory mechanisms and provide intuitions about possible results of different policies over time.

3.2.1 Coordination Mechanisms Formalization

In this subsection, possible coordination mechanisms will be presented and formalized. All of the coordination mechanisms in this subsection were implemented and be accessed in appendix A.

3.2.1.1 Forward Auctions

First, I will start by introducing the forward auctions present in this model, or in other words, auctions that have one seller and multiple buyers. This is the case of auctions like the one present in schemes like ETS, where one central regulator in each European country sells carbon credits to multiple corporations. All of the auctions presented are of the sealed-bid type, meaning that agents do not know about the bids of any other agent. These auctions are also executed in a single round.

Considering $sellingVolume_1$ the initial number of carbon credits that the regulator is selling in the auction, and b the bid of an agent in an auction, so that $b = \{bp, bv\}$, being bp the bid price for one unit of carbon credits and bv the bid volume, or in other words, the number of units of carbon credits to be bought. The first step is to order the bids in the natural order, or in other words, in decreasing order, so that $bp_1 \geq bp_2 \geq ...bp_n$. After that, bids are satisfied in that order, and for each bid, the selling volume is decreased by $sellingVolume_{i+1} = sellingVolume_i - bv_i$ until the point that $sellingVolume_i \leq bv_i$, the number of credits that remain to be sold is not enough to satisfy the entire bid volume. In that case, that bid is satisfied only partially. k is the index of the breakeven bid, in other words, the last successful bid. The price that bidders will have to pay for the credits depends on the type of auction. For *discriminatory-price* auctions, each bidder pays for each carbon credit their bid price. For *uniform-price* auctions, each successful bidder pays the clearing price of the auction. In other words, they pay bp_k. Finally, for *second-price* auctions, each bidder i pays b_{i+1}, so that the highest-placed bidder pays the second-highest price, the second highest-placed bidder pays the third-highest price, and so on.

3.2.1.2 Double Auctions

Double auctions are a type of auction in which there are multiple buyers and sellers. In the context of the implementation of this model, double auctions can be used for corporations with more carbon credits that they need (when they bought more credits than the total of their emissions) to sell them for a profit to corporations that do not have enough credits to compensate for their own emissions.

Considering $b = \{bp, bv\}$, the buying bids like presented in the previous subsection, and $s = \{sp, sv\}$ the selling bids, being sp the selling asking price and sv the volume of carbon credit units to be sold. After that, we break down each buying and selling bid, so that each $b_i = \{bp_i, 1\}$ and $s_i = \{sp_i, 1\}$. Then we order buying and selling bids in the natural order, meaning that buying bids are ordered in a decreasing way, so that $bp_1 \geq bp_2 \geq ...bp_n$, while selling bids are ordered in an increasing way so that $sp_1 \leq sp_2 \leq ...sp_n$. Finally, we get k, the breakeven index, or the largest index such that $bp_k \leq sp_k$. The matching of buying and selling bids is done depending on the mechanism being used. We implemented three mechanisms: *average mechanism, McAfee's mechanism and a Vickrey-Clarke-Groves' mechanism.*

Starting with the average mechanism, it states that the auction price is given by the expression $p = (bp_k + sp_k)/2$, so that all the first k sellers sell the credits to all the first k buyers for that price.

Then, the McAfee's mechanism states that the price p is given by the expression $p = (b_{k+1} + s_{k+1})/2$. Then, if $p \in [sp_k, bp_k]$, the first k sellers sell the credits to the first k buyers for the price of p. Otherwise, the first $k-1$ sellers sell their credits for s_k and the first $k-1$ buyers buy their credits for b_k. In this second case, the regulator running the auction has to subsidize the trade.

Finally, the Vickrey-Clarke-Groves' mechanism states that for each bid until the breakeven index k, the trade is made, and the buyer pays sp_k while the seller receives bp_k. This mechanism is also dependent on subsidies from the regulator or auctioneer.

3.2.2 ODD Protocol

For the formalization of this instantiation of the model, I will use the revised version of the ODD Protocol [29]. The ODD protocol is a commonly used standard for ABM descriptions, facilitating comparison and more precise communication.

3.2.2.1 Purpose

The purpose of this model is to simulate the interactions of agents that pollute the environment through their actions, with regulatory mechanisms, like carbon markets and carbon taxation and understand how different configurations of those mechanisms can lead to varying results in regards to the intended emission reduction.

3.2.2.2 Entities, state variables and scales

This model incorporates three types of agents or entities: An **Individual** represents a person who can do sustainable actions that results in rewards in the form of carbon credits, which can later be sold. A **Corporation** represents a company that participates in a market to sell its products, in competition with other agents of the same type, and has its emissions regulated by certain mechanisms. A **Regulator** is an agent that imposes mechanisms, incentives, penalties and sets rules that other agents being regulated will have to comply with.

Each of those entities has a different set of state variables:

1. Regulator:
    - **Aggregator**. Boolean that indicates if the regulator is acting as an aggregator of credits from individuals.
    - **Direct regulations**. List of objects representing direct regulation that the agent imposes on other agents.
    - **Mechanisms**. List of objects representing coordination mechanisms that the agent currently oversees.
    - **Participants**. List of objects representing agents that the regulator currently regulates.
    - **Priority**. An integer representing the hierarchical feature of regulators and determines the order by which they should be run.
2. Corporation:
    - **Bidding strategy probability**. List of floats with values between [0,1], representing the probability for the agent to choose bidding strategy 1, 2 or 3, respectively.

- **Current bidding strategy**. Integer in [1,3].
- **Cost per product**. An integer representing the production cost of a unit of production.
- **Credits**. An integer representing the current number of carbon credits in possession of the agent.
- **Emissions**. An integer representing the number of tonnes of CO2 emitted by the agent in the current tick.
- **Emissions per product**. Float representing the number of emissions that result from the production of one unit.
- **Production**. An integer representing the number of products produced by the agent in the current tick.
- **Profit rate**. Float representing the profit rate to be added to the production final sale price.
- **Profit**. An integer representing the resulting profit of the operation of the agent in the current tick.
- **Regulators**. List of objects of the type Regulator that are regulating the agent.
- **Reservation price**. Float representing the maximum price that a carbon allowance can have while still being viable for the agent.
- **Sales**. An integer representing the value earned by the agent by selling goods in the market in the current tick.

3. Individual:

   - **Credits**. An integer representing the current number of carbon credits in possession of the agent.

In terms of scale, one time step in the model currently represents one full day.

3.2.2.3 Process overview and scheduling

The scheduling of this model is based on the same phases as the metamodel previously presented. The content of those phases, as summarized in the flow diagram of figure 3.4, and further explained in the 'submodels' section. The figure represents the processes involved in the execution of each regulator and concern only agents that they regulate. Regulators are executed by order of priority.

3.2.2.4 Design concepts

- **Basic principles:** This model is built on the assumption that agents act purely rationally with the sole concern of increasing their individual utility, or in the case of corporations, their profit.

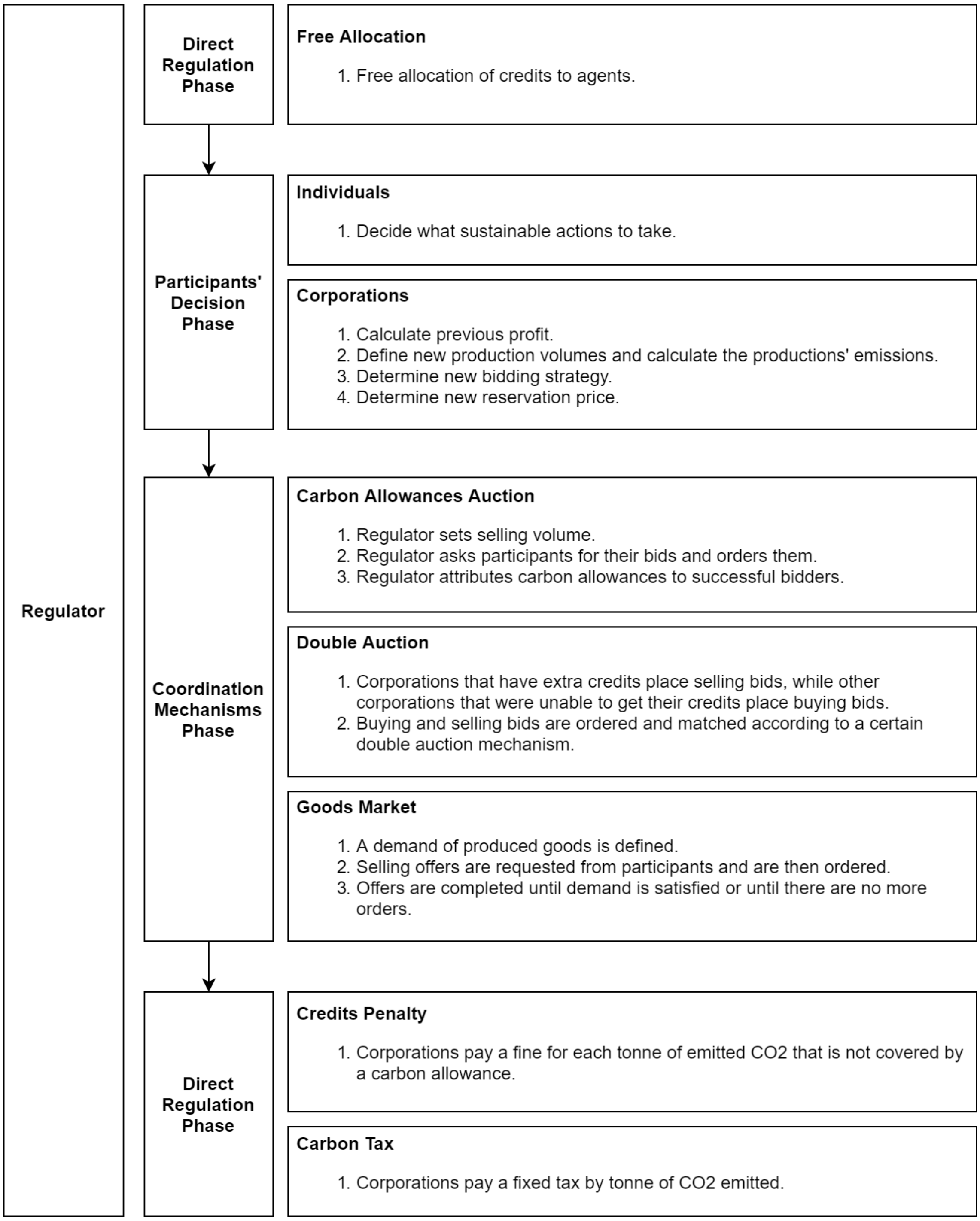

Figure 3.4: Model process scheduling

- **Emergence:** The main result expected to *emerge* from the execution of the model in a complex and possibly unpredictable way is the clearing price of carbon auctions. It is based on the adaptive behaviour of bidding strategy decision-making of the agents. There are other results, as the total emissions of the system, that are more tightly imposed by the rules of the model and its mechanisms, so they should not be considered as truly emergent features.

- **Adaptation:** Corporations take at every turn two decisions that are adaptive. First, they decide how much of their product they want to produce. Then, they decide what will be their strategy in terms of bidding for carbon allowances. Both decisions are based on their previous results in terms of profitability, taking into account previous decisions.
- **Objectives:** The objective of the corporations is to increase their profit. The aim of the regulators is to reduce total emissions.
- **Learning:** Corporations compare their previous decisions with their results and use that information to make new decisions.
- **Sensing:** There are no local or network structures that enable agents to sense individual information, however, there are global sets of data, like the previous clearing price of an auction, that are communicated to all agents.
- **Prediction:** In this model, none of the agents' processes implements any kind of future condition estimations.
- **Interaction:** Individuals and corporations interact with other agents of the same type only through coordination mechanisms. Regulators interact with the other types of agents by means of coordination mechanisms and through direct regulation.
- **Stochasticity:** Some features of the model do have a factor of randomness. The bidding strategy of corporations is defined according to previous profit results. However, because that information is not available in the first time step of the simulation, it is randomly determined. The same thing happens with the price of their first bid, which has a random value between 0 and their reservation price.
- **Collectives:** Although the metamodel enables a more complex usage of collectives, with individuals and corporations being part of other corporations, that feature is not implemented in this instantiation of the model. What is used is the possibility of aggregation of credits earned by individuals that can later be sold in bulk to corporations.
- **Observation:** Data generated by this model is collected through the tools provided by the Data Collection Module of the MESA package. A set of model reporters were implemented:
  - **Total emissions**: Calculates the total number of tonnes of CO_2 emitted by all agents in a certain time step.
  - **Supply**: Calculates the total production of all agents in a certain time step.
  - **Increased production**: Calculates the number of corporations that increased their production in a certain time step.
  - **Decreased production**: Calculates the number of corporations that decreased their production in a certain time step.

- **Maintained production**: Calculates the number of corporations that maintained their production levels in a certain time step.
- **Credits cost (total)**: Calculates the total value spent on credits in a certain time step.
- **Credits cost (average)**: Calculates the average value per agent spent on credits in a certain time step.
- **Clearing price**: Calculates the clearing price of the carbon allowances auction in a certain time step.
- **Double auction highest price:** Calculates the highest price paid in a double auction in a certain time step.
- **Top fifty polluters emissions**: Calculates the total emissions, for a certain time step, of the fifty biggest emitters at the start of the simulation.
- **Top fifty efficient emissions**: Calculates the total emissions, for a certain time step, of the fifty smallest emitters at the start of the simulation.
- **Fifty average emissions**: Calculates the total emissions, for a certain time step, of the fifty agents closer to average emissions at the start of the simulation.
- **Top fifty polluters production**: Calculates the total production volume, for a certain time step, of the fifty biggest emitters at the start of the simulation.
- **Top fifty efficient production**: Calculates the total production volume, for a certain time step, of the fifty smallest emitters at the start of the simulation.
- **Fifty-average production**: Calculates the total production volume, for a certain time step, of the fifty agents closer to average emissions at the start of the simulation.

3.2.2.5 Initialization

For the results presented in this dissertation, this model is initialized with a thousand corporations. In the case of using a carbon credits aggregator, an additional thousand individual agents are initialized. A single regulator is initialized, and it regulates all the agents. The mechanisms and direct regulations imposed by the regulator are initialized with different parameters for the different simulations, which will be explored in more detail in chapter 4 that discusses simulation results.

3.2.2.6 Input data

This model does not use input data to represent time-varying processes.

3.2.2.7 Submodels

In this section, I will explain in more detail the submodels that represent the processes listed in the subsection "Process overview and scheduling".

– **First Direct Regulation Phase - Free Allocation**
A number of credits can be allocated free of cost for the agents. This number can either be a fixed amount, variate over time, or be pegged to the total emissions of the agent, for example.

– **Participants' Decision Phase - Individuals**
In this process, individual agents decide if they want to practice sustainable actions that generate rewards. Those rewards can be in the format of carbon credits that can later be aggregated by a regulator and then sold to corporations. This idea is summarized in figure 3.5.

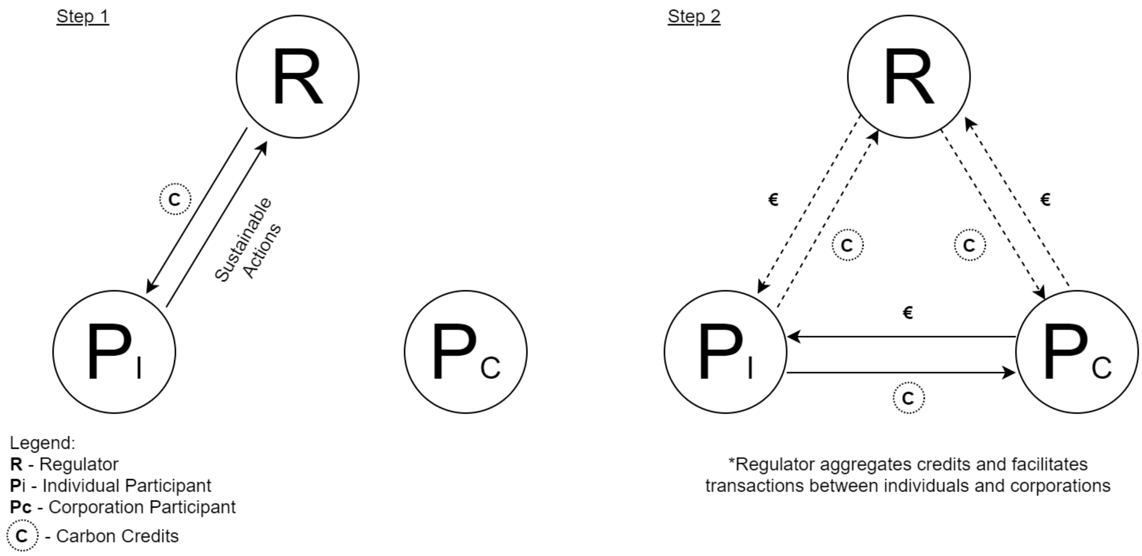

Figure 3.5: Individual credits aggregator

– **Participants' Decision Phase - Corporations**
In this phase, corporation agents start by **calculating the profit** $\pi_{c,t}$ of their operation in the previous time step. The profit is given by the following equation

$$\begin{aligned}\pi_{c,t} =& sales_{c,t} - (costPerProduct_c * productionVolume_{c,t}) - allowancesCost_{c,t} \\ & - penalties_{c,t} - carbonTaxes_{c,t}\end{aligned}$$

being c a corporation agent, t a time step, $sales$ the value in sales earned, $costPerProduct$ the cost to produce a single unit of a product, $productionVolume$ the quantity of products made, $allowancesCost$ the cost of acquisition of carbon credits, $penalties$ the value spent on fines, and $carbonTax$ the value spent of carbon taxation.
After that, agents have to decide on their **new production volume**, in other words, their new output. That is done through a reasoning process that takes into account the variation of the agents' profit results over time. This is the phase when the fruits of the regulations and mechanisms like carbon markets materialize; that is, it is the

phase when incentives and penalties result in changes in production volumes, ideally by the expansion of production by the most efficient agents and by the retraction of the biggest polluters. That reasoning is explained in the flowchart in figure 3.6, being *itemsSold* the number of products sold in one time step, Δ_π the profit variation threshold for changes in output, $\alpha \in]1,+\infty[$ the output increase factor and $\beta \in]0,1[$ the output decrease factor.

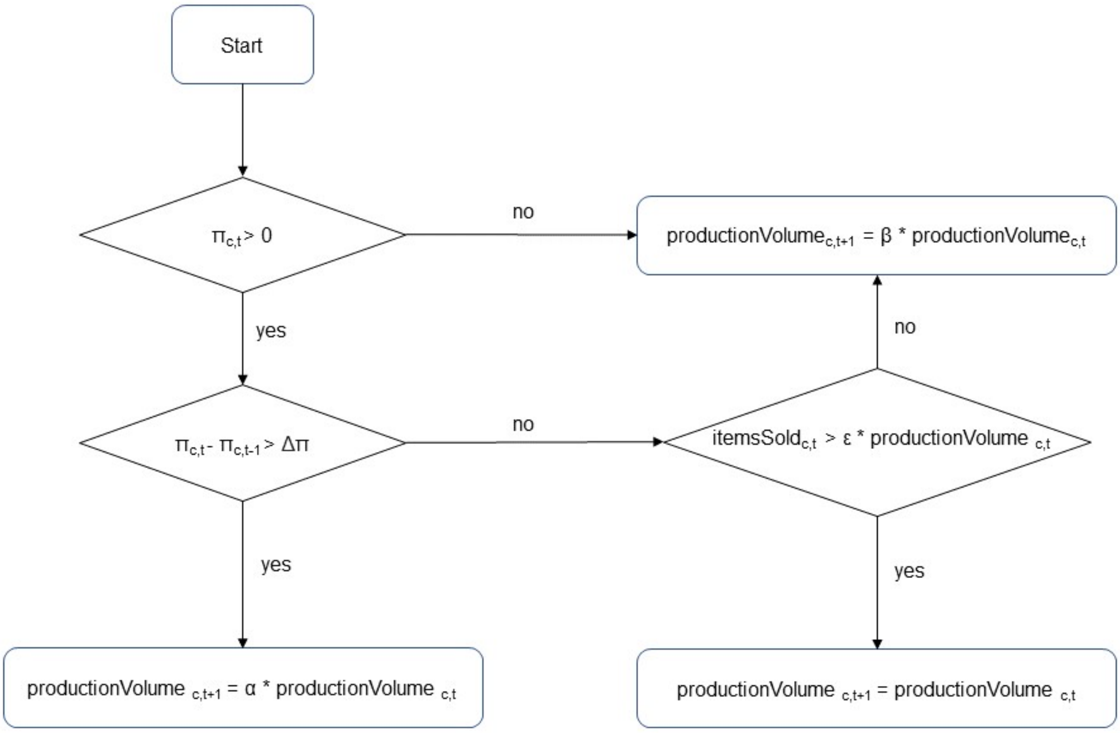

Figure 3.6: Production volume decision flowchart

This new production is responsible for a certain amount of CO2 emissions that are given by

$$emissions_{c,t} = productionVolume_{c,t} * emissionsPerProduct_c$$

being *emissionsPerProduct* the amount of CO2 emissions that the production of a single unit of product is responsible for.
After all that, agents have to decide on how to deal with the carbon market. Bids in the carbon market have two components: the number of carbon allowances to buy, in other words, the bid volume, and the value to pay for each of those allowances, or the bid price. The bid volume $bidVolume_{c,t}$ is given by

$$bidVolume_{c,t} = emissions_{c,t} * \eta$$

being $\eta \geq 1$. If $\eta > 1$, that means that the agent buys more credits than necessary and is able to sell them for a profit in a future double auction.

The bid price is more complex. To calculate it, the agent has to follow a strategy based on a certain strategy ([13, 63]) and a reservation price. The reservation price $rp_{c,t}$ is the maximum value that a corporation is willing to pay for a carbon allowance (one unit). It is given by the equation:

$$rp_{c,t} = \frac{sales_{c,t} - costPerProduct_{c,t} * productionVolume_{c,t}}{emissions_{c,t}}$$

There are three possible strategies for bid price definition:

* Risky strategy : $bidPrice_{c,t+1} = cp_{r,t} + \frac{3}{4}(rp_{c,t+1} - cp_{r,t})$
* Neutral strategy : $bidPrice_{c,t+1} = cp_{r,t} + \frac{1}{2}(rp_{c,t+1} - cp_{r,t})$
* Conservative strategy : $bidPrice_{p,t+1} = cp_{r,t} + \frac{1}{4}(rp_{c,t+1} - cp_{r,t})$

being $cp_{r,t}$ the last clearing price of the auction market of the regulator associated with the corporation agent. The clearing price is the lowest price for which an allowance was sold in the last auction. At t=0, the bid price is a random value so that $bidPrice_{c,0} \in [0, rp_{c,0}]$. The initial probability of selecting each strategy, $prob_{c,t,s}$ is 1/3, being $s_{c,t} \in \{1,2,3\}$ the strategy chosen by the polluter. Each strategy's probability is based on the propensity $prop_{c,t,s}$ towards each strategy.

$$prop_{c,t+1,s} = (1-g)prop_{c,t,s} + \psi_{c,t,s}$$

$$\psi_{c,t,s} = \begin{cases} (1-e)\pi_{c,t}, & s = s_{c,t} \\ \frac{e}{2}\pi_{c,t}, & s \neq s_{c,t}. \end{cases}$$

where $\pi_{c,t}$ denotes the agent's profit, and e and g are parameters representing experiment and recency and are experimentally set to be 0.2 and 0.1, respectively [13]. Finally, the probability for each strategy is given by:

$$prob_{c,t+1,s} = prop_{c,t+1,s} / \sum_{x=1}^{3} prop_{c,t+1,x}$$

– **Coordination Mechanisms Phase - Carbon Allowances Auction**

In this phase, the carbon allowances regulator auction mechanism is executed. The number of carbon allowances to be auctioned for each regulator r is an emissions cap. It is usually a percentage of the emissions of a certain initial point in time, for example, $cap_r = \sum emissions_{c,0} * 0.9$, meaning that in that scenario, the goal is to reduce by 10% the number of current CO2 emissions. The cap can also decrease over time. Each regulator asks all the agents it is regulating for their bids and orders them by price, following descending order. Credits are then allocated until there are no more credits to allocate. In this process, the last bid to which allowances are allocated can be entirely fulfilled or only partly. The price that successful bidders have to pay for the credits depends on the type of auction. This model implements three types of auctions: first-price auctions, discriminatory-price auctions, and second-price auctions. In the case of first-price auctions, the last successful bid price is the new clearing price, meaning that all successful agents bids with prices higher than that one were successful too, and all agents pay the clearing price for their credits. In the case of discriminatory-price auctions, the difference is that bidders pay for their credits the price they bid instead of the clearing price. Finally, the second-price auction is a type of auction that preserves some of the characteristics of the Vickrey auction [28, 36]. In that type of auction, the highest bidder pays the price of the second-highest bid, the second-highest bidder pays the price of the third-highest bid, and so on. The clearing price is an essential indicator of the calculation of the bids' prices by the polluters. All of the auctions have a sealed-bid property, meaning that agents who are bidding cannot see the bids of other agents.

– **Coordination Mechanisms Phase - Double Action**
  At this moment, some of the corporations already have a number of carbon credits acquired in the previous phase's auction. However, while most of the agents may have more than the credits they need to cover for their emissions, some others may not have enough emissions in the case that their bid in the previous auction failed. The double auction mechanism is a valuable answer for this problem. It enables agents to sell their excess credits to agents that do not have enough of them. There are a multitude of mechanisms that can be used to implement double auctions. In this model, I implemented three of the most common: average mechanism, VCG mechanism and McAfee's mechanism. Those mechanisms were introduced in the previous section.

– **Coordination Mechanisms Phase - Goods Market**
  In this phase, the goods produced by the corporations are sold on a market. It is assumed that all corporations participate in the same goods market, and it is also assumed that they sell the same product and are all in competition with each other. Selling orders consist of a selling volume, $sellVolume_{c,t} = production_{c,t}$ and a price that includes the production costs, a profit margin, and the cost of the carbon allowance bought in the previous step. It is given by the equation

$$sellPrice_{c,t} = costPerProduct_c * (1 + profitRate_c) + (allowancesCost_{c,t} / production_{c,t}))$$

  After all the selling orders have been placed, they are ordered by price in ascending order. The orders are then satisfied until the market demand has been fulfilled. In this instantiation, the demand is a fixed value. However, it would be interesting to utilize a different demand function that can reproduce more complex phenomena, like the one proposed in [64]. Finally, the total sales of a polluter are

$$sales_{c,t} = \begin{cases} sellVolume_{c,t} * sellPrice_{c,t}, & \text{if successful sale,} \\ 0, & \text{if not.} \end{cases}$$

– **Second Direct Regulation Phase - Credits Penalty**
After the coordination mechanisms' phase, another direct regulation phase starts. Firstly, the fine ($penalties_{c,t}$) that agents have to pay for all their emissions that are not covered by carbon allowances are calculated, according to the following equation

$$penalties_{c,t} = penaltyFactor_{r,t} * lastClearingPrice_{r,t} * (emissions_{c,t} - allowances_{c,t})$$

being $penaltyFactor_{r,t}$ a value determined by the regulator and that represents the severity of the fine and $lastClearingPrice_{r,t}$ the clearing price of the last carbon credits auction.

– **Second Direct Regulation Phase - Carbon Tax**
Finally, the last phase is when a carbon tax is applied to emissions made by corporation agents. It is given by the expression

$$carbonTaxes_{c,t} = carbonTax_{r,t} * emissions_{c,t}$$

being $carbonTax_{r,t}$ the value that regulators define that corporations have to pay per tonne of CO2 emitted.

3.3 Summary

In this chapter, we provided a proposal for the conceptualization of our metamodel and explained its implementation in Python, using features provided by the python package MESA. This explanation is accompanied by UML compliant diagrams that allow for an easier understanding of the concepts mobilized by the metamodel and of its structure in terms of classes in the object-oriented programming paradigm. This metamodel, capable of being used in different contexts of sociotechnical systems, is built around two main concepts: agents, that can be either be participants (specifically corporations or individuals) or regulators; and coordination mechanisms, or in other words, the mechanisms by which agents interact with one another. The simulation of this metamodel is run following a strict order of different phases: an initial direct regulations phase, a participants' decisions phase, a coordination mechanisms phase and a final direct regulations phase. Each of the phases of this framework can contain a multitude of different mechanisms.

We then outlined the implementation of the metamodel framework into a model to study carbon markets and emissions regulation in general. First, we started by formalizing a number of possible mechanisms of auctions. We then used the ODD Protocol standard to produce documentation regarding our instantiation of the metamodel into the context of carbon emissions regulation.

In this second part of the chapter, we provided a formalization of our model, explaining in a mathematical and logical way how the implemented mechanisms work and how agents make their decisions and interact with one another.

Chapter 4

Experiments and Results

In this chapter, we will present the results of experimentation of the implemented model with different parameters and mechanisms, showing the versatileness of the metamodel. We will analyse and compare results with the purpose of extracting meaningful insights from them.

4.1 Parameterization

All the simulations were started with 1000 corporation agents and one regulator responsible for the regulation of all the agents. Simulations were run during 2500 time steps, as by looking at the results, it seems like a sufficient duration to observe general tendencies. All corporation agents are initialized with $profitRate = 0.1$, $costPerProduct = 20$, initial production of $productionVolume = 10000$ and a random value of $emissionsPerProduct$ following a normal distribution with mean equal to 0.1 and standard deviation of 0.01. All the simulations include a goods market where corporations sell their production to a fixed demand equal to the total initial production of the agents. Results were collected through the data collector functions presented in section 3.2.2.4.

4.2 Carbon Markets

In this section, we will explore different carbon market mechanisms. These simulations include a carbon auction mechanism and a direct regulation that works as a carbon credits penalty - when an agent does not have enough credits to cover its emissions, it has to pay a fine equal to the last clearing price times a penalty factor. This factor was initialized as $penaltyFactor = 5$. The total number of credits circulation on the market is always 90% of the total initial emissions of the system. The bid volume factor, η is set as 1.

4.2.1 Forward Carbon Auctions

Starting with the forward carbon auctions presented and formalised in the previous chapter, we compared three mechanisms that determine the prices that bidders have to pay in a sealed-bid single round auction. Those mechanisms are *Uniform-price*, *Discriminatory-price* and *Second-price*. In figures 4.1, 4.2 and 4.3, we can see the evolution curve of the total production of three agent groups: the fifty corporations with the biggest *emissionsPerProduct* values, the fifty corporations with the lowest values and the fifty agents closer to average values. As we can see, the discriminatory-price and the second-price graphs are very similar, while the uniform-price graph is just slightly different, showing a more abrupt reduction of production values of both the most pollutant and the average group. In figures 4.4, 4.5 and 4.6, we can see the evolution of the clearing prices in the different types of auctions. In all auctions, the clearing prices tend to get higher, but the prices of the second-price auction tend to be lower than the ones of the other auctions. This may happen because this type of auction preserves some of the characteristics of the Vickrey mechanism, and it has been proven [36] that second-price auctions prevent bidders from overpaying, ending up with closer to reality pricing. Finally, in figure 4.7 we can observe the results in terms of the global utility of the system. We can see that all of the three auction mechanisms reduced similarly the total emissions of the agents. The reduction happened in the same proportion as the available ratio of credits compared to the total initial emissions. Having the same final result in terms of emissions, it is clear that the second-price mechanism seems better than the other for the simple reason that it makes the application of the mechanism less costly, as the average price of a unit of carbon credit is lower.

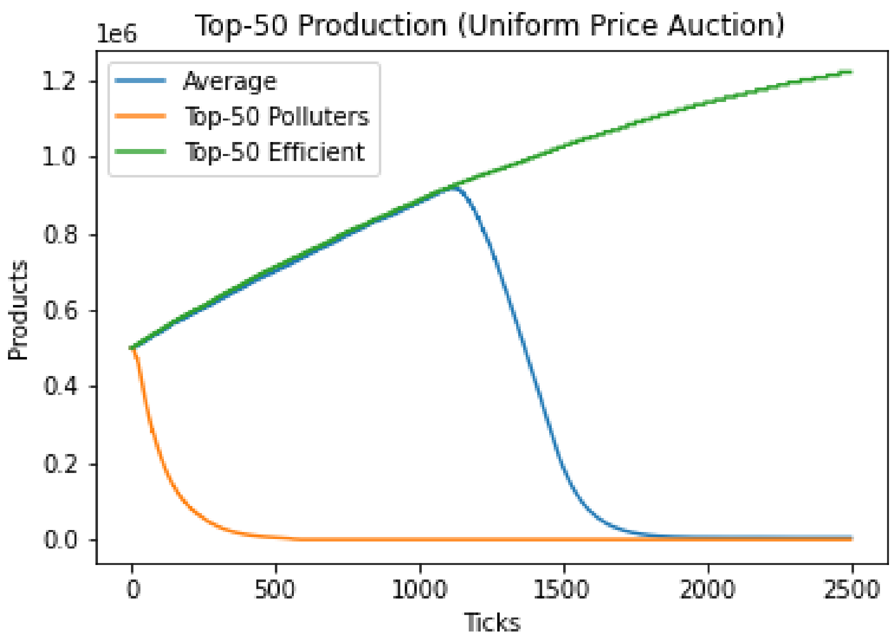

Figure 4.1: Uniform-price emissions per group

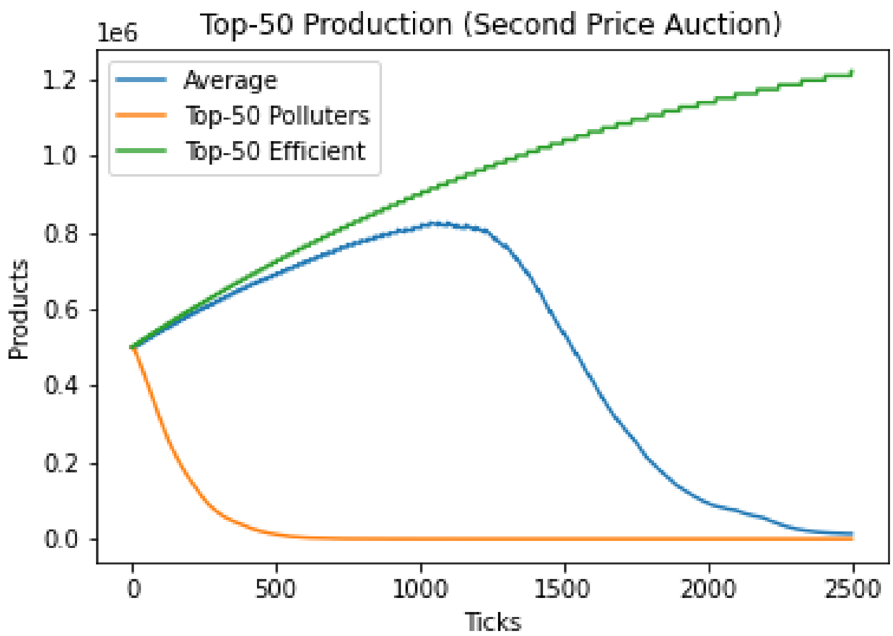

Figure 4.2: Second-price emissions per group

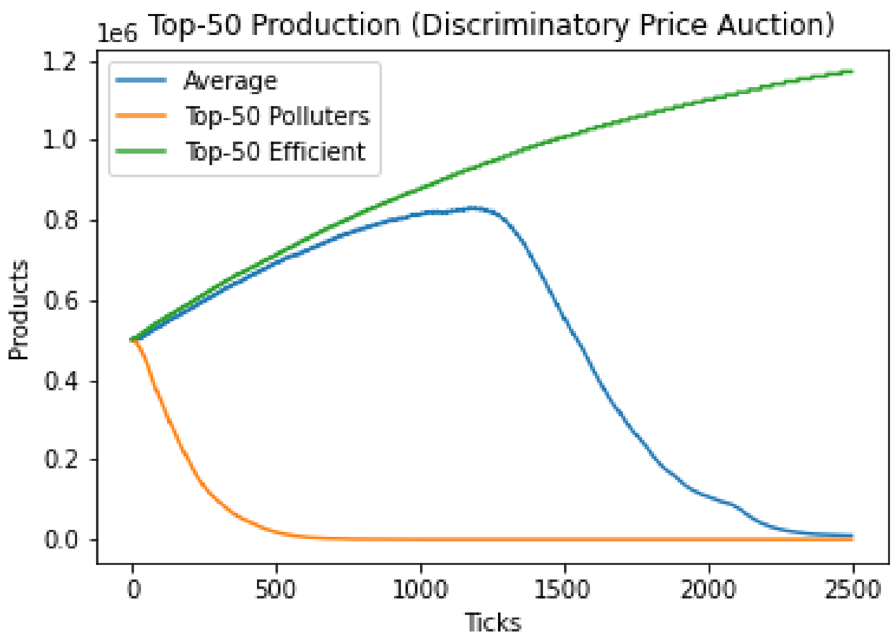

Figure 4.3: Discriminatory-price emissions per group

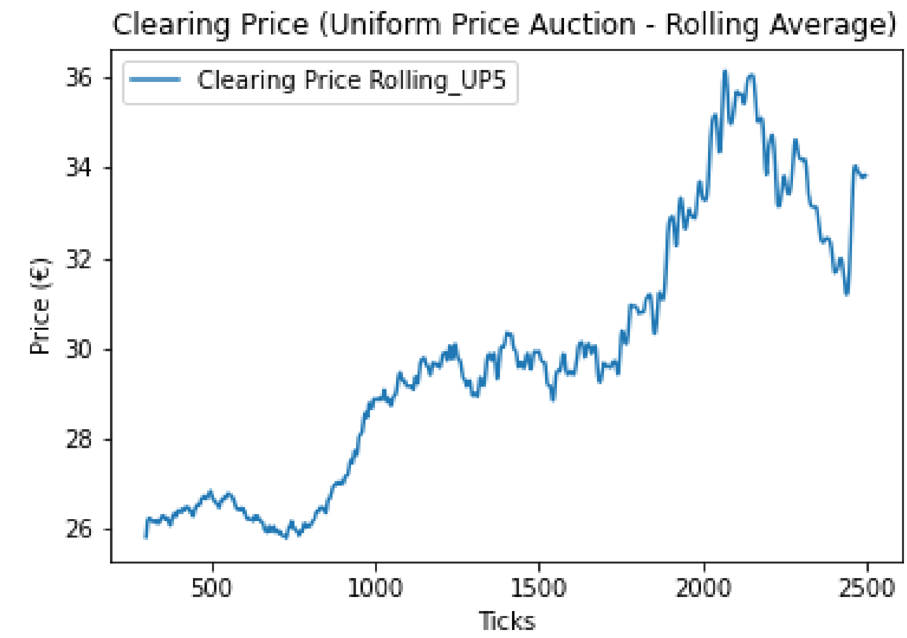

Figure 4.4: Uniform-price clearing prices

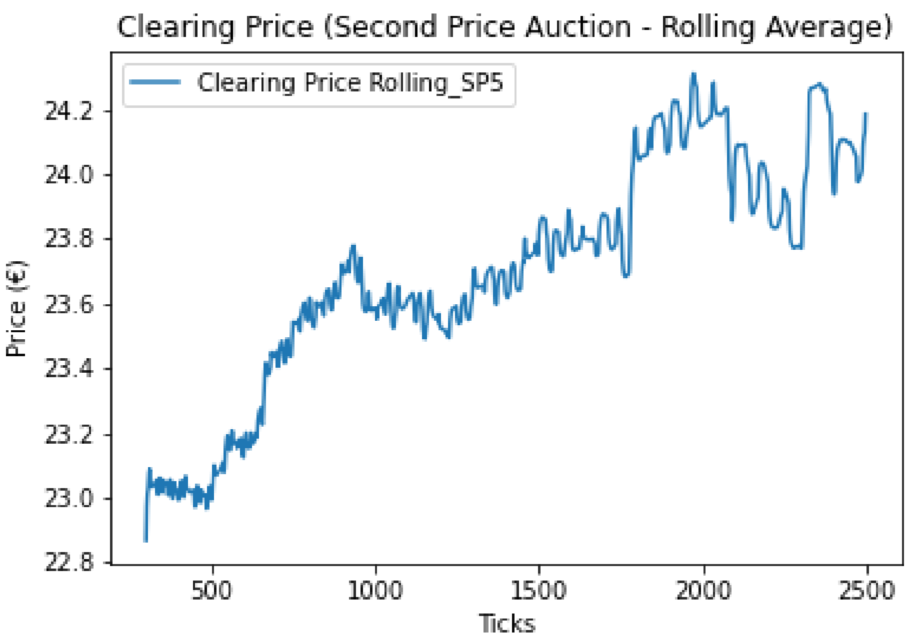

Figure 4.5: Second-price clearing prices

4.2.2 Double Carbon Auctions

In simulations with double auctions we utilised a uniform-price auction mechanism where agents can initial buy their credits, some of them to be then sold in the double auction. The excess

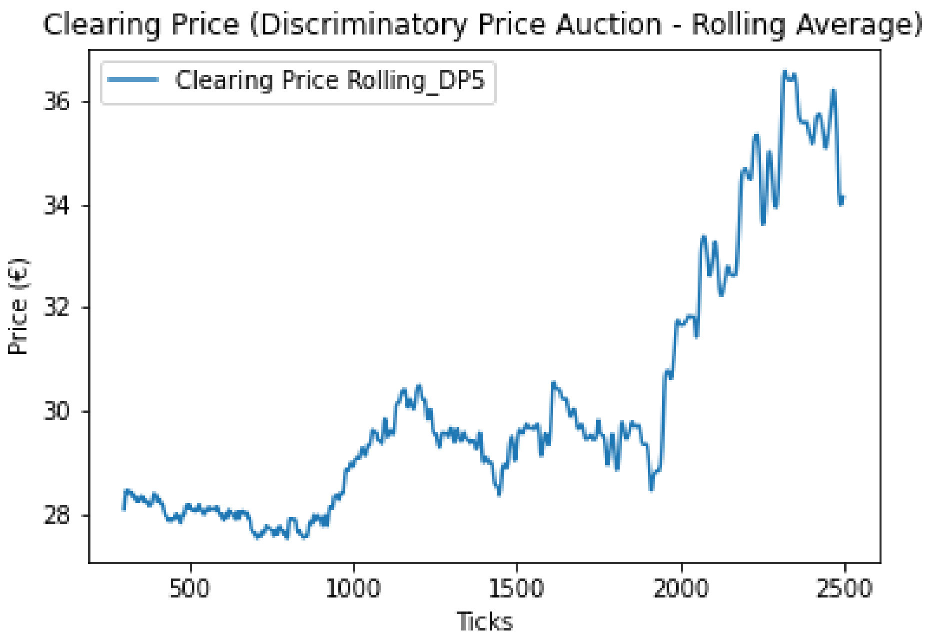

Figure 4.6: Discriminatory-price clearing prices

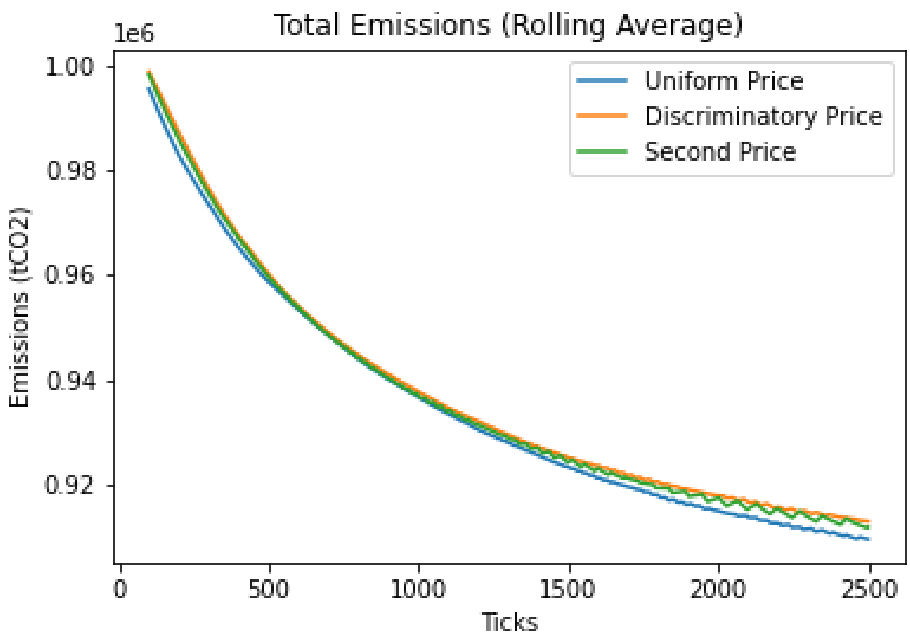

Figure 4.7: Total emissions of all forward auction types

of credits is given by the parameter $\eta = 1.30$, being η the bid volume factor, as explained in the previous chapter. Three mechanisms of double auctions were explored: *average mechanism*, *McAfee's mechanism* and the *Vickrey-Clarke-Groves mechanism*. In figures 4.8, 4.9 and 4.10 we can see the evolution curve of the total production of three previously described agent groups. As we can see, the three mechanisms have very similar curves. However, the variation is much sharper than the one present in the simulations of carbon markets without following double auctions. In figures 4.11, 4.12 and 4.13, we can see the evolution of the clearing prices in the different types of double auctions. The prices vary to a high degree, without a clear tendency. We can see a small general growth in prices, probably accompanying the prices in the forward auction. We can also observe that prices in the double auctions are much higher than in the forward auctions, punishing, even more, the agents that could not acquire credits from their regulators in the first auction. This may explain the sharper variance in production volume numbers as seen is figures 4.8, 4.9 and 4.10.

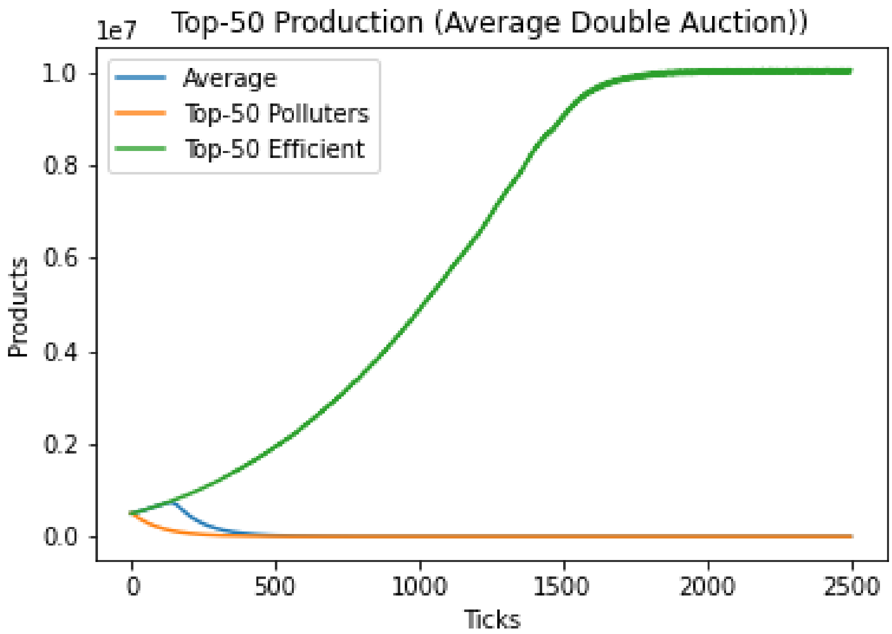

Figure 4.8: Average mechanism emissions per group

4.3 Carbon Tax

Finally, we did some experiences on the efficacy of a particular type of mechanism to regulate carbon emissions - carbon taxes. In these simulations, no carbon market was run. Instead, direct regulation made agents pay a specific value for each unit of emissions resulting from their production processes. As we can see in figure 4.14, the variance in production per group of agents is very different from the one found in simulations that relied on the usage of carbon markets. While with carbon markets, the best of the best corporations in terms of efficiency used to absorb all production, with most companies going bankrupt and stop production as time passes, this is not what

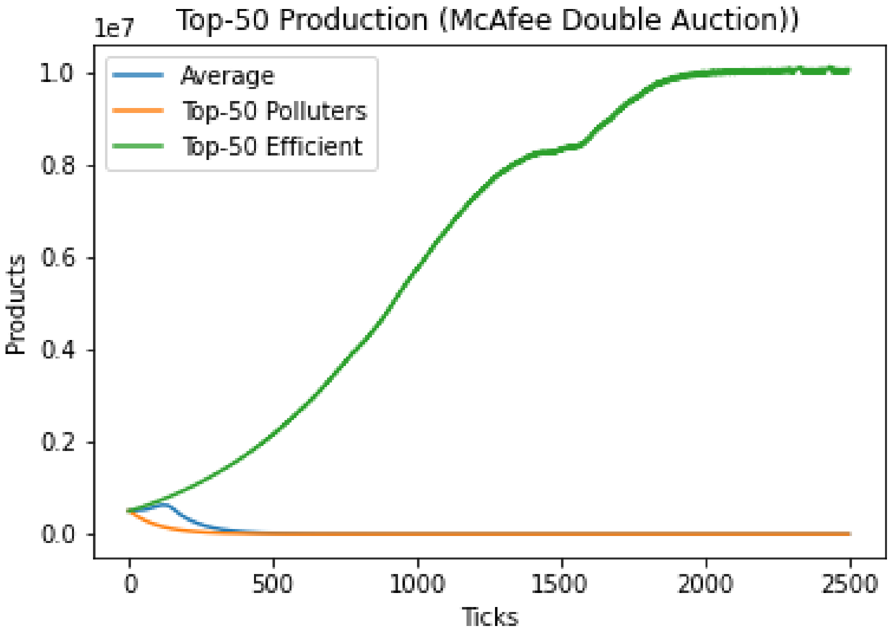

Figure 4.9: McAfee’s mechanism emissions per group

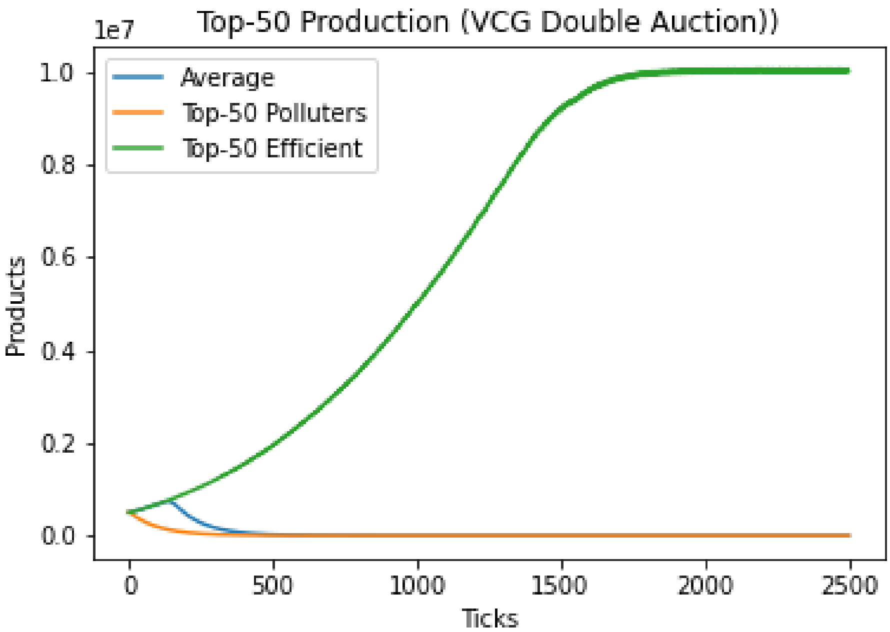

Figure 4.10: Vickrey-Clarke-Groves emissions per group

happens with carbon taxes. What happens is a reduction of production in less efficient corporations and an increase in output in the most efficient ones, but **only** until an equilibrium point, when the production volumes stagnate again. This may indict a desirable outcome for real-life situations

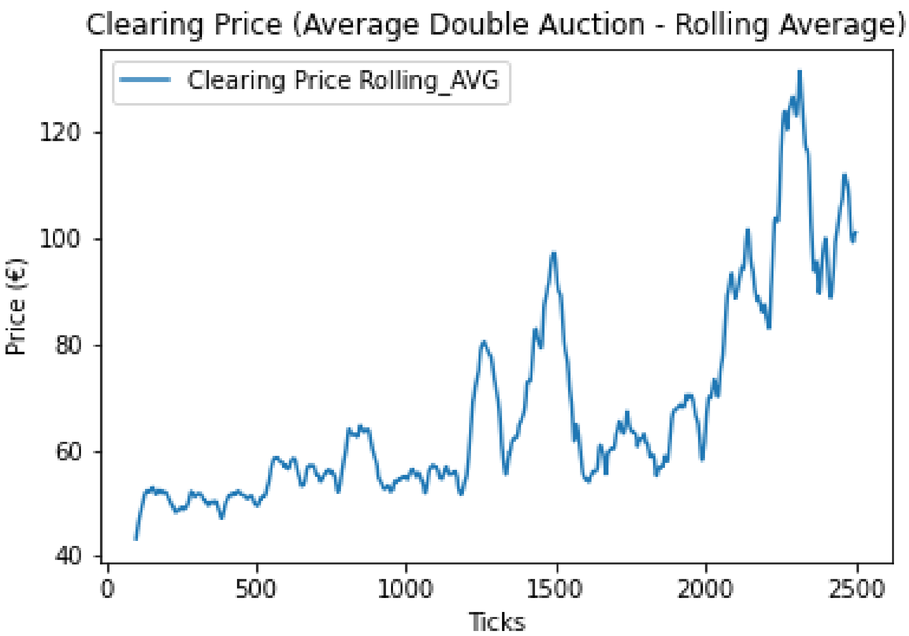

Figure 4.11: Average mechanism clearing prices

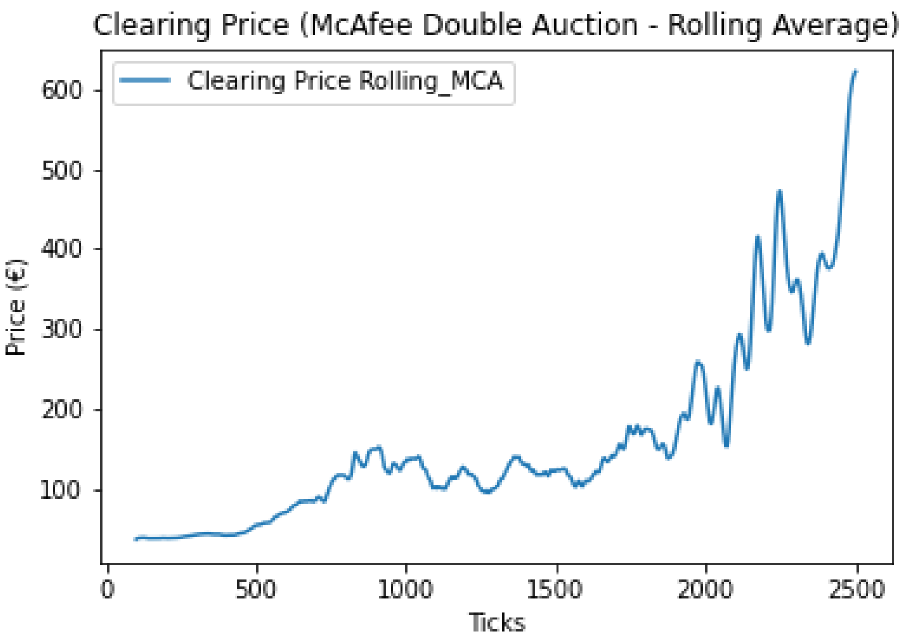

Figure 4.12: McAfee's mechanism clearing prices

where monopolies are intended to be avoided, as well as the minimisation of economic shocks. While there is no cap to determine, a priori and precisely, the intended results of the regulation in terms of target total emissions, it is possible to adjust its impacts by changing the tax value. As

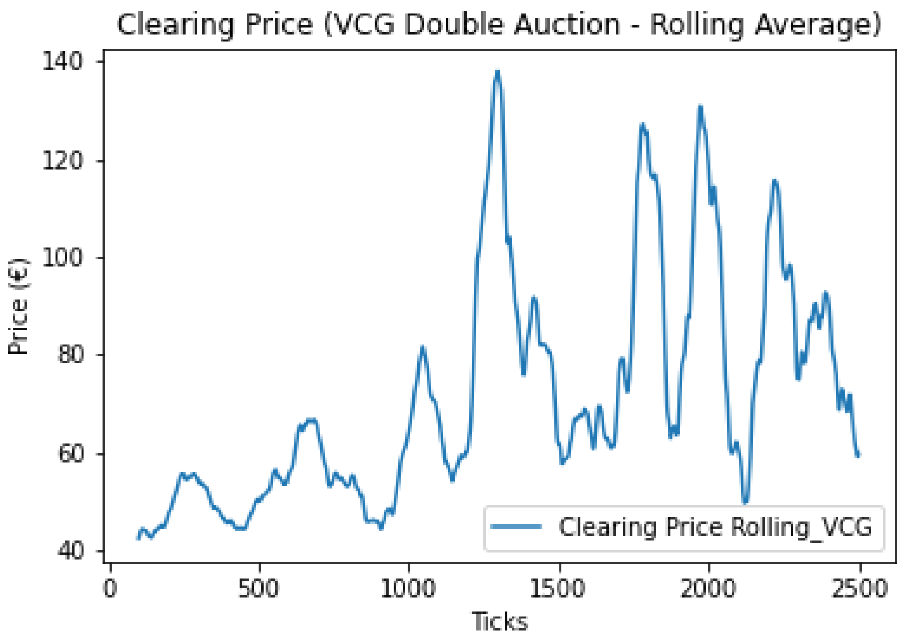

Figure 4.13: Vickrey-Clarke-Groves mechanism clearing prices

seen in figure 4.15, changes in the carbon tax value make the total emissions vary widely. Another interesting feature we can observe is that the bigger the tax is, not only the reduction of emissions is more significant, but its variation happens in a softer, slower way. This "gentleness" in economic variations may be another point favouring the implementation of carbon taxes in the case of the pursuit of bolder goals. Finally, in figure 4.16 we can see a comparison of auction-based mechanisms and carbon taxes in terms of the ultimate metric of this model, the total emissions of its agents. We can see that both types of mechanisms are able to provide the intended results, even though they have different paces to get to those goals.

4.4 Summary

In this section, we provided results for the experimentation of different mechanisms. We compared various carbon credits forward auction and double auction mechanisms, namely the Vickrey-Clarke-Groves mechanism, as well as other regulatory mechanisms, specifically carbon taxes, that do not use auctions or market-based mechanisms. This chapter shows the adaptability and robustness of this framework, as it can handle a wide variety of mechanisms and provide meaningful results.

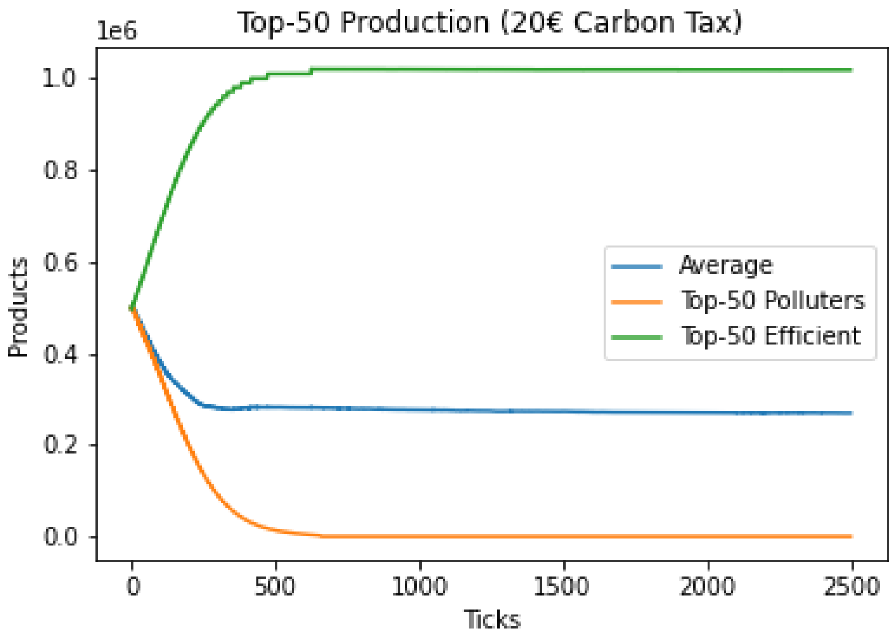

Figure 4.14: Carbon tax emissions per group

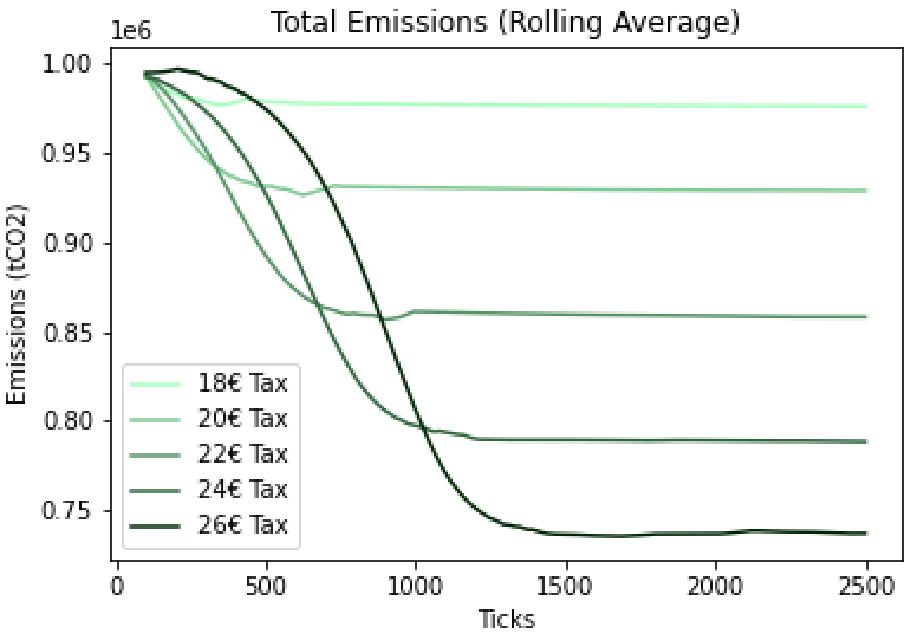

Figure 4.15: Total emissions of all carbon taxes

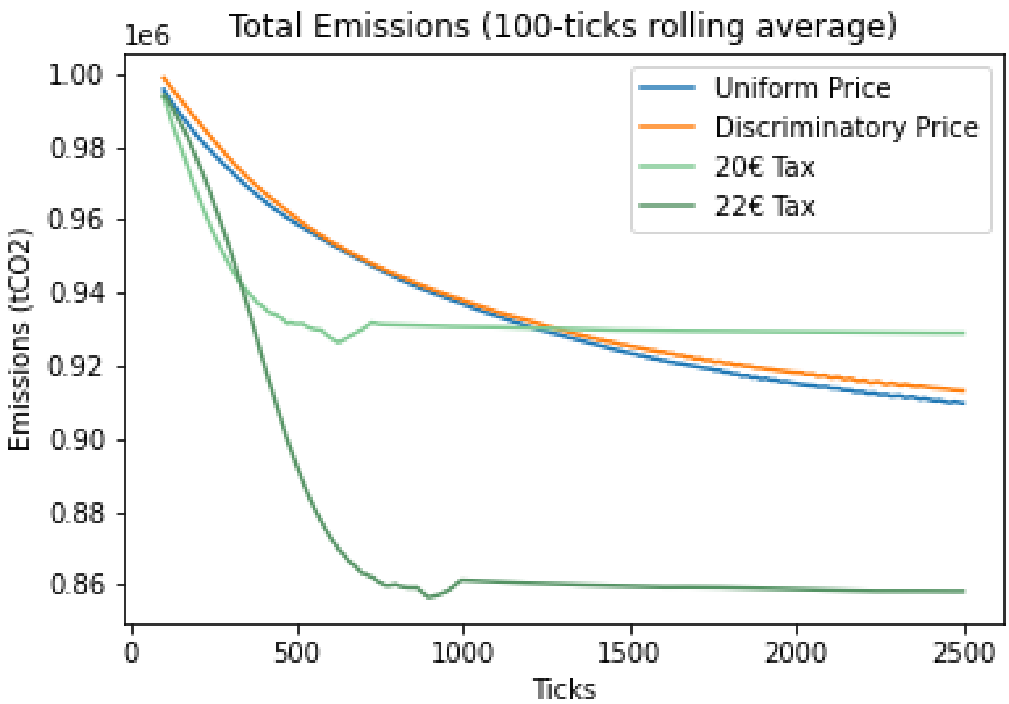

Figure 4.16: Comparison of the total emissions of the different mechanisms

Chapter 5

Conclusions

This section wraps up this dissertation by presenting this work's main contributions and findings and provides a possible perspective for future work.

5.1 General Overview

This dissertation aimed to create an agent-based social simulation metamodel capable of being used as a framework for developing models of socio-technical systems, and carbon markets in particular, capable of extracting insights that may apply and help solve real-world problems. For this, we took several preliminary steps. First of all, it was necessary to investigate scientific concepts and ideas worth mobilizing to make us closer to our goal. Those concepts came mainly from the fields of evolutionary game theory, social simulation and complex systems. Then, it was necessary to develop a study on a specific kind of environmental policy - emission trading schemes - as that is one of the real-life contexts on which the intended model will be applied. That context will also serve as a proof of concept by implementing a carbon emissions regulation model. It was also essential to perform extensive research on existing models for the problems addressed in this project. After those preliminary steps were fulfilled, it became easier to identify this dissertation's challenges, strengths, and weaknesses. The goal of it is to create a reference model that is hierarchical and parametric, thus having the advantage of being applicable to a wide range of real-life problems. These intentions come with a drawback, as it may be harder to develop a more general model and ensure it is relevant to various contexts. Moreover, an essential epistemological question should be addressed regarding the validity of the model's simulation results. The way and degree those results are translated into real insight about mechanism design and agents behaviour is another challenge. One way to address it is to include a wide array of performance metrics that consider as many aspects of the problem being studied as possible. For example, for the study of environmental policies and carbon markets, it is necessary to include metrics on carbon emissions and the economic performance of agents and the system and take into account aspects that are not as obvious. One example of that is inequality. A common disadvantage of market-based emission trading schemes, according to some authors, is that the commodification of emissions act as an incentive for capital accumulation and may penalize disproportionately less wealthy participants. As with any scientific and technological project, with the aggravating factor that this dissertation deals with policies that impact human activity, it is necessary to have a big concern for ethical issues and to understand the discussions around them.

After we took those preliminary steps and a body of knowledge was constructed, the intended metamodel was devised and presented in this document, first at a conceptual and more abstract level and then by explaining the developed Python code. Subsequently, we implemented the model in the context of carbon markets. Possible coordination mechanisms were formalized and implemented, and the model implementation was then documented following the standards of the ODD protocol. Finally, some experimentation with the model was conducted to prove its versatileness and extract some insights from the comparison of different parameterizations and mechanisms.

5.2 Main Contributions

The work conducted in this dissertation aimed to provide scientific, technical and application contributions.

Starting with the scientific ones, we believe this dissertation was able to compile a body of knowledge necessary for the development of valuable and valid models of complex phenomena. It was also able to summarize information and provide a taxonomy of carbon markets - global, local, voluntary or mandatory. Finally, concepts of game theory were mobilized, and different coordination mechanisms were formalized.

In terms of technology, this work provides a metamodel framework, hierarchical, scalable and parameterizable, that can be used to implement a wide range of multi-agent simulation models. The metamodel is well documented, facilitating further usage.

In the applicational domain, the metamodel can be applied to the study of real-world problems, as demonstrated in the chapter on experiments and results. Comparisons of different mechanisms and policies can be made with the goal of extracting insights to help the decision-making processes of a multitude of regulator entities, from small communities to big cities, countries or even worldwide endeavours.

Finally, the work carried out throughout this dissertation also resulted in a scientific paper, which was accepted and will be presented at the 2021 EPIA Conference on AI [18].

5.3 Future Perspectives

There is a significant potential for the future of our metamodel. Even though its simplicity can be an advantage when it comes to using it and does not provide apparent limitations, it is also true that some features could be improved if more time is dedicated to its development in the future. Namely, its scheduling could be more flexible and allow the user to determine what phases to implement instead of providing a rigid execution flow. Its hierarchical nature could also be made more robust, and the integration of agents into groups could be made more obvious with the intention of exploring emergence features of complex systems.

In terms of more general ideas for even further work, mechanisms developed by users of the metamodel could be integrated into it, providing an ever-growing library of different mechanisms. Another crucial future endeavour that this work may contribute to is the study of voluntary and local carbon markets, as this kind of market is quickly gaining traction worldwide, and there is an obvious necessity to undertake further research on the area, namely with the help of multi-agent simulation.

5.4 Final Remarks

The ultimate goal of this dissertation is to provide a small and humble contribution to solving huge societal problems like climate change, and generally speaking, any problem that involves the coordination of people with different interests, goals, plans and ideals. With the development of this metamodel and by enabling the implementation of more advanced valid models that help us maximize global utility on any kind of decision-making process, we believe the objective of this thesis was achieved.

Appendix A

Python Code

The python code of the metamodel framework is available in:

https://github.com/Whiskas123/SociotechnicalMetamodel

The python code of the implemented carbon market model, the .csv data files with the results, and the notebook that generated the graphs are available in:

https://github.com/Whiskas123/CarbonMarketSimulator

Appendix B

Simulation Results

	Emissions	Top-50 Polluters Supply	Avg. Polluters Supply	Top-50 Efficient Supply
0	999963	500000	500000	500000
100	987297	220012	541610	546900
200	978803	85580	585920	592417
300	967804	34374	623167	631786
400	960500	12799	662515	672723
500	954639	5260	700531	711891
600	951939	0	739923	748615
700	946864	0	776115	784714
800	940840	0	812491	818656
900	937989	0	846423	852780
1000	935382	0	881750	886982
1100	930755	0	914106	917407
1200	927997	0	846131	946667
1300	929221	0	655058	975065
1400	926699	0	421900	1001441
1500	920947	0	189592	1024810
1600	921656	0	69853	1052261
1700	920665	0	26501	1076354
1800	915693	0	11218	1097258
1900	917631	0	6351	1122986
2000	915769	0	5324	1142896
2100	910911	0	5225	1156056
2200	911072	0	5185	1175747
2300	911599	0	4832	1195033
2400	909498	0	4707	1207422

Table B.1: Uniform-price auction results

	Emissions	Top-50 Polluters Supply	Avg. Polluters Supply	Top-50 Efficient Supply
0	1001727	500000	500000	500000
100	994266	348802	536162	549421
200	983650	193458	577722	593380
300	971459	95718	617617	635333
400	963054	46190	655537	674258
500	957301	18399	692447	712064
600	951207	5794	721522	750193
700	946766	1871	752616	785565
800	941014	669	776448	817612
900	939975	185	799293	849255
1000	935399	0	813284	876974
1100	933514	0	820635	907125
1200	931118	0	828005	933958
1300	929348	0	796780	960988
1400	924897	0	690005	984177
1500	922487	0	554013	1005493
1600	922019	0	426535	1028207
1700	923127	0	313751	1050023
1800	920076	0	218883	1066793
1900	918428	0	148845	1083964
2000	918131	0	107557	1101485
2100	914117	0	81510	1113656
2200	915502	0	36855	1133847
2300	913453	0	18974	1147210
2400	912262	0	12019	1159500

Table B.2: Discriminatory-price auction results

	Emissions	Top-50 Polluters Supply	Avg. Polluters Supply	Top-50 Efficient Supply
0	1000648	500000	500000	500000
100	993693	308363	543330	551594
200	981038	155901	584873	597290
300	969668	68351	621246	640387
400	967017	31985	661454	686581
500	953350	11780	688857	721589
600	954349	3410	724904	765937
700	942858	1111	747893	797001
800	944588	270	778452	837653
900	941274	142	799864	871662
1000	932555	0	812660	898081
1100	935642	0	824153	934538
1200	932660	0	811257	962853
1300	931684	0	766080	992067
1400	923871	0	661986	1012043
1500	927823	0	538105	1042757
1600	923758	0	413172	1063733
1700	921931	0	298643	1085109
1800	921691	0	204110	1106662
1900	913710	0	135621	1117521
2000	915766	0	93545	1139977
2100	919533	0	74352	1162886
2200	915243	0	52857	1174517
2300	911846	0	27406	1186244
2400	909363	0	16821	1198120

Table B.3: Second-price auction results

	Emissions	Top-50 Polluters Supply	Avg. Polluters Supply	Top-50 Efficient Supply
0	999963	500000	500000	500000
100	987297	220012	541610	546900
200	978803	85580	585920	592417
300	967804	34374	623167	631786
400	960500	12799	662515	672723
500	954639	5260	700531	711891
600	951939	0	739923	748615
700	946864	0	776115	784714
800	940840	0	812491	818656
900	937989	0	846423	852780
1000	935382	0	881750	886982
1100	930755	0	914106	917407
1200	927997	0	846131	946667
1300	929221	0	655058	975065
1400	926699	0	421900	1001441
1500	920947	0	189592	1024810
1600	921656	0	69853	1052261
1700	920665	0	26501	1076354
1800	915693	0	11218	1097258
1900	917631	0	6351	1122986
2000	915769	0	5324	1142896
2100	910911	0	5225	1156056
2200	911072	0	5185	1175747
2300	911599	0	4832	1195033
2400	909498	0	4707	1207422

Table B.4: Uniform-price auction results

	Emissions	Top-50 Polluters Supply	Avg. Polluters Supply	Top-50 Efficient Supply
0	1002944	500000	500000	500000
100	968913	188385	683185	687056
200	941219	69002	454807	918842
300	917116	25315	166440	1199057
400	899516	9386	60947	1544804
500	884095	3393	22337	1935492
600	871988	0	8272	2388589
700	858997	0	1840	2891343
800	847480	0	0	3464641
900	838557	0	0	4126521
1000	829373	0	0	4861508
1100	828416	0	0	5709246
1200	819869	0	0	6482019
1300	809674	0	0	7385336
1400	803702	0	0	8304477
1500	802792	0	0	9060182
1600	800033	0	0	9650932
1700	795542	0	0	9865120
1800	789208	0	0	9949428
1900	785524	0	0	9996353
2000	786057	0	0	10055595
2100	777481	0	0	9985082
2200	776943	0	0	10018935
2300	778932	0	0	10063173
2400	774967	0	0	10048209

Table B.5: Average mechanism double auction results

	Emissions	Top-50 Polluters Supply	Avg. Polluters Supply	Top-50 Efficient Supply
0	1005917	500000	500000	500000
100	967202	187890	607479	708619
200	936320	68810	338960	974388
300	913102	25241	124060	1300366
400	891179	9358	45446	1683776
500	879396	3379	16699	2160092
600	864049	0	6057	2713619
700	853919	0	889	3360657
800	844030	0	0	4056143
900	835529	0	0	4826113
1000	827667	0	0	5722443
1100	825188	0	0	6583613
1200	815346	0	0	7280178
1300	814827	0	0	7879550
1400	809104	0	0	8192903
1500	804162	0	0	8289815
1600	807410	0	0	8597184
1700	799698	0	0	9140203
1800	798088	0	0	9632195
1900	790120	0	0	9872496
2000	784248	0	0	9982706
2100	783076	0	0	10037454
2200	775971	0	0	9998301
2300	778104	0	0	10066773
2400	773409	0	0	10043115

Table B.6: McAfee's mechanism double auction results

	Emissions	Top-50 Polluters Supply	Avg. Polluters Supply	Top-50 Efficient Supply
0	999772	500000	500000	500000
100	965284	188125	680183	686356
200	936853	68904	454965	923683
300	912582	25280	166500	1203314
400	894383	9372	60965	1539404
500	885111	3386	22351	1951489
600	872259	0	8267	2430110
700	857440	0	1820	2943128
800	851364	0	0	3546903
900	845057	0	0	4259088
1000	831931	0	0	4991650
1100	827307	0	0	5823740
1200	822044	0	0	6711368
1300	812280	0	0	7593471
1400	808944	0	0	8538905
1500	806792	0	0	9228925
1600	798489	0	0	9589522
1700	797796	0	0	9879285
1800	795474	0	0	10001188
1900	787819	0	0	9978457
2000	788242	0	0	10031541
2100	785606	0	0	10033589
2200	786352	0	0	10064911
2300	784323	0	0	10065972
2400	780497	0	0	10008080

Table B.7: Vickrey-Clarke-Groves mechanism double auction results

	Emissions	Top-50 Polluters Supply	Avg. Polluters Supply	Top-50 Efficient Supply
0	995724	500000	500000	500000
100	990912	221796	546517	546850
200	979983	84248	563141	563255
300	975052	31224	568763	568876
400	979804	11628	574537	574538
500	978399	4514	574378	574506
600	977740	1031	574450	574241
700	977605	655	574191	574330
800	977381	468	574387	574177
900	977328	244	574362	574152
1000	977176	185	574331	574011
1100	977087	130	574295	573986
1200	976973	130	574152	574187
1300	976852	130	574129	574036
1400	976768	130	574105	574004
1500	976616	130	574185	573978
1600	976578	130	574150	574062
1700	976484	130	574126	573915
1800	976453	120	573978	573770
1900	976358	120	574066	573964
2000	976387	112	573930	573828
2100	976327	112	574014	574031
2200	976244	112	573871	574009
2300	976218	112	573734	573979
2400	976237	112	573804	573961

Table B.8: 18€ carbon tax results

	Emissions	Top-50 Polluters Supply	Avg. Polluters Supply	Top-50 Efficient Supply
0	1004231	500000	500000	500000
100	985919	354050	381734	686240
200	955180	197118	307509	844931
300	936967	89247	280923	942229
400	931869	35441	280556	990293
500	931494	13334	282140	1009962
600	925089	5234	281300	1009920
700	931213	0	280458	1019560
800	930970	0	279262	1019903
900	930703	0	277749	1019835
1000	930607	0	276537	1019540
1100	930344	0	275490	1019458
1200	930197	0	274797	1019399
1300	929975	0	273481	1019117
1400	929727	0	273906	1018846
1500	929656	0	273216	1018549
1600	929472	0	271860	1018894
1700	929365	0	271182	1018847
1800	929318	0	271283	1018794
1900	929185	0	270661	1018728
2000	929172	0	270591	1018481
2100	929098	0	269733	1018624
2200	929049	0	269641	1018378
2300	929012	0	269816	1018324
2400	928930	0	269476	1018460

Table B.9: 20€ carbon tax results

	Emissions	Top-50 Polluters Supply	Avg. Polluters Supply	Top-50 Efficient Supply
0	1000325	500000	500000	500000
100	990670	459286	458012	789046
200	970856	389514	382963	1195676
300	938177	292986	280440	1707648
400	908988	187782	165237	2252715
500	881630	96147	79063	2665091
600	864752	40223	32206	2881679
700	863909	15629	12183	2995448
800	859902	6009	4778	3024542
900	861395	0	0	3055746
1000	861011	0	0	3054749
1100	860585	0	0	3053159
1200	860339	0	0	3052804
1300	859949	0	0	3052975
1400	859721	0	0	3052595
1500	859465	0	0	3052282
1600	859387	0	0	3051942
1700	859291	0	0	3052158
1800	859148	0	0	3051796
1900	858856	0	0	3052064
2000	858620	0	0	3051763
2100	858352	0	0	3051460
2200	858194	0	0	3050605
2300	858294	0	0	3051515
2400	858217	0	0	3051211

Table B.10: 22€ carbon tax results

	Emissions	Top-50 Polluters Supply	Avg. Polluters Supply	Top-50 Efficient Supply
0	996081	500000	500000	500000
100	991917	487600	487600	801044
200	988852	467450	467627	1299323
300	970831	429151	429320	2047018
400	942846	371250	371394	3138212
500	911482	296449	296680	4607469
600	870984	205981	205496	6313337
700	833156	119542	113405	7903323
800	816418	56880	51662	9074397
900	803822	23193	20548	9621094
1000	795638	8671	7501	9813060
1100	792610	3053	646	9908762
1200	789401	0	0	9905474
1300	789187	0	0	9903699
1400	789345	0	0	9906394
1500	789327	0	0	9906839
1600	789335	0	0	9907230
1700	788852	0	0	9901485
1800	789204	0	0	9906194
1900	789039	0	0	9904375
2000	788888	0	0	9902537
2100	788674	0	0	9900179
2200	788803	0	0	9901554
2300	788798	0	0	9901787
2400	788349	0	0	9895958

Table B.11: 24€ carbon tax results

	Emissions	Top-50 Polluters Supply	Avg. Polluters Supply	Top-50 Efficient Supply
0	1000440	500000	500000	500000
100	1000167	497302	497302	564243
200	1004290	494800	494800	688038
300	994937	482546	482546	884270
400	979080	462702	462864	1193180
500	959700	433758	434083	1694921
600	949214	398465	398949	2489816
700	913553	337806	338215	3603471
800	867754	259142	259556	5065667
900	831384	176634	176776	6776302
1000	789429	98250	96610	8290848
1100	759597	45300	42816	9263194
1200	743964	17833	16611	9725968
1300	742430	6777	6384	9970504
1400	736441	0	0	10054977
1500	736013	0	0	10050239
1600	735122	0	0	10039149
1700	736505	0	0	10058695
1800	736118	0	0	10054129
1900	737074	0	0	10067192
2000	737021	0	0	10066478
2100	738226	0	0	10082786
2200	737203	0	0	10069153
2300	737466	0	0	10072662
2400	736999	0	0	10066532

Table B.12: 26€ carbon tax results

References

[1] Scott T. Allison, James K. Beggan, and Elizabeth H. Midgley. The quest for "similar instances" and "simultaneous possibilities": Metaphors in social dilemma research. *Journal of Personality and Social Psychology*, 71(3):479–497, 1996.

[2] Kenneth J. Arrow. *Social Choice and Individual Values*. Yale University Press, 2012.

[3] International Air Transport Association. What you need to know about emissions trading?, 2007.

[4] Reuven Avi-Yonah and David Uhlmann. Combating global climate change: Why a carbon tax is a better response to global warming than cap and trade. *Stanford Environmental Law Journal*, 28, 2008.

[5] Robert Axelroad. Advancing the art of simulation in the social sciences. In Rosaria Conte, Rainer Hegselmann, and Pietro Terna, editors, *Simulating Social Phenomena*, pages 21–40, Berlin, Heidelberg, 1997. Springer Berlin Heidelberg.

[6] Robert M. Axelrod. *The evolution of cooperation*. Basic Books, New York, rev. ed edition, 2006.

[7] Huimin Bi, Hao Xiao, and Kejuan Sun. The impact of carbon market and carbon tax on green growth pathway in china: A dynamic CGE model approach. *Emerging Markets Finance and Trade*, 55(6):1312–1325, 2018.

[8] Devi K. Brands, Erik T. Verhoef, Jasper Knockaert, and Paul R. Koster. Tradable permits to manage urban mobility: Market design and experimental implementation. *Transportation Research Part A: Policy and Practice*, 137:34–46, 2020.

[9] CEIIA. Ayr. Available at https://www.ceiia.com/ayr.

[10] Maxime C. Cohen, Ruben Lobel, and Georgia Perakis. The impact of demand uncertainty on consumer subsidies for green technology adoption. *SSRN Electronic Journal*, 2014.

[11] European Comission. EU ETS handbook. Available at https://ec.europa.eu/clima/sites/clima/files/docs/ets_handbook_en.pdf, 2015.

[12] European Comission. EU ETS website. Available at https://ec.europa.eu/clima/policies/ets_en, 2021.

[13] Rong-Gang Cong. Auction design for the allocation of carbon emission allowances: Uniform or discriminatory price? *International Journal of Energy and Environment*, 1, 2010.

[14] Klaus Conrad. Price competition and product differentiation when consumers care for the environment. *Environmental & Resource Economics*, 31(1):1–19, 2005.

[15] Peter A. Corning. The re-emergence of ?emergence?: A venerable concept in search of a theory. *Complexity*, 7(6):18–30, 2002.

[16] Maria Eduarda Santos Cunha, Rosaldo J. F. Rossetti, and Pedro Campos. Modelling smart cities through socio-technical systems. In *2020 IEEE International Smart Cities Conference (ISC2)*, pages 1–8, 2020.

[17] André Czauderna. Tinkering with political utopias and dystopias in Democracy 3. an educational perspective. In *Playing Utopia*, pages 69–98. transcript Verlag, December 2019.

[18] João Bernardo Narciso de Sousa, Zafeiris Kokkinogenis, and Rosaldo J. F. Rossetti. Carbon market multi-agent simulation model. In *EPIA Conference on Artificial Intelligence*. Springer, 2021.

[19] Kevin J. Dooley. A complex adaptive systems model of organization change. *Nonlinear Dynamics, Psychology, and Life Sciences*, 1(1):69–97, 1997.

[20] Johannes Eckert, David López, Carlos Lima Azevedo, and Bilal Farooq. A blockchain-based user-centric emission monitoring and trading system for multi-modal mobility. In *2020 Forum on Integrated and Sustainable Transportation Systems (FISTS)*, pages 328–334. IEEE, 2020.

[21] T.Huw Edwards and John P Hutton. Allocation of carbon permits within a country: a general equilibrium analysis of the united kingdom. *Energy Economics*, 23(4):371–386, 2001.

[22] Norfolk Island Carbon / Health Evaluation. Norfolk island carbon/health evaluation study. Available at https://web.archive.org/web/20121228190331/http://www.norfolkislandcarbonhealthevaluation.com/. Accessed: 2021-01-05.

[23] Tina Fawcett and Yael Parag. An introduction to personal carbon trading. *Climate Policy*, 10:329–338, 2010.

[24] Stephanie Forrest. Emergent computation: Self-organizing, collective, and cooperative phenomena in natural and artificial computing networks. *Physica D: Nonlinear Phenomena*, 42(1-3):1–11, 1990.

[25] Anthony Giddens. Structuralism and the theory of the subject. In *Central Problems in Social Theory*, pages 9–48. Macmillan Education UK, 1979.

[26] N. Gilbert. Emergence in social simulation in: Artificial societies: the computer simulation of social life. *UCL Press, London, pp*, pages 144–156, 1995.

[27] Herbert Gintis. *Game Theory Evolving*. Princeton University Press, 2009.

[28] Renato Gomes and Kane Sweeney. Bayes–nash equilibria of the generalized second-price auction. *Games and Economic Behavior*, 86:421–437, 2014.

[29] Volker Grimm, Uta Berger, Donald L. DeAngelis, J. Gary Polhill, Jarl Giske, and Steven F. Railsback. The ODD protocol: A review and first update. *Ecological Modelling*, 221(23):2760–2768, 2010.

[30] Bernard Grofman and Scott L. Feld. If you like the alternative vote (a.k.a. the instant runoff), then you ought to know about the coombs rule. *Electoral Studies*, 23(4):641–659, 2004.

[31] Garrett Hardin. The tragedy of the commons. *Science*, 162(3859):1243–1248, 1968.

[32] John H. Holland. Studying complex adaptive systems. *Journal of Systems Science and Complexity*, 19(1):1–8, 2006.

[33] Mark Jacobsen. Environmental Economics Lecture 6–7, UCSD Econ 131, 2016.

[34] Diego Kiedanski, Daniel Kofman, and José Horta. Pymarket-a simple library for simulating markets in python. *Journal of Open Source Software*, 5(46):1591, 2020.

[35] Gary Koop and Lise Tole. Forecasting the european carbon market. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 176(3):723–741, 2012.

[36] Brendan Lucier, Renato Paes Leme, and Eva Tardos. On revenue in the generalized second price auction. In *Proceedings of the 21st international conference on World Wide Web - WWW '12*. ACM Press, 2012.

[37] David Masad and Jacqueline Kazil. Mesa: An agent-based modeling framework, 2015.

[38] Humberto R. Maturana and Francisco J. Varela. *Autopoiesis and Cognition*. Springer Netherlands, 1980.

[39] M. Milinski, R. D. Sommerfeld, H.-J. Krambeck, F. A. Reed, and J. Marotzke. The collective-risk social dilemma and the prevention of simulated dangerous climate change. *Proceedings of the National Academy of Sciences*, 105(7):2291–2294, 2008.

[40] Hideyuki Mizuta, Sei Kato, and Hideki Tai. Agent-based simulation of CO2 emissions trading and large-scale traffic flow. In *2008 SICE Annual Conference*. IEEE, 2008.

[41] Roger B. Myerson. *Game Theory*. Harvard University Press, 2013.

[42] Y Narahari. *Game Theory and Mechanism Design*. World Scientific / Indian Institute Of Science, Inda, 2014.

[43] Easwaran Narassimhan, Kelly S. Gallagher, Stefan Koester, and Julio Rivera Alejo. Carbon pricing in practice: a review of existing emissions trading systems. *Climate Policy*, 18(8):967–991, 2018.

[44] Jonathan Newton. Evolutionary game theory: A renaissance. *Games*, 9(2):31, 2018.

[45] Noam Nisan and Amir Ronen. Algorithmic mechanism design. *Games and Economic Behavior*, 35(1-2):166–196, 2001.

[46] Michael J North, Nicholson T Collier, Jonathan Ozik, Eric R Tatara, Charles M Macal, Mark Bragen, and Pam Sydelko. Complex adaptive systems modeling with repast simphony. *Complex Adaptive Systems Modeling*, 1(1), 2013.

[47] Elinor Ostrom. Beyond markets and states: Polycentric governance of complex economic systems. *Transnational Corporations Review*, 2(2):1–12, 2010.

[48] Elinor Ostrom. *Governing the Commons*. Cambridge University Press, 2015.

[49] International Carbon Action Partnership. Korea emissions trading scheme, 2021.

[50] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[51] Istituto Superiore per la Protezione e la Ricerca Ambientale. Bologna carbon market. Available at http://www.sinanet.isprambiente.it/gelso/banca-dati/comune/comune-di-bologna/bologna-carbon-market, 2020.

[52] Mohammadhussein Rafieisakhaei, Babak Barazandeh, Amirbahador Moosavi, Masoud Fekri, and Kaveh Bastani. Modeling dynamics of the carbon market: A system dynamics approach on the co2 emissions and its connections to the oil market, 2016.

[53] Roberto Rodríguez-Ibeas. Environmental product differentiation and environmental awareness. *Environmental and Resource Economics*, 36(2):237–254, 2006.

[54] Thiago RPM Rúbio, Zafeiris Kokkinogenis, Henrique Lopes Cardoso, Eugénio Oliveira, and Rosaldo JF Rossetti. Resmas-a conceptual mas model for resource-based integrated markets. In *International Conference on Practical Applications of Agents and Multi-Agent Systems*, pages 117–129. Springer, 2017.

[55] Thiago RPM Rúbio, Zafeiris Kokkinogenis, Henrique Lopes Cardoso, Rosaldo JF Rossetti, and Eugénio Oliveira. Regulating blockchain smart contracts with agent-based markets. In *EPIA Conference on Artificial Intelligence*, pages 399–411. Springer, 2019.

[56] Ciro Russo, Tobias Grossauer, Emanuele Nardone, Zafeiris Kokkinogenis, and Rosaldo JF Rossetti. How smart and green? a simulation model of demand cost perception in the electricity market. In *2020 IEEE International Smart Cities Conference (ISC2)*, pages 1–8. IEEE, 2020.

[57] David Seidl. Luhmann's theory of autopoietic social systems. *Munich Business Research*, 2:1–28, 2004.

[58] Amartya Sen. *Collective choice and social welfare*. Harvard University Press, Cambridge, Mass., 2019. OCLC: 1125316580.

[59] Yoav Shoham and Kevin Leyton-Brown. *Multiagent systems: Algorithmic, game-theoretic, and logical foundations*. Cambridge University Press, 2008.

[60] J. C. Sousa, Z. Kokkinogenis, R. J. F. Rossetti, and J. T. Saraiva. Electricity market and renewable energy integration: An agent-based conceptual model. In *1st International Workshop on Simulation for Energy, Sustainable Development and Environment, SESDE 2013, Held at the International Multidisciplinary Modeling and Simulation Multiconference, I3M 2013*, pages 101–108, 2013. Cited By :6.

[61] György Szabó and Gábor Fáth. Evolutionary games on graphs. *Physics Reports*, 446(4-6):97–216, 2007.

[62] Ling Tang, Jiarui Shi, and Qin Bao. Designing an emissions trading scheme for china with a dynamic computable general equilibrium model. *Energy Policy*, 97:507–520, 2016.

[63] Ling Tang, Jiaqian Wu, Lean Yu, and Qin Bao. Carbon allowance auction design of china's emissions trading scheme: A multi-agent-based approach. *Energy Policy*, 102:30–40, 2017.

[64] Precha Thavikulwat. Modeling market demand in a demand-independent business simulation. *Simulation & Games*, 20(4):439–458, December 1989.

[65] UNFCC. The Paris Agreement, 2015.

[66] United Nations. Climate Change. Available at https://www.un.org/en/sections/issues-depth/climate-change/. Accessed: 2020-01-11.

[67] United Nations. Issues in Depth. Available at https://www.un.org/en/sections/issues-depth/. Accessed: 2020-01-10.

[68] United Nations. Sustainable Development Goals. Available at https://sdgs.un.org/goals, 2015. Accessed: 2021-01-10.

[69] David Leo Weimer and Aidan R. Vining. *Policy analysis: concepts and practice*. Routledge, Taylor & Francis Group, New York, sixth edition edition, 2017.

[70] U. Wilensky. Netlogo 3.1.3, 2006.

[71] M. Zhang, Y. Liu, and Yunpeng Su. Comparison of carbon emission trading schemes in the european union and china. *Climate*, 5:70, 2017.

[72] Rui Zhao, Xiao Zhou, Jiaojie Han, and Chengliang Liu. For the sustainable performance of the carbon reduction labeling policies under an evolutionary game simulation. *Technological Forecasting and Social Change*, 112:262–274, 2016.

[73] Meirong Zhou, Ming Zhou, Yanchun Pan, Zhimin Chen, and Jun Zeng. Multi-agent-based simulation for policy evaluation of carbon emissions. In *Theory, Methodology, Tools and Applications for Modeling and Simulation of Complex Systems*, pages 265–272. Springer Singapore, 2016.