D4.4 - New actor types in electricity market simulation models

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Executive Summary

The modelling of agents in the simulation models and tools is of primary importance if the quality and the validity of the simulation outcomes are at stake. This is the first version of the report that deals with the representation of electricity market actors' in the agent-based models (ABMs) used in TradeRES project. With the AMIRIS, the EMLab-Generation (EMLab), the MASCEM and the RESTrade models being in the centre of the analysis, the subject matter of this report has been the identification of the actors' characteristics that are already covered by the initial (with respect to the project) version of the models and the presentation of the foreseen modelling enhancements.

For serving these goals, agent attributes and representation methods, as found in the literature of agent-driven models, are considered initially. The detailed review of such aspects offers the necessary background and supports the formation of a context that facilitates the mapping of actors' characteristics to agent modelling approaches. Emphasis is given in several approaches and technics found in the literature for the development of a broader environment, on which part of the later analysis is deployed. Although the ABMs that are used in the project constitute an important part of the literature, they have not been included in the review since they are the subject of another section.

The identification of modelling needs follows the operational and behavioural characterization of actors that has already concluded with the release of the first version of D3.2. The operational attributes and the behaviour aspects that have been assigned to actor classes are used as a reference for the review of the four ABMs used in the project. The initial versions of the models have been reviewed against those relations, revealing the not covered relations, which are considered as potential modelling enhancing activities. Such modelling enhancing directions are identified and allocated to models, with the outcome of this process being reported through an extra layer of information that is positioned on top of the relational tables that have been previously deployed, in the context of D3.2.

A more detailed consideration of the ABMs follows next, which includes a model-by-model analysis of the agent instances of the initial versions and a description of the scheduled improvements. As the agent modelling enhancement is a part of the broader process of ABMs evolution and coupling for enabling them to assess the market design propositions of D3.5, this work is closely related to other WP4 deliverables. With some being developed concurrently with this report and others being forthcoming there are several points where links are made to the deliverables related to flexibility options modelling (D4.1-D4.3) and the market design modelling requirements (D4.5).

Finally, the next version that is foreseen at the end of the modelling enhancing activities, would include further details on agent functioning implementations as the modelling will be at a more mature stage and other related tasks will have been completed.

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List of Abbreviations

Term	Description
ABM	Agent-Based Model
aFRR	Automatic Frequency Restoration Reserve
BM	Balancing Market
CEC	Citizen Energy Community
CES	Community Energy Storage
CfD	Contract for Difference
CM	Capacity Market
DDPG	Deep Deterministic Policy Gradient
DER	Distributed Energy Resources
DG	Distributed Generation
DNN	Deep Neural Network
DQN	Deep Q-Network
DR	Demand Response
DRL	Deep Reinforcement Learning
DSM	Demand Side Management
DSO	Distribution System Operator
DyLR	Dynamic Line Rating
ESCo	Energy Service Company
ESS	Energy Storage System
EV	Electric Vehicle
GA	Genetic Algorithm
GTM	Game Theoretic Modelling
H&C	Heating and Cooling
HyPP	Hybrid Renewable Power Plant
KKT	Karush-Kuhn-Tucker
MADDPG	Multi-agent Deep Deterministic Policy Gradient
MDP	Markov Decision Process
mFRR	Manual Frequency Restoration Reserve
MPEC	Mathematical Programs with Equilibrium Constraints
NPV	Net Present Value
P2P	Peer-to-Peer
PFS	Power Flow Service
PV	Photovoltaic
PX	Power Exchange
RBC	Rule-Based Control
RES	Renewable Energy Sources
RL	Reinforcement Learning
SARL	Single-Agent Reinforcement Learning
SLR	Seasonal Line Rating
ToU	Time-of-Use
TSO	Transmission System Operator
VPP	Virtual Power Plant
vRES	Variable Renewable Energy Sources

1. Introduction

Market simulation models and tools have been for several years widely used in supporting decision making and assisting in the formation of evidence-based policy recommendations. Their evolvement has been remarkable, following the digital revolution progress, with the more recent versions incorporating state-of-the-art approaches that follow contemporary trends in areas related to artificial intelligence, big data and cloud computing.

Major advancements have been made in simulating systems of multiple agents that are characterised by complex dynamics due to multidirectional interactions, with the more notable case being that of electricity markets simulation tools. The agent-based modelling approaches present several advantages in that context, while they face certain challenges. The easier and more flexible representation of market structures through the adopted interaction framework, along with the modularity of the implementations, are among the advantages compared to other modelling approaches that aim to be solved analytically. Issues related to scalability combined with limitations inherited from learning and adaptation processes are some indicative drawbacks.

Important part of the modelling implementation is the representation of agents inside the models, with the incorporation of behavioural and operational aspects being directly connected to the realism level of the simulation framework. The agents are at least described by attributes that assign characteristics and methods that provide the required functionality properties imposed by the operations. The identification of actors' behavioural and operational characteristics that enhance the realism and support the validity of models is a challenge that modellers usually face, while they try to maintain a balance between the model complexity, the quality of results, the value of the extracted conclusions and the traceability of causality relationships.

1.1 Scope of the deliverable

This deliverable focuses on the representation of electricity markets' actors in the market simulation models and tools used in TradeRES projects, while aims to identify modelling priorities, sketch directions of enhancements and pave the ground towards agent-related developments. The four agent-based models (ABMs) that are to be linked within the model linkage toolbox developed in WP4 are namely the AMIRIS, the EMLab-Generation, the MASCEM and the RESTrade, which have been presented in D4.6. With these models putting their focus on either the investment recovery or the operational dispatch problem, while the combinations emerging from their potential coupling cover both, the incorporation of actors' characteristics can support the impact assessment of market designs. This work has been conducted in the context of T4.2 that aims to tackle the representation of actors, markets and policies into the models. The incorporation of elements resulted from the characterization of market players, especially in the case of new flexible players, that took place in WP3 and provided the qualitative context for the further analysis is expected to empower the models to assess the performance of players and evaluate the proposed market designs. Finally, it should be mentioned that an update of this first version of the "New actor types in electricity market simulation tools" report with more details and further implementation concerns is about to follow on M29.

1.2 Structure of the deliverable

The deliverable initially provides an overview of the agents in market simulation tools and agent-based models. Section 2 considers modelling approaches at a high-level with the literature review providing the ground for the further, more project specific, technical elaboration, that follows at later parts of this report. Moreover, the consideration of different modelling approaches when certain market components and involved actors are at stake, provides some state-of-the-art indications about modelling improvements. Some methods of agent functioning are also covered, with emphasis on learning approaches since other aspects are covered afterwards.

The conceptualization framework of actors in electricity markets that have been reported in D3.2 is taken into consideration in Section 3 and direct linkage is employed, following the survey activity that took place under the umbrella of the T3.2 and T4.2.1. An extra layer of information has been added on top of the relational tables deployed in D3.2, which provided a mapping of relations between actor classes and technologies, operational and behavioural characteristics. The extra layer of information describes the coverage by the initial versions[1] of the ABMs, while at the same time points out the directions of modelling enhancements that have been identified.

Section 4 elaborates further and extends the initial version description highlighting the enhancement direction on a per model basis. The analysis starts with a description of agent representation principles and agent-related modelling concepts that have been adopted in the initial version of each of the ABMs. In the second subsection new agents plans and other model enhancing directions are presented, giving extensive overview of the undergoing interventions for incorporating additional characteristics, improving the agent representation and supporting superiority of model outcomes.

Finally, this report concludes in Section 5 with a summary of the approaches and technics adopted for the translation of actors' types to agents by the initial versions of the simulation models used in TradeRES project and an encapsulation of the foreseen directions and prospects of model enhancements.

1.3 Relationship with other deliverables and tasks

This deliverable builds upon concepts initially tackled in WP3 and extends the work conducted in T3.2 around the characterization of electricity market actors in both the behavioural and operational dimension. Therefore, the inputs received from D3.2 have been several, with the key actor categories, the relational tables and the Actor-ID cards being among

[1] Initial are considered the versions with respect to the project. These are the most recent versions of the models that have been developed outside of TradeRES project and are used as the basis for modelling enhancements. Each model follows its own versioning system.

the most notable ones. Following the progress made in T4.2 and more specifically the identified modelling priorities and the implementable technics some feedback is expected to be provided back to the actor characterization framework considered in WP3, in the context of the final reporting of T3.2 developments.

There is a strong connection with other WP4 deliverables and tasks as well. More precisely, this report considers the agent implementations of various actor classes such as producers, suppliers, aggregators and prosumers, which are directly related to flexibility aspects, namely the temporal, the sectoral and the spatial one. Several agents inherit characteristics and incorporate aspects originating from distributed generation (DG), demand side response (DR), energy storage systems (ESS) and electric vehicles (EVs), the representation of which has led to several interrelations between tasks and deliverables. The market design dimension that affects the incorporation of flexibility options puts also the framework of actors' participation in markets and sets the interaction context of agents. Therefore, there is influence from D3.2 and D4.5 as well. Figure 1 depicts this information exchange between tasks and the interrelation of the deliverables.

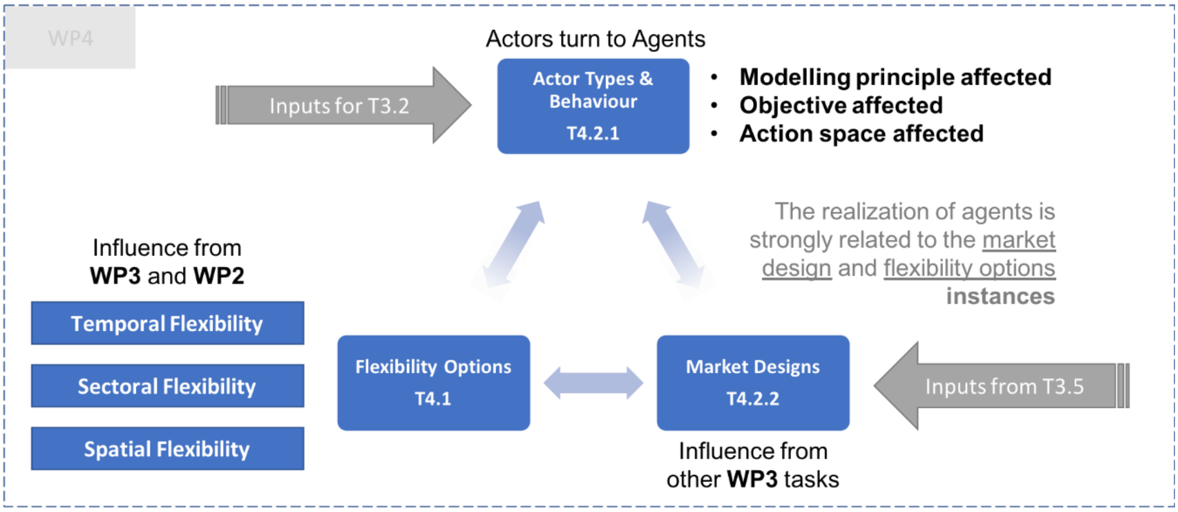

Figure 1: Schematic representation of relations with other tasks and deliverables

This deliverable is accompanied by a series of other deliverables from TradeRES Work Package 4. All of these deliverables are to be published within a timeframe of a few months. Please refer to these deliverables to gain deeper insights on their specific topics:

- Deliverable 4.1 covers model enhancements with respect to temporal flexibility.
- Deliverable 4.2 focusses on the implementation of sectoral flexibility within TradeRES models.
- Deliverable 4.3 describes spatial flexibility options and their implementation in TradeRES models.
- Deliverable 4.5 covers modelling requirements for new market designs and policy options that shall be studied within TradeRES.

2. Overview of actors in market simulation tools

2.1 Overview of electricity markets and agent-based approaches

Power systems across the world are currently undergoing fundamental changes, turning from fossil fuels to clean energy sources, mainly driven by the need of reducing the increasing levels of greenhouse gases emission and mitigating the associated environmental and climate change concerns, while taking into consideration the increasing demand peaks and the electrification of other sectors. To this end, power systems are facing the challenge of decarbonization and there is increasing attention to the deployment of renewable energy sources (RES), such as solar, wind, hydro, tidal, biomass. However, the majority of these sources are inherently characterized by high variability and limited predictability and controllability.

Furthermore, the ongoing efforts towards the deregulation of power systems have introduced competition among multiple self-interested (profit-driven) market actors, leaving behind the centralized models of social welfare maximization, that were imposing perfect competition conditions through the price-taking assumption and the marginal cost consideration. Such competitions exhibit everywhere in generation, supply, and consumption sectors [1]. This paradigm change implies that traditional centralized models face many limitations when accurate market-related insights are at stake, since self-interested market agents' actions are not generally aligned with social optimality and externalities exist. New market models are required instead, which should be capable to simulate complex behaviours and even capture the strategic (price-making) interaction of self-interested market agents, for the assessment of market outcomes, which emerge from the interactions of these agents and can be controlled through the market design.

Figure 2 presents a general perspective of energy interactions among different levels of power system decision makers in the deregulated electricity markets. In this framework, electricity producers are the first-level decision makers, electricity suppliers and aggregators are the second-level decision makers and end-customers (e.g., consumers, prosumers, distributed energy resources (DER), local energy market) are considered as the third-level decision makers [2]. Other participants, due to their functionalities, may be located at each level of this framework. A detailed analysis of the of actors in electricity markers has been already performed in the project, with the overview being available in D3.2. The first- and second-level decision makers are coupled with each other in the wholesale electricity market, which is managed by the market operator. The second- and third-level decision makers are coupled with each other in the retail electricity market level. Finally, a part of end-customers (e.g., micro-generators and distributed energy storages) providing local generation and storage capability are coupled with local demands into local energy markets. As far as the markets are concerned, more details along with market design consideration that have been deployed for the needs of TradeRES project can be found in D3.5.

So far, the existing techniques solving the deregulated electricity markets with imperfect competition and strategic behavioural concerns, mainly focus on the game theoretic modelling (GTM) [3], [4], of which Bi-level optimization constitutes the most widely employed methodological framework for developing such market models over the last decades. The popularity of this methodology lies in its ability to capture the interaction between the strategic decision making of self-interested players (modelled in the upper level - UL) and the competitive clearing of the electricity market (modelled in the lower level - LL) [5]. The Bi-level optimization problems are usually solved after converting them to single-level Mathematical Programs with Equilibrium Constraints (MPEC), through the replacement of the LL problem by its equivalent Karush-Kuhn-Tucker (KKT) optimality conditions. Nevertheless, this modelling framework exhibits several fundamental limitations: 1) the UL agents require knowledge of the computational algorithm of the market clearing process and the operating parameters of their competitors; 2) the LL problem does not include any binary/integer decision variables since the derivation of the equivalent KKT optimality conditions is only possible when this problem is continuous and convex; 3) the stochastic parameters of the market models are difficult to handle, since the computation cost is significantly increased with the scenario-based stochastic optimization problem [6].

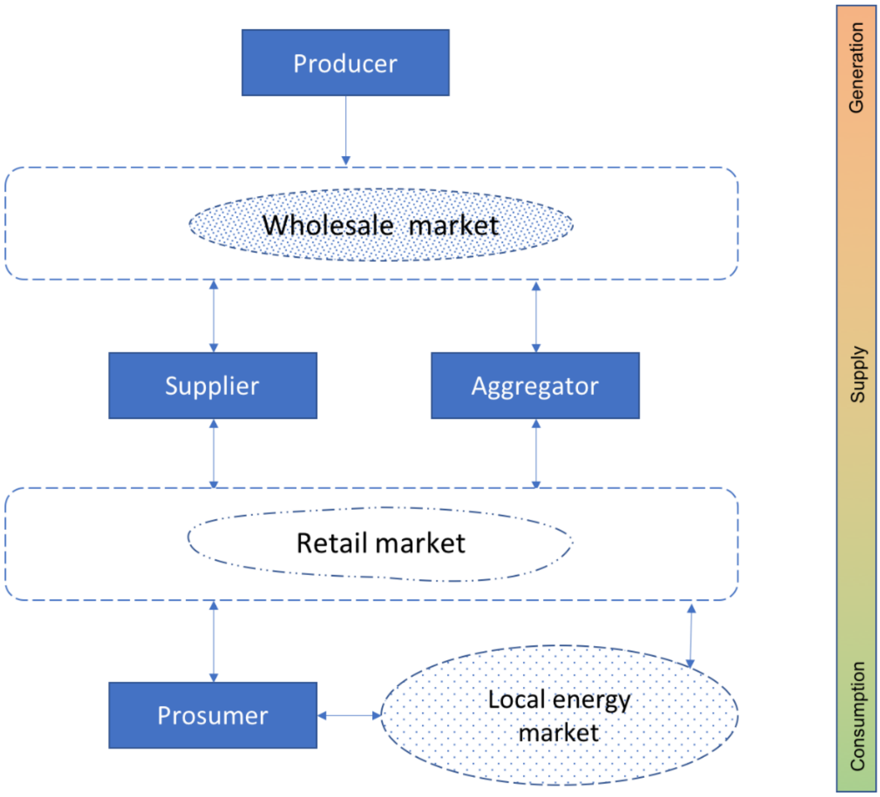

Figure 2: The deregulation of electricity markets [7]

Agent-based modelling (ABM) has received increasing attentions in recent years owing to its advantages in modelling large-scale complex and stochastic systems [8]. ABM refers to a category of computational models that invoke dynamic action, reaction and intercommunication protocols amongst the agents in their shared environment, which is very suitable for current deregulated electricity market. These models incorporate these aspects for evaluating the performance of agents and also, derive insights about their emerging properties and behaviour. Therefore, ABM can model the complex issues in the electricity markets as they can model the complex behaviour of the system participants including asymmetric information, different bidding strategies etc. Also, for large systems with various system participants interacting with each other and playing different roles, ABM is more suitable as they can reproduce the decision behaviours of real-world market participants. Although the optimal solutions are not guaranteed with respect to the game-theoretic modelling, ABM have been successfully used for investigating many real-world complex electricity market problems [9].

Rule-based control (RBC), Genetic algorithm (GA), and Reinforcement learning (RL) constitute the main methods adopted from agents in ABM approaches. RBC is the simplest control method that consists of a knowledge base and an inference engine. The prior defines the set of rules that govern the operations, and the latter takes actions based on the input data and the corresponding rules [10]. GA, on the other hand, is a set of machine learning algorithms which are used to search for the optimal solution of a problem. The term "genetic" refers to the evolutionary searching manner which imitates the evolution processes in nature: selection, crossover, and mutation [11]. Reinforcement learning (RL) is one of the most popular methods for Digital agents in recent years. RL solves the problem in a recursive fashion, the agents (i.e., electricity producers) gradually learn how to improve their strategies by utilizing experiences acquired from their repeated interactions with the environment (i.e., market clearing algorithm). In detail, the electricity market problems are formulated a dynamic programming, where the agents interact with the environment by acquiring the experiences from bidding strategies, market outcomes of clearing prices, quantities, and profits. As a result, the agent does not require any information of the market clearing algorithm, while assuming it as a black box. In addition, instead of solving a scenario-based optimization problem, RL captures system dynamics and stochasticity by learning from the interaction with the environment. Finally, once the model is well trained, the policy can be tested in any dataset in milliseconds, with solving an optimization [6].

The electricity market is operated including different stakeholders, who are capable of interacting with each other and are represented in ABMs via agents. As discussed in Section 2.1.1, the wholesale market links the operation between electricity producers and electricity suppliers and aggregators, which in its organised form usually features a centralized market clearing mechanism. The focus of the research around the wholesale side is on the market and auction design as well as on the investment and bidding strategies of large traders (e.g., electricity producers) [12]. Agent instances have been proposed to help these large traders adaptively adjust their decisions in a highly competitive, stochastic, and dynamic market. On the other hand, consumers (prosumers) in the retail market have less ability to affect the market outcomes but are difficult to be managed by the suppliers and aggregators, since consumers in the distribution levels are characterized by their large quantities and diversities. To this end, strategic retail pricing scheme offered by suppliers is a symmetrical manner to address this issue and somehow mitigates the risks from both wholesale and retail sides. ABMs with agents that adopt learning algorithms have been recently used for modelling electricity retailer problems. The cases where learning technics have been incorporated for the forecasting of the served demand consumption (e.g., Long short-term memory) [13], and the pinpointing of strategic retail prices for consumers (e.g., RL) [14] are among the indicative ones. Finally, with the development and deployment of smart meter technologies, consumers with flexibility are encouraged to response to the retail price signals by shifting part of their demand from peak periods with high prices to the off-peak periods with low prices, so as to reduce the energy bills and demand peaks. ABM is adopted here for its advantages of modelling the heterogeneity of consumers [15].

2.2 Representation of actors through agents

Having reviewed the electricity market mechanisms of wholesale market, retail market and local energy market as well as the approaches of ABM in Section 2.1, this section lies in discussing about the modelling approaches around the representation of operations and behaviours of certain key actors, including electricity producers, suppliers, aggregators, local consumers / prosumers (e.g., distributed DR, DG, EVs, and ESS).

2.2.1. Electricity producers

Electricity producers play the role of energy production and behave in two-level decision-making processes of short-term operation and long-term planning, as depicted in Figure 3 [16].

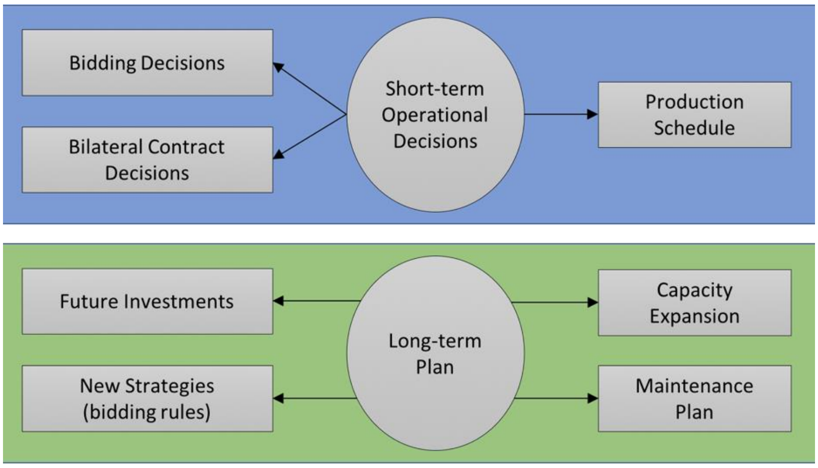

Figure 3: Two-level decision making by electricity producers.

In the first level, electricity producers participate into electricity market by submitting the short-term strategic offers and the interest of studies is focused on the resulting market efficiency or the excursion of market power [17]. Therefore, one of the key aspects of any electricity market design is the bidding structure, i.e., the format based on which market participants submit their techno-economic characteristics, preferences, and requirements to the market clearing engine. The key challenge behind determining a suitable bidding structure lies in the fact that the physical operating characteristics of most market participants are complex, time-coupling and non-convex. Simple bids usually consist of a set of pairs of energy quantity and desired price. The market clearing process lies in building a supply and a demand curve considering the submitted simple bids and determining the market clearing outcome from their intersection. Complex bids allow the market participants to explicitly reveal all their complex operating characteristics and factor these in the market clearing process, rendering the market operator responsible for satisfying the physical constraints of the market participants. In addition to price-quantity pairs, complex bids include a representation of the entire set of the participants' cost components and technical constraints. Outside of the wholesale market, electricity producers are also allowed to sign bilateral contracts directly with the suppliers and large consumers. In this case, the market risks caused by the renewable energy and demand consumptions can be mitigated via the pre-determined contract.

In the second level, long-term planning strategies are developed, with the interest of the studies being on the electric power system transition and the time scale varying from years to decades. These studies are usually performed to assess the influence of specific factors such as renewable energy support design and CO_2 market design on the evolution of the system [18]. On the one hand, new market-based generation investment planning models are required in current deregulated setting, capturing the effort of self-interested electricity producers to maximize their long-term profits while accounting for the impact of their investment decisions on the competitive electricity market. On the other hand, a strategic investment decision is required to handle the stochasticity and dynamics of the market conditions over the planning horizon.

2.2.2. Electricity suppliers and aggregators

Suppliers in the retail electricity market are supposed to purchase electricity in the wholesale electricity market and resell it to their subscribed end-user customers through assigning appropriate retail prices, either in a temporal variance way or at a flat rate. Currently, the electricity retailer is usually operated as an entity that is independent of any generation or distribution company [19]. A retailer (which is a role that can also be taken in practice by electricity suppliers) represents a large number of end-consumers in the wholesale market and coordinate their operation according to the market conditions (day-ahead planning, real-time rescheduling) and the consumer types (residential, commercial, industrial) to maximize its overall profit. The decision-making process involved in buying and selling strategies usually contains some volatile market risks. Especially with the further deregulation of the electricity market, along with the development of demand response (DR) and the proliferation of DERs, suppliers participating in both the wholesale market and the retail market should carefully design their buying-selling trade-off and electricity portfolio [19].

Aggregators are responsible to coordinate local DERs to reduce the upstream generation and transmission capacity requirements, by providing local flexibility, avoiding network reinforcement, reducing energy costs, etc. [20]. The concept of aggregators has been proposed to coordinate these local agents as virtual power plants (VPPs). A range of strategies have been investigated to operate a VPP, which can be broadly divided into two categories: direct strategies that control individual resources, and indirect strategies that send signals (e.g., price signals) to influence the consumption and generation decisions of prosumers. Different strategies have advantages for specific applications. The optimality is guaranteed under the direct strategies since VPP as a central coordinator can directly optimize the energy schedules of all resources. However, knowing all the operation models and technical parameters are normally impractical for real-world applications. To address this issue, indirect strategies via digital agents are proposed to optimize the energy schedules, that only require limited information.

2.2.3. Electricity consumers and prosumers

In most scenarios, customers play a role of energy consumption in retail electricity, purely serving as consumers of energy at the retail side. However, decentralization constitutes one of the main features of the emerging smart grid. Specifically, a large number of small-scale DERs, including flexible loads, micro-generators and micro-storages, are increasingly being connected to the distribution network, with the overall objective of providing the much required flexibility to support the cost-effective development of low-carbon electricity systems. Subsequently, traditional electricity consumers evolve to prosumers, who can proactively schedule their energy consumption, production and storage of electricity [21].

Flexible demand (FD) is based on the idea that the electricity use of consumers changes from their normal consumption patterns to the price of electricity over time. On the one hand, FD is used to induce lower electricity use at periods of high retail prices and higher electricity use at periods of low retail prices. On the other hand, FD involves temporal redistribution of consumers' energy requirements. As a large number of researchers have stressed, consumers' flexibility regarding electricity use mainly involves shifting of their loads' operation in time instead of simply avoiding using their loads. In other words, load reduction during certain periods is accompanied by a load recovery effect during preceding or succeeding periods. This shift of energy demand from different periods drives a demand profile flattening effect.

As the energy storage system (ESS) technology is becoming more economically viable, the role of ESS in energy trading will be more prominent. For large-scale renewable generation (e.g., solar arrays, wind farms), the ESS will be used to smooth out the output of the system. For end-user applications, (distributed) community-based energy storage systems have already gained popularity. In this case, the goal is to deploy small size storage units in the residential feeders to accommodate the demand of several houses during peak demand.

Even though the primary goal of electric vehicles (EVs) is to offer environmentally friendly and cost-effective transportation options, the foreseen capability of EVs to store a large amount of electric power makes them a natural player in energy trading mechanism. With the use of bidirectional chargers, EVs can exchange electric power with the power grid or other market participants, representing as Grid-to-Vehicle and Vehicle-to-Grid.

However, this paradigm changes greatly complicate the operation of the system, as the effective coordination of such large numbers of DERs involves very significant communication and computational scalability challenges as well as privacy concerns, since DER owners, in certain cases, may not be willing to disclose private information and be directly controlled by external entities. To develop strategies for these challenges, policy makers and planners need knowledge of how these DER can be integrated effectively and efficiently into a competitive electricity market. Local energy market (LEM) [22] has recently emerged as an interesting approach to deal with these coordination challenges, as the global coordination burden is broken down to the coordination of local market clusters, each grouping a number of customers with DERs, coordinating the energy exchanges between them and the upstream grid and addressing local network problems. Beyond this coordination benefit, the local matching of power reduces net demand peaks and network losses, resulting in avoidance or deferral of capital-intensive network reinforcements.

2.3 Methodologies for agent-based decision-making process

2.3.1. Rule-based Control

Although RBC requires domain-specific expertise and knowledge to define the decision-making criteria, a rule-based nature is easy to understand as it provides transparent links between causes and effects. Therefore, solutions generated by RBC can be easily interpreted and justified. Currently, RBC is widely used for automatic control problems in smart grid applications. Authors in [23] proposed a predictive rule-based control to activate the energy flexibility of a residential building. Authors in [24] proposed a two-step rule-based strategy for prosumers participating into local energy sharing market. Furthermore, RBC is also a popular method as the benchmark for many advanced algorithms, e.g., RBC is constructed as the baseline of reinforcement learning algorithm for local trading behaviour modelling [25] and EV real-time smart charging behaviour [26]. However, rule bases do not scale efficiently; thus, RBC becomes inadequate for large and complex problems.

2.3.2. Genetic Algorithm

GA a type of evolutionary algorithms that can be used for optimization. GA is widely used in complex electricity market applications due to its ability to find good solutions with a limited number of simulation iterations. Compared to the RBC, GA does not require any knowledge of the examined market, but improves its solutions based on the fitness functions acquired from the market clearing outcomes. In [27] the authors proposed a framework for a generation expansion planning applicable in a competitive environment using GA. Authors in [28] used GA to find a strategic bidding decision in electricity market with the objective of maximizing economic profits and minimizing the financial risks. On the retail side, authors in [29] proposed a bi-level optimization approach between strategic retail pricing and demand response problems, while GA is adopted to overcome the infeasibility of conventional Karush–Kuhn–Tucker (KKT) approach considering that the lower-level demand response problem is non-convex.

2.3.3. Reinforcement learning

- **Single-agent reinforcement learning**
  We now describe the background of single-agent reinforcement learning (SARL) [13]. In reinforcement learning, there are two objects that can interact: the agent and the environment.
  1. ***Agent*** can sense the status of the external environment (State) and the reward of feedback (Reward), and learn and make decisions (Action). The decision-making function of the agent refers to making different actions according to the

state of the external environment, and the learning function refers to adjusting the strategy according to the reward of the external environment.

2. ***Environment*** is everything outside the agent, and its state is changed by the action of the agent, and the corresponding reward is returned to the agent.

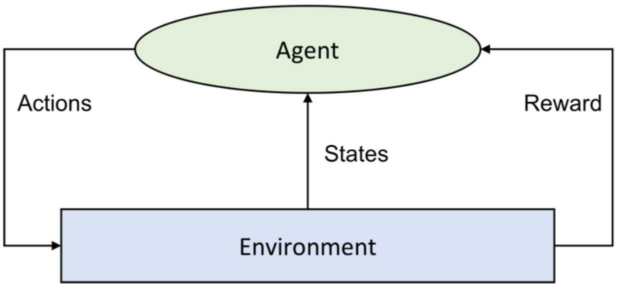

Figure 4: Agent-environment interactions in SARL [30]

In SARL, an agent acts within an environment by sequentially taking actions over a sequence of time steps $t \in T$, in order to maximize a cumulative reward, as illustrated in Figure 4. RL can be defined as a Markov Decision Process (MDP) which includes:

a) a state space $\mathcal{S}$: a collection of the environment state;

b) an action space $\mathcal{A}$: a collection of the agent's actions;

c) a policy $\pi(a|s)$: a function of the agent to decide the next action according to the environmental state;

d) a dynamics distribution with conditional transition probability $p(s_{t+1}|s_t, a_t)$, satisfying the Markov property, i.e. $p(s_{t+1}|s_t, a_t) = p(s_{t+1}|s_1, a_2, \dots, s_t, a_t)$, represents the probability that the environment will change to the state s_{t+1} at the next time step after the agent makes an action a according to the current state s_t;

e) a reward $r: \mathcal{S} \times \mathcal{A} \to \mathbb{R}$, that is, after the agent makes an action according to the current state s_t, the environment will give an immediate reward r_t to the agent, and this reward is related to the next state s_{t+1} after the action a_t.

The agent's decision in terms of which action at is chosen at a certain state s_t is driven by a policy $\pi(s_t) = a_t$. The agent deploys its policy to interact with the MDP and emit a trajectory of states, actions and rewards: $\tau = s_0, a_0, r_1, s_1, a_1, r_2, s_2, \dots, s_{T-1}, a_{T-1}, r_T, s_T$ over $\mathcal{S} \times \mathcal{A} \times \mathbb{R}$. The agent starts from the perceived initial environment s_0, then decides to take a corresponding action a_1, the environment feeds back to the agent an instant reward r_1 and changes accordingly to the new state s_1, and then the agent makes one action a_1 according to state s_1, reward r_2 is rewarded and the environment is changed to s_2 accordingly. This interaction can continue until the end of the episode T.

Previous works employing RL in electricity market modelling have employed conventional Q-learning algorithms and its variants [30]. Authors in [31], [32], [33], [34], [35], [36] and [37] have successfully applied Q-learning method to the strategic bidding problem of electricity producers in a deregulated electricity market. In terms of retailer /aggregator, previous works [38], [39], [40] and [41] employ Q-learning to the strategic retail pricing problems with the objective of maximizing the selling revenues. Finally, a vast number of papers put efforts to the consumer/prosumer sides, including demand response problems [42], [43], [44] and EV smart charging strategies [45], [46]. This type of algorithms relies on look-up tables to approximate the action-value function for each possible state-action pair and thus requires discretization of both state and action spaces. Therefore, it suffers severely from the curse of dimensionality; as the number of considered discrete states and actions increases, the computational burden grows exponentially, soon rendering the problem intractable. If on the other hand a small number of discrete states and actions are considered, the feedback the agents receive regarding the impact of their actions on the environment is distorted and the feasible action space is adversely affected, leading to sub-optimal bidding decisions. This challenge is aggravated in the setting of the examined market modelling problem, since both states of the environment (market clearing prices and dispatches) and agents' actions (strategic bidding decisions) are not only continuous, but also multi-dimensional (due to the multi-period nature of the problem).

In the context of addressing such dimensionality challenges, deep reinforcement learning (DRL) [30] which combines RL with deep learning principles and is driven by the universal function approximation properties of deep neural networks (DNN), has been a growing interest in a new promising research area. As an extension of Q-learning on multi-dimensional continuous state space, authors in [47] proposed the deep Q-network (DQN) method which employs a DNN to approximate the action-value function and has performed at the level of expert humans in playing Atari 2600 games. Inspired by this pioneering work, several recent papers have employed the DQN method to various electricity market applications such as strategic bidding problem of electricity producers [48], smart pricing determinations [49], and demand response problem of consumers [50] - [51] and smart EVs [52]. However, although previous work has demonstrated high quality performance of the DQN method in problems with continuous state spaces, its performance in problems with continuous action spaces is less satisfactory because the employed DNN is trained to produce discrete action-value estimates rather than continuous actions, which significantly hinders its effectiveness in addressing the examined market modelling problem, since market players' actions are continuous and multi-dimensional. In order to address the curse dimensionality of DQN method in discrete action space, deep deterministic policy gradient (DDPG) method [53] featuring an actor-critic architecture, which is able to handle the high-dimensional continuous state and action spaces. The exist literature has successfully applied DDPG method to the strategic bidding problem of electricity producer in a non-convex unit commitment (UC) problem [6], strategic pricing problem of an EV aggregator considering EV discrete charging levels [14], and the real-time home energy management problem [54].

- **Multi-agent reinforcement learning**

  If there are multiple agents in the electricity market, the Partially Observable Markov Game, an extension of Markov Decision Process (MDP) under a multi-agent setting, is normally considered as a concept. The electricity market problem includes I agents indexed by $i \in \mathcal{I} = \{1,2,\dots,I\}$ with a set of environment state $\mathcal{S}$ representing the global state; a collection of agents' action sets $\mathcal{A} = \{\mathcal{A}_1,\dots,\mathcal{A}_I\}$, and a collection of private observations $\mathcal{O} = \{\mathcal{O}_1,\dots,\mathcal{O}_I\}$. Each agent i employs a policy conditioned on its own private observation $\pi_i(a_1|o_1): \mathcal{O}_i \times \mathcal{A}_i \to [0,1]$ to choose actions executed to the environment and transit to the next state based on the transition function $\mathcal{T}: \mathcal{S} \times \mathcal{A}_1 \times \dots \times \mathcal{A}_I \to \mathcal{S}$. At each time step t, all agents $i \in \mathcal{I}$ simultaneously take actions $a_{i,t}$ according to their individual observation $o_{i,t}$, then each obtains the immediate reward $r_{i,t}: \mathcal{S} \times \mathcal{A}_i \to \mathbb{R}$ as well as a new private observation $o_{i,t+1}$. The objective of each agent i is learning a policy that can maximize its own total expected return over the game.

  Prior applications of MARL approaches in the area of power systems are still limited but emerging. The independent learning approach aims at training a policy for each agent by mapping its private observations to an action, and has been adopted for producers' bidding problem [55], demand response problem of consumers [56], and peer-to-peer (P2P) energy trading problem [57]. However, training independent policies does not generally scale well to large numbers of agents and the change in the policies makes the environment dynamics non-stationary in the view of any individual agent and may lead to instability.

  To overcome the non-stationarity issue, the multi-agent deep deterministic policy gradient (MADDPG) method has been employed by various researchers to address the optimal demand response problem in a smart city context [58] and energy management problem for manufacturing systems [59]. The advantage of this method lies in the employment of a central critic network which takes the observations and actions of all agents as the input for eliminating the environmental non-stationarity. Furthermore, authors in [15] propose a parameter sharing (PS) method, an extension of MADDPG, to optimize the P2P energy trading problem among a large number of prosumers.

  If the agents are homogeneous and exhibit similar learning behaviours, their policies may be trained more efficiently using PS. Under this approach, all agents are allowed to share the parameters of a single policy, which enables the policy to be trained with the experiences of all agents simultaneously and the learned policy becomes a generalized strategy for agents. In addition, each agent can benefit from other agents' episodic experience and learned knowledge. This substantially accelerates the learning speed and reduces the computational burden of the algorithm. However, in the large-scale multi-agent systems, training of the centralized critics is intractable since the joint action and state spaces grow exponentially with the number of agents, a common bottleneck for both MADDPG and PS approaches. Furthermore, the assumption of agents' homogeneity in terms of their energy characteristics fails to capture the natural diversity of agents with respect to their economic and environmental perspectives.

3. Modelling improving directions

Beyond any model coupling and information exchange between models that is to take place in the context of TradeRES project, the four ABMs, namely AMIRIS, EMLab-Generation, MASCEM and RESTrade, are also enhanced to incorporate further options and enable more extensive evaluation of market designs. Subject to improvements are also the optimization models used in the project, Backbone and COMPETES, with the relevant work taking place in WP2 and the details foreseen to be reported in D2.2.

Three main pillars of improvement are about including flexibility options into the models from the temporal, sectoral and special point of view and for those special attention is paid, with the analysis and the implementations taking place in the relevant subtasks of WP4 and being presented in the corresponding deliverables, namely D4.1, D4.2 and D4.3. These aspects are also combined and supported by market functionality implementations that will enable the simulation and assessment of proposition of D3.5. The other improving aspect is that of the agent modules, which should get harmonised with all other modelling interventions and being enhanced towards directions that emerge from the synthesis of work conducted in D3.2 and follow the two dimensions identified there, the operational and the behavioural one, respectively.

Based on D3.2, there have been eight classes of actors that have been identifies as playing a key role in electricity markets. These are the prosumer, the producer, the supplier, the aggregator, the trader, the ESCo, the operator and the regulator, with a summary of the adopted definitions, the technologies with which an interrelation exists, the operational and the behavioural characteristics being provided in a per actor basis by the Actor-ID cards of Section 5 of D3.2. Another critical part of the qualitative analysis of actors that took place in T3.2 have been the relational tables that were also reported in D3.2. Following a table-based survey that was circulated among the TradeRES project consortium, the intensity of relations the suggested actors have with a wide range of technologies, many operational attributes and several behavioural aspects were identified. The three so-called relational tables of D3.2, using a heatmap visualization approach, presented through the intensity the importance the relations play in modelling, since they were perceived solely from the perspective of project needs, while further elaboration and details are provided in the corresponding deliverable.

For the identification of the direction of improvements, given the relational tables of D3.2, an extra layer of information is added on top of each table for indicating either the coverage by initial versions of the models or the need for consideration for future inclusion (Figure 5). This per ABM indication, although it adds some extra complexity in the already informational-rich relational tables, constitutes a systematic and compact representation that supports (i) the identification of enhancing directions towards which the modelling efforts should focus, (ii) the provision of an actor-related coverage overview that facilitates the coordination of intervention priorities and (iii) the monitoring of the extent the improvements fulfil the identified needs. The concept of developing enhanced relational tables that include the extra layer of information about the ABMs' coverage is presented in the schematic of Figure 5 and aims to make the mapping of actors and agents, by linking D3.2 with the current deliverable.

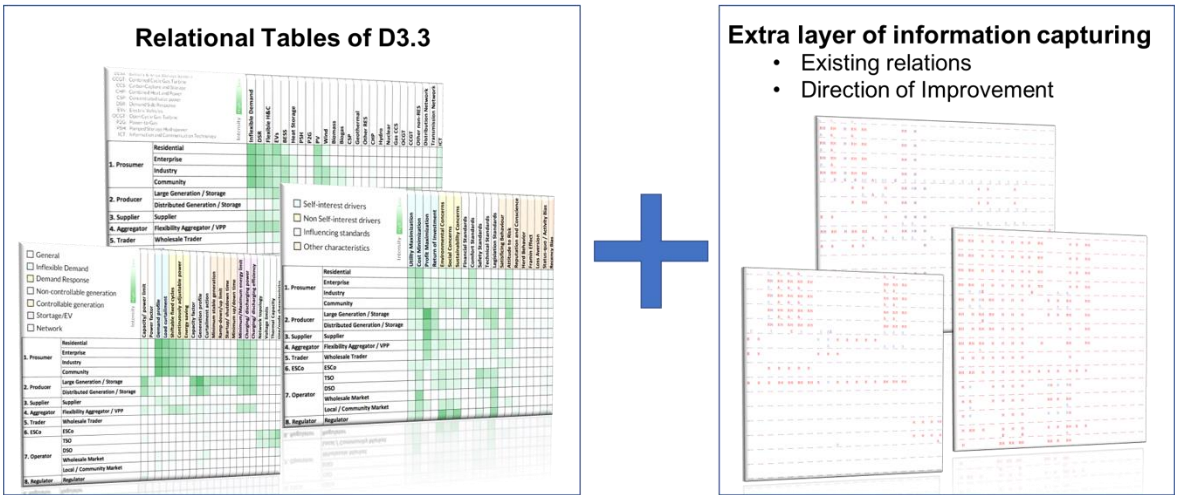

Figure 5: Development of enhanced relational tables with extra layer of information.

Following the order of D3.2, the first enhanced relational table is the one that links actor classes with the technologies. On the one hand, technologies act as enablers and as they go through the lifecycle stages, they drive the emergence of new actors and roles, while on the other hand, influence directly the operation of assets as they set boundaries due to technical limitation and dictate the interaction of components. Table 1 includes the eight actor classes along with their type and various technologies given previous project developments. By considering equivalent agent classes, the extra layer of information that consist of a set of coloured letters positioned in each corresponding cell, represents (i) the relations that are present in the initial versions of the models, (ii) the relations that indicate directions of new developments and (iii) the relations that although are already present are to be extended or improved. Those three cases are indicated by the colour of the letters, while “A” stands for AMIRIS, “E” for EMLab-Generation, “M” for MASCEM and “R” for RESTrade.

Considering in more detail Table 1, it can be seen that regarding the prosumers there has been some coverage of inflexible demand and distributed generation by certain models, with potential of improvements, while the incorporation of DR, EVs and ESS is foreseen by the majority of the models with operational orientation. Producers, which are considered being either large or distributed and represent either generation or storage, are and will be further represented in models. EMLab-Generation, the long-term investment ABM that participates includes a wide range of technologies found in large scale power generation and storage, while the slight enhancement of certain existing ones is expected. On the other hand, operational ABMs concentrate their interest in flexible technologies (EVs, ESS) and renewable generation technologies with distributed versions by introducing new components into their models. Certain technologies are also to be related to suppliers, aggregators, and traders as after their introduction at the distributed level through the prosumers and producers, the concentration for participation/expression in markets is required. Moreover, relations of operators and the regulator with several technologies that exist through the anticipation of technical parameters in operations are present and enhanced in some cases. Overall, by observing Table 1 it can be said that there the overall coverage of the identified relations is extensive, with only some minor ones not being covered by a model.

Table 1: Relational table between actors and technologies with ABM coverage

BESS: Battery Energy Storage System
CCGT: Combined Cycle Gas Turbine
CCS: Carbon Capture and Storage
CHP: Combined Heat and Power
CSP: Concentrated solar power
DSR: Demand Side Response
EVs: Electric Vehicles
OCGT: Open Cycle Gas Turbine
P2G: Power-to-Gas
PSH: Pumped Storage Hydropower
ICT: Information and Communication Technology

Intensity: High – Low

Actor		Inflexible Demand	DSR	Flexible H&C	EVs	BESS	Heat Storage	PSH	P2G	PV	Wind	Biomass	Biogas	CSP	Geothermal	Other RES	CHP	Hydro	Nuclear	Gas CCS	OCGT	CCGT	Other non-RES	Distribution Network	Transmission Network	ICT
1. Prosumer	Residential	A RM	A RM	M	A RM	RM				RM	M															
	Enterprise	A RM	A RM	M	A RM	RM				RM	M															
	Industry	A RM	A RM	M	RM	RM				RM	M															
	Community	A RM	A RM	M	RM	RM				RM	M															
2. Producer	Large Generation / Storage	E	E	E	E R	AE R	AE	AE M	E	E RM	E RM	E M	E	E	E	E	E	E R	E R	E	E	E R	E			
	Distributed Generation / Storage				R	A RM	A	A M		RM	M							R	R			R				
3. Supplier	Supplier	R	R					M		M	M	M					E		E	E	E	E	E			
4. Aggregator	Flexibility Aggregator / VPP	RM	RM	M	RM	RM		M		A RM	A RM	M						A R	A		A	A	A			R
5. Trader	Wholesale Trader	R	R		R	A R	A	A	A	A	A	M	A					A	A		A	A	A			
6. ESCo	ESCo																									
7. Operator	TSO		R							M	M	M														
	DSO		R			M				M	M	M														
	Wholesale Market	A	A R		A	A	A	A	A	A M	A RM	M	A					A	A		A	A	A		A	
	Local / Community Market	R	R			M				M	RM	M														
8. Regulator	Regulator	A	A		A	A	A	A		A	A		A				E	A	A	E	AE	AE	A			

A: AMIRIS E: EMLab R: RESTrade M: MASCEM

Existing Direction Both

3.1 Operational Dimension

The operational dimension as considered in the technoeconomic analysis framework of D3.2 aimed to focus on the technical side of the relation of actors to either a single or a set of technologies that either set the nature of their role by providing the main characteristics or impose operational constraints. Several operational attributes, such as the flexible and inflexible demand, the controllable and non-controllable generation, the storage and the EVs, and the networks, were considered for the for the various groups of technologies taken into account in TradeRES project and mentioned earlier. An in-detail presentation of the most common parameters involved is provided in D3.2.

As far as the modelling initial and future status of those relations is concerned, Table 2 gives an overview. By observing the table, it can be said that many modelling interventions are expected, which will lead to almost all identified operational aspects to be incorporated in the final versions. Detailed presentation of operational aspects in the initial model versions, which constitute the starting point of the model enhancement process, are provided in Section 4.1. Moreover, elaboration on the modelling priorities identified for the enhancement of each model, along with presentation of the implementation plans, are provided in Section 4.2.

The operational dispatch models focus particularly on the improved representation of prosumers as it can be been seen in Table 2, where although the initial concern has been limited in the inflexible demand part and especially in the profiles, the plan is the consideration of load shedding options, flexible demand and storage asset capabilities. AMIRIS has the ability to simulate generic prosumers with an inflexible demand, through the cost minimising dispatch. RESTrade considers prosumers in the context of retail markets, where they can negotiate bilateral contracts with suppliers. MASCEM assumes they are able to buy or sell in the market, at the defined price and according to their goals. As far as the investment simulation model EMLab-Generation is concerned a single agent for consumers is considered for the representation needs of the demand.

Large generation has been found to be affected by the capacity and the power limits, while the generation profile seems to be among the important aspects for the case of non-controllable units. Many of those, along with all other generation attributes are considered in several ABMs. The main agents included in EMLab-Generation are the electricity generation companies that possess a portfolio of generators. The producer agents sell electricity, purchase fuels based on their expected fuel prices, and acquire CO_2 emission rights, apart from making investment or disinvestment decisions. On the operational dispatch models, large as well as distributed producers are aggregated as for example in AMIRIS, including conventional and renewable electricity generation as well as the operation of flexibility options. RESTrade's producer agents are operators of a set of power plants of various technologies and where suitable are enabled to assess their optimal market strategic participation between spot and bilateral markets, considering a profit maximization and taking into account technical and economical characteristics of the underlying technologies. In MASCEM, the producer agent is connected with the aggregator, the wholesale market and the local/community market agents, while its objective is to sell in the market, with its bids being set according to its goals/generation costs. Similarly for storage, either large or distributed, attributes like the energy limit, the charging/discharging limit and charging/discharging efficiency appear to matter and getting incorporated in AMIRIS model.

The supplier and aggregator classes that are next in order in Table 2, are also among the classes of actors that are interrelated to demand response attributes and generation as well as storage characteristics. In terms of modelling, related agents inherit operational properties by the entities they aggregate. Therefore, operational dispatch models such as RESTrade and MASCEM pay much attention in the integration of those aspects. On RESTrade suppliers, the goal of which is to maximize their return, can negotiate bilateral agreements with end-use consumers obtaining a private portfolio to manage. At the same time, on the production side, wind power plants are aggregated with ultimate goal of their unified representation to the market the increase of the value of products/services offered. In MASCEM aggregator's agent objective is close to the prosumer's one, as it aims to serve its goals be managing resources of its portfolio and participating in the market. In AMIRIS, aggregators are a subclass of traders but as they optimize supply and demand of an energy community the relative operational relations have been accounted in energy communities of prosumers. Optimisation of demand response for industrial consumers through load shedding and load shifting as well as consideration of flexible heating with heating storage for households are foreseen for consideration in AMIRS, with the attributes accounted in the relevant prosumer types.

Finally, the TSO and the DSO have been related to network operational attributes since their operations are affected by the topology of the networks, the line characteristics and the technical limits. In RESTrade, where the TSO agent is responsible for managing the balancing markets and the cross-border exchange, beyond being equipped with the corresponding market mechanisms of the balancing markets, considers the line characteristics in the either constant seasonal or dynamic line rating (DyLR) approaches deployed. The validation of the transmission or distribution network operation is the objective of the TSO and DSO agent in MASCEM, respectively, while power flows are considered with several operational attributes being under consideration.

Table 2: Relational table between actors and operational attributes with ABM coverage.

General
Inflexible Demand
Demand Response
Non-controllable generation
Controllable generation
Stortage/EV
Network

Intensity: Low – High

Actor	Type	Capacity/ power limit	Power factor	Demand profile	Load curtailment	Shiftable fixed cycles	Continuously adjustable power	Energy saving	Capacity factor	Generation profile	Curtailment action	Minimum stable generation	Ramp-down/up limit	Startup/ shutdown time	Minimum up/down time	Minimum/Maximum energy limit	Charging/ discharging power	Charging/ discharging efficiency	Network topology	Voltage limits	Thermal Capacity	Line/node characteristics
1. Prosumer	Residential	–	–	A RM	A RM	A RM	A RM	RM	–	–	–	–	–	–	–	A RM	A RM	RM	–	–	–	–
	Enterprise	–	–	A RM	A RM	A RM	A RM	RM	–	–	–	–	–	–	–	A RM	A RM	RM	–	–	–	–
	Industry	–	–	A RM	A RM	A RM	A RM	RM	–	–	–	–	–	–	–	A RM	A RM	RM	–	–	–	–
	Community	–	–	A RM	A RM	A RM	A RM	RM	–	–	–	–	–	–	–	A RM	A RM	RM	–	–	–	–
2. Producer	Large Generation / Storage	E R	R	E	–	E	E	–	E R	AE R	R	R	R	R	R	A	A	A	–	–	–	–
	Distributed Generation / Storage	R	R	–	–	–	–	–	R	A R	R	–	–	–	–	A	A	A	–	–	–	–
3. Supplier	Supplier	–	–	R	R	R	R	R	–	–	–	–	–	–	–	–	–	–	–	–	–	–
4. Aggregator	Flexibility Aggregator / VPP	R	R	R	RM	RM	RM	RM	R	R	R	R	R	R	R	RM	RM	RM	–	–	–	–
5. Trader	Wholesale Trader	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
6. ESCo	ESCo	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
7. Operator	TSO	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	M	M	M	RM
	DSO	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	M	M	M	M
	Wholesale Market	–	–	–	–	–	–	–	–	–	A	–	–	–	–	–	–	–	–	–	–	A
	Local / Community Market	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
8. Regulator	Regulator	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–

A: AMIRIS E: EMLab R: RESTrade M: MASCEM

Existing Direction Both

3.2 Behavioural dimension

Regarding the behavioural dimension, characteristics that influence and govern the behaviour of actors have been highlighted in D3.2. Several behavioural aspects have been considered in the qualitative part of the analysis, which have been grouped into four categories. These are the self-interest drivers, the non-self-interest drivers, the influencing standards and the other characteristics that are common in behavioural economics.

The self-interest drivers, which conceptualize the most common goals of actors, are the utility maximization, the cost minimization, the profit maximization and the return on investments. These follow the assumptions of classical economics for modelling of consumers, social planners, producers and investors, respectively and capture the main behavioural driver of actors when they interact and participate in the markets. Table 3 offers a full overview of the coverage offered by each ABM on the identified relations from behavioural point of view, considering the initial versions of the models as well as the intervention directions that have been prioritised.

On the generation side, profit maximizing rules are used in AMIRIS for conventional power plants, while renewable units use mechanics for market participation that depend on the assumed support instruments. Traders have a central role as they contract producers and determine the bidding strategies, and hence, they constitute an important component as far as decision making is concerned. Selection of the most suitable among the support instruments, choice of the most appropriate marketplace and finally determination of bidding strategies are the decisions that the class of traders is expected to undertake. Several strategy variations can be implemented, with indicative example for the storage trader case being the minimization of system's cost or the maximization of own profits with or without using market power.

In RESTrade, prosumer agents are equipped with utility and optimization functions and consequently are able to respond to dynamic price signals, adapting their consumption patterns following the notion of elasticity of demand. Producers on the other side are able to assess their optimal participation between markets given their profit maximization goal. Suppliers and aggregators operate with the maximization of their returns as their main driver and of the overall revenue streams of the aggregated wind plants in the case of VPPs, with their allocation being subject to the adopted business model.

Environmental, social and sustainability concerns as well as internalization of legislation standards are applicable to almost all actors and will be considered in an appropriate way in MASCEM. In addition, cost minimization, utility maximization and profit maximization behaviours are to be related to prosumers, producers, suppliers, aggregator, wholesale trader, ESCo and for the local/community market. Comfort standards are to be accounted as well, especially for prosumers and the aggregator, safety standards for TSO, DSO and regulator, and, finally, attitude to risk, for prosumers, producers, suppliers and aggregator.

Finally, on the investment side special attention is to be paid to the attitude to risk as in EMLab-Generation where energy producer agents are modelled as risk neutral investors, meaning they are economically rational, will be extended so that a risk aversion factor is incorporated.

Table 3: Relational table between actors and behavioural aspects with ABM coverage.

Self-interest drivers
Non Self-interest drivers
Influencing standards
Other characteristics

Intensity: High – Low

Actor		Utility Maximization	Cost Minimization	Profit Maximization	Return of Investment	Environmental Concerns	Social Concerns	Sustainability Concerns	Financial Standards	Comfort Standards	Safety Standards	Technical Standards	Legislation Standards	Satisficing Behaviour	Attitude to Risk	Reputation and Conscience	Herd Behavior	Framin Effect	Loss Aversion	Status-quo / Activity Bias	Recency Bias
1. Prosumer	Residential	RM	RM	M	M	M	M	M	R	RM			M	R	RM						
	Enterprise	RM	RM	M	M	M	M	M	R	RM			M	R	RM						
	Industry	RM	RM	M	M	M	M	M	R	RM			M	R	RM						
	Community	RM	RM	M	M	M	M	M	R	RM			M	R	RM						
2. Producer	Large Generation / Storage	RM	A M	AE RM	RM	M	M	M	E		R	A R	A RM		RM						
	Distributed Generation / Storage	RM	A M	A RM	RM	M	M	M			R	A R	A RM		RM						
3. Supplier	Supplier	RM	M	E RM	RM	M	M	M					M		RM						
4. Aggregator	Flexibility Aggregator / VPP	RM	RM	RM	M	M	M	M		M			RM		RM						
5. Trader	Wholesale Trader	M	M	A M	M	M	M	M					M								
6. ESCo	ESCo	RM	RM	M	M	M	M	M	R	R	R	R	M	R	R						
7. Operator	TSO	M	R		M	M	M	M			RM	R	RM								
	DSO	M	R		M	M	M	M			RM	R	RM								
	Wholesale Market	M	A R			M	M	M			R	R	A RM								
	Local / Community Market	M	RM	M		M	M	M			R	R	RM	R	R						
8. Regulator	Regulator	M				E RM	RM	E RM			RM	R	A RM								

A: AMIRIS E: EMLab R: RESTrade M: MASCEM

Existing Direction Both

4. Model capabilities and enhancements

The previous section provided an overview of the coverage that participating ABMs offer through their initial versions and highlighted the main directions of enhancing the models towards a more complete, realistic and contemporary representation of actors in market simulation tools. This analysis begun by considering the relations of actor classes with the operational attributes and the behavioural characteristics that have been identified earlier in the project and continued by bringing the agents' implementation into that canvas. In this section, the ABMs participating in TradeRES project are reviewed in detail with respect to their agent representations, while the foreseen enhancements are further described.

4.1 Existing agents and modelling principles

The presentation of the agents in the initial versions of the model is performed in an alphabetical order, considering the four participating ABMs. It is worth mentioning that not all of the models represent all the classes of actors through their agents, as according to the special objective of each model the attention is paid to certain segments of the actor scene or the perspective is more micro- or macro- founded.

4.1.1. AMIRIS

The agent-based simulation model AMIRIS offers an innovative approach for the analysis and evaluation of energy policy instruments and mechanisms for the integration of renewable energies into the electricity markets. One of the main focusses of AMIRIS is to model the energy market actors' micro-economic behaviour under imperfect foresight and information asymmetries. AMIRIS represents energy system actors by prototypical agents which are assumed to behave economically rational under given but possibly incomplete information. Due to this approach most of the agents seek to maximise their profit using, e.g., rule-based strategies. These might not always result in the best possible solution, but contain model calculation efforts.

In general, the number of agents is not defined in AMIRIS and can be scaled up arbitrarily. Thus, it would be technically possible to simulate every individual participant of the energy system. However, the level of (dis-)aggregation should be adjusted to the research question and available data – to retain a parsimonious and computationally feasible model. More details about the models can also be found in D4.1, while in the paragraphs that follow some key remarks about the actor classes in the initial model version are provided.

- ***Prosumers:***
  In AMIRIS' current state, national power demand is modelled as an aggregated block at first. With regard to the special case of energy communities, AMIRIS can simulate the cost minimising dispatch of generic prosumers with an inflexible demand (see item 4, "Aggregators"). Those prosumers are depicted as agents without potential for demand response.

- ***Producers:***
  Large as well as distributed producers are aggregated for AMIRIS simulations by

their generation technologies. They cover conventional and renewable electricity generation as well as the operation of flexibility options. For conventional generation typically one fleet of power plants per energy carrier and technology type is used. Parameters for this fleet are fuel type, minimum and maximum efficiency, total installed power, power per plant, etc. Conventional generation is marketed using the same profit maximizing rules for all power plants.

Renewable generation can be split into power segments. These segments can consider any criterion for distinction (e.g., power limits, remuneration preconditions, location, etc.). As of now, one segment per technology is considered in the default configuration. Time series for the yield potential are used to determine the feed-in of fluctuating renewable units. Marketing mechanics of renewable units depend on the associated support instrument.

Storage units are modelled using aggregated and generic power-to-X-to-power storage units. Technical specifications for these units include energy-to-power ratio, charge & discharge power and efficiencies. Other parameters control the marketing strategies and the numeric precision of dispatch scheduling.

It must be mentioned that in AMIRIS producers are contracted to wholesale traders who determine the bidding strategies. Producers are only tasked to determine which power generation unit of their fleet to dispatch in order to fulfil any awarded bid, i.e., to deliver sold energy. Due to this separation of concerns, agents for plant operation and trading require a strong communication link within AMIRIS.

- ***Suppliers:***
  The class of suppliers is not yet directly considered in AMIRIS. However, the "community aggregator" agent integrates some functions of suppliers. It is managing the electricity load and feed-in of the local grid with households as inflexible prosumers and an energy community storage (see item 4, "Aggregators").

- ***Aggregators:***
  Aggregators are represented as a subclass of traders in AMIRIS. They optimize supply and demand of an energy community. The aggregator in an energy community manages electricity load and feed-in of the local grid. In the current implementation, households as inflexible prosumers and a community energy storage (CES) are assigned to a retailer, serving as the energy community aggregator. The retailer can apply strategies like maximisation of its profit and maximisation of the energy community's autarky to the operation of the CES.

- ***Traders:***
  Previous work in the model development of AMIRIS has focused on direct marketing of renewable electricity in Germany. Therefore, existing central actors in the model are differently prototyped trading agents. These contract suppliers, either electricity generators or flexibility option operators and sell their generated electricity to the electricity markets. The electricity demand is also modelled by trading agents which request energy from the market to satisfy electric load and charging of storages.

Accordingly, the class of traders covers the widest scope of decision making in AMIRIS. They choose available support instruments, marketplaces and bidding strategies. Depending on the actual trading agent, often several strategy variations are implemented. For the storage trader, e.g., strategies to minimise system cost, to maximise own profits with or without using market power are available. In addition, traders may decide upon including individual markups and markdowns for conventional and renewable generation units.

Forecast errors are artificially created at the central forecasting agent. However, the trader agents can control the level of error they have to deal with – similar to a real-world situation where traders may improve their forecast quality, e.g., by combining multiple different forecasts.

Typically, one wholesale trader is assigned to market the volume for one conventional power plant fleet, although less or more coarse assignments can be made. The same applies for marketing of renewable electricity generation technologies. However, by default the trading agents are distinct with respect to the support instrument they offer to the associated power plants.

- ***ESCos:***
  The class of ESCos is not implemented in AMIRIS.

- ***Operators:***
  AMIRIS provides several classes of operators: The agent representing the wholesale market operator clears the market, determines the wholesale power price and disburses the market revenue to the corresponding agents according to their awarded bids and asks. For the calculation of the market clearing price a merit order model is implemented.

- ***Regulators:***
  AMIRIS features a regulator class to host support instruments and provide remuneration to market participants. A second agent is planned to collect dues from the market participants. These agent types, however, do not feature active decision making but rather provide pre-configured policy instruments to other agents.

4.1.2. EMLab

The purpose of modelling generation investment with an agent-based approach is to simulate imperfect behaviour of investors due to limited information. In comparison to optimization models, in ABMs producers might over- or under invest, as it occurs in reality. In EMLab, agents are programmed as objects. The agents' decisions change their own portfolio but also affect the surrounding. An overview of the agents can be found in Table 4.

The main agents are the electricity generation companies "EnergyProducer" that possess a portfolio of generators. In the basic implementation of EMLab, the "EnergyProducer" agents are modelled as risk neutral, meaning they are economically rational. This can be modified to add a risk aversion factor. In its current version, EMLab does not consider investors potential strategic behaviour, nor market power dynamics.

To make an investment decision, each simulation year, the agents make a forecast of a future electricity market. Taking past data (4 to 6 years) of the demand, fuel prices and CO_2 prices, these variables are projected to a future reference year. In each iteration a randomly selected agent simulates the cash flow of a new plant with the projection of future prices. The projected plants are expected to run if their variable costs are below the expected electricity prices. Their cash flow is calculated considering the revenues from the future electricity prices (which consider the forecasted fuel prices), the running hours and the costs of the projected plant. For the net present value (NPV) calculations, the construction time and the expected lifetime of the plant is considered. This iteration is done for all new possible technologies. The agent in turn selects the technology with the highest NPV and if it has a sufficient cash flow for the down payment, then it invests. The equity costs are considered immediately, and the debt costs are considered during the depreciation time on future cash flows. This procedure is repeated for the next agent which projects the future system considering the plant that the previous agent decided to invest in. The iteration continues until the agents stop being willing to invest because the projected cash flows are negative (negative NPV) or because their cash flow is insufficient to finance the equity. The agents make disinvestment decisions by considering the age or the profitability of the power plants. If the cash flow of a plant is negative for several years (user-defined) and it is also forecasted to have a negative cash flow, then the plant is dismantled. A more detailed description of the model can be found in [60].

The intermittence of renewable energies is taken into account considering the ratio of their capacity to be available during the different load duration segments. To simulate the renewable energy support, a renewable target investor agent "TargetInvestor" is implemented. If the investment in renewable generation is below the policy target, then this agent covers the difference between the target and the invested capacity. The investment is made even if the technologies are not profitable, resembling the subsidies that these technologies receive.

Apart from investment the "EnergyProducer" agents sell electricity, purchase fuels based on their expected fuel prices, and acquire CO_2 emission rights. The demand is represented by a single "EnergyConsumer" agent.

An agent called "Government" defines the rules for the CO_2 market (CO_2 caps, CO_2 penalty, CO_2 price trend, etc) and the market stability reserve. Similarly, there are other agents that define the rules of mechanisms, such as the Strategic reserve operator. The rest of the agents (PowerPlantManufacturer, PowerPlantMaintainer, BigBank, CommoditySupplier, ElectricitySpotMarket, CommodityMarkets) have simple functions and are unique agents that do not present group interactions nor emergent behaviour.

Table 4: Agents in EMLab Generation [60]

Agent Names	Complexity	Class
EnergyProducer	High	domain.agent.EnergyProducer
TargetInvestor	Simple Rules	domain.agent.TargetInvestor
PowerPlantManufacturer	Accounting	domain.agent.PowerPlantManufacturer
PowerPlantMaintainer	Accounting	PowerPlantMaintainer
BigBank	Accounting	domain.agent.BigBank
CommoditySupplier	Accounting	domain.agent.CommoditySupplier
EnergyConsumer	Accounting	domain.agent.EnergyConsumer
Government	Simple Rules	domain.agent.Government
ElectricitySpotMarket	High	domain.market.electricity.ElectricitySpotMarket
CommodityMarkets	Simple Rules	domain.market.electricity.CommodityMarket

4.1.3. MASCEM

MASCEM is also a simulation and modelling tool developed for studying and simulating electricity market operation. To achieve its design goals, MASCEM models the main market entities and their interactions, with players' decisions being in accordance with their specific characteristics. The main market entities are implemented as software agents and in the current version of the model there are eight different classes of actors that can be classified as follows:

- ***Prosumer:***
  one agent with as many instances and parameters as needed by the case study.
- ***Producer:***
  One agent with as many instances and parameters as needed by the case study.
- ***Supplier:***
  One agent with as many instances and parameters as needed by the case study.
- ***Aggregator:***
  One agent with as many instances and parameters as needed by the case study.
- ***TSO:***
  One agent with one instance.
- ***DSO:***
  One agent with one instance.

- ***Wholesale market:***
  Three agents, MIBEL (Iberian Electricity Market), EPEX (Environment for Parallel Execution) and NordPool (Nominated Electricity Market Operator).

- ***Local/Community market:***
  One agent with one instance.

In what concerns the model's functionality, in the scope of TradeRES none of the actors is considered to undertake autonomous decisions. These agents perform specific tasks in the market environment, with their actions being specified a-priori. For example, the prosumer, producer, supplier and the aggregator need to define the price, volume and any specifications to be submitted in the market for each negotiation period.

Furthermore, when considering the objective function or the agent´s objective in this model:

- For the TSO and DSO, the objective is to validate the network, either at a transmission or distribution network level, considering the market economic results; and communicate these validated results to the respective market operator, so that actions may be performed in case there are power flow problems;
- For the wholesale market and the local/community market agents, the objective is to run the market itself, calculating the market social welfare, finding the market price and defining accepted/refused bids from all market players for each market negotiation period;
- For the prosumer, the goal is to buy or sell in the market, at the defined price according to its goals.
- The objective of the producer is to sell in the market, at the defined price according to its goals/generation costs.
- Finally, the aggregator's objective is close to the prosumer's one, it is to buy or sell in the market, at the defined price according to its objectives and the resources being managed by it.

Table 5 illustrates the existing direct connections between the different actors. It is important to notice that the aggregator is the only entity that interacts with all other actors, being able to manage consumers, generators and prosumers, participating in wholesale and local markets, and potentially enrolling in power network validation roles as well. The DSO and TSO interact (besides the aggregator) with the local market and wholesale market operators, respectively; for power network validation purposes, at the different levels. Prosumers, producers and suppliers are able to participate in the market directly, and also indirectly, via an aggregator.

Table 5: Direct connections between actors

	Prosumer	Producer	Supplier	Aggregator	TSO	DSO	Wholesale Market	Local/Community Market
Prosumer	-	-	-	x	-	-	x	x
Producer	-	-	-	x	-	-	x	x
Supplier	-	-	-	x	-	-	x	x
Aggregator	x	x	x	-	x	x	x	x
TSO	-	-	-	x	-	-	x	-
DSO	-	-	-	x	-	-	-	x
Wholesale Market	x	x	x	x	x	x	-	x
Local/Community Market	x	x	x	x	-	x	x	-

Based on the current stage of the model and the purpose and characteristics of the project, some enhancements regarding the actors' capabilities are planned as described in Section 4.2.3.

4.1.4. RESTrade

RESTrade – LNEG's open-access model - is supported by the Multi Agent Trading in Electricity Markets (MATREM) system that has been developed at LNEG [61] in recent years. MATREM is capable of simulating long-term futures, bilateral and contracts for differences (CfDS) but also short-term day-ahead, intraday, and balancing markets (BMs). It is equipped with traditional models of consumers, suppliers, and producers' agents, but also of the Power Exchange (PX) that is equipped with the markets algorithms of the aforementioned markets, with exception of BMs that are managed by the Transmission System Operator (TSO). Although MATREM is available for use within TradeRES project, it is not an open-access system.

RESTrade is an ABM model that includes the agents and features below.

- ***Consumers*:**
  RESTrade is capable of representing traditional consumers. On RESTrade these agents are only able to operate in retail markets and negotiate bilateral contracts

with suppliers [62]. They are equipped with utility and optimization functions that enable them to respond to time-of-use (ToU) rates, changing their consumption behavior according to their elasticity, considering shifting or curtailing demand, i.e. demand-side management (DSM). While negotiating bilateral contracts they are also able to negotiate a direct load control mechanism with suppliers, that consists of a demand-response (DR) program [63]. Their optimization functions have the goal of minimizing costs according to ToU rates and their flexible demand. RESTrade also supports coalitions of consumers [64]. For the time being RESTrade does not models prosumers.

- ***Producers*:**
RESTrade's producer agents can be operators of a power plant or a set of power plants of the following technologies: a) fuel oil, b) carbon, c) natural gas CCGT , d) nuclear, e) hydro, and f) vRES. Producers with traditional technologies are equipped with the technical and economical characteristics of these technologies enabling them to assess their optimal market strategic participation between spot and bilateral markets considering a profit maximization function [65], [66], [67]. The producers receive the prices of current bilateral contracts and expected prices of future bilateral and spot markets. Furthermore, they also receive their vRES plants production to plan their market participation and dispatch. These agents set agreements/make a bid for each power plant considering (only) its marginal cost, except for hydroelectric power plants. For hydro plants, that are also equipped with a water value function, the agent enables producers to compute and maximize each time step's economic value between selling energy and the expected value of stored water [68]. The power plants that can participate in balancing markets are pre-defined according to their technical characteristics and they are obliged to do. All producers can also negotiate bilateral agreements with suppliers or send bids to the balancing markets managed by the TSO [69].

- ***Suppliers***:
A supplier agent can participate both in wholesale and retail markets. On RESTrade suppliers can negotiate bilateral agreements with end-use consumers obtaining a private portfolio to manage. Their goal consists in maximizing their return. Considering a target return, they propose tariffs to end-use consumers based on expected spot prices [70]. Then, they buy energy from spot markets to satisfy their portfolios. While negotiating different tariffs with consumers, suppliers incentivize DSM and can also negotiate and contract DR programs with them [71].

- ***Aggregators***:
Currently, RESTrade only has aggregators of wind power plants. These aggregators have the goal of increasing the wind power value to the market, by improving the forecast accuracy, when the combined power output of these power plants is used [72]. This aggregation is spatially limited to a control region within the power system. They only negotiate at spot markets [73].

- ***TSO***:
  Under the TradeRES project, the TSO agent of RESTrade will only be responsible for managing the balancing markets and the cross-border exchange using constant seasonal line rating (SLR) or dynamic line rating (DyLR) approaches [74]. It is equipped with the market mechanisms of the balancing markets [75]. This agent is responsible for the aFRR capacity procurement, using the ENTSO-E recommended formulation [76]. It is also responsible for clearing the aFRR capacity and mFRR energy market based on the marginal pricing approach. It also can detect cross-border congestion when using SLR. For this situation, a DyLR approach is applied to (potentially) obtain an extra capacity, thus avoiding those grid congestions whenever feasible [74].

  Under this project, the TSOs functions of MASCEM (developed by ISEP) and RESTrade are being coupled using the Spine Toolbox and will be applied to MIBEL's case study. On Spine Toolbox, the TSO agent already has the market algorithms of the day-ahead and balancing markets.

Table 6 illustrates the main characteristics of these agents.

Table 6: RESTrade's agents characteristics

Class of Actor	Number of Agent(s)	Functions	Interacts with
Consumer	>10 aggregated	Minimize costs, maximize utility. Respond to DSM and DR programs	Suppliers
Producer	>10 with multiple power plants	Maximize profit or utility. Bids based on optimal operation and marginal costs.	Suppliers and TSO
Supplier	~6 representatives of the Iberian market	Maximize return or utility. Incentivize DSM and DR programs.	Consumers, Producers and TSO
Aggregator	>10 considering the number of control zones	Minimize deviations and maximize profit.	TSO
TSO	1	Manage the balancing markets and cross-border congestion.	Producers, Suppliers and Aggregators

4.2 New agents and other agent enhancements

The enhancements as well as the introduction of new agents is presented in this sub-section, in a model-by-model way, following the same sequential order as before. Several implementation plans are described here, while there are many links to other deliverables, e.g. D4.1, D4.2 and D4.3, that include details on flexibility options modelling.

4.2.1. AMIRIS

It is planned to include new agents as well as to improve the representation on the prevalent ones in AMIRIS in the course of TradeRES. Besides the agent enhancements described in the following, it is planned to improve parameterization and granularity for the case studies in TradeRES Work Package 5. Please refer also to the deliverables D4.1, D4.2 and D4.5 for a more complete picture of TradeRES-related enhancements of AMIRIS.

- ***Prosumers:***
  The representation of demand side flexibility has been developed within the aggregators' strategies (see item 4, "Aggregators").

- ***Producers:***
  No immediate enhancements are foreseen with respect to the representation of Producers in AMIRIS since corresponding implementations are already quite detailed.

- ***Suppliers:***
  It is not intended to enhance suppliers beyond existing implementations.

- ***Aggregators:***
  A new class of aggregators in AMIRIS is optimising demand response for industrial consumers. Demand response can be operated in two ways: Load shedding and load shifting. To depict load shedding, the overall demand is sliced into segments. There is one agent marketing all the demand segments at their attributed value of lost load. The number of segments can be adapted as required. Load shifting is implemented using a dynamic programming approach with a newly developed two-dimensional state definition comprising the time spent for load shifting and a corresponding energy level.

  Another new class of aggregators is optimising heat pumps with heat reservoir capacities for households. Corresponding operation strategies have been already developed and will be integrated into the latest version of AMIRIS. The required data has to be calibrated in accordance to the scenario data defined in WP 2.

  To represent the demand of electric vehicles and its potential for flexibility a further class of aggregators has to be developed in the future course of TradeRES. It is foreseen to use a method similar to the two-dimensional dynamic programming approach taken for operation of load-shifting portfolios.

- ***Traders:***
  In AMIRIS the newly developed demand response aggregator agents (see item 4,

“Aggregators”) are classified as trader agents. Thus, corresponding developments would fit here, too. Beyond that it is not planned to create new trader-agent classes in the context of TradeRES, since traders have already experienced a very high degree of differentiation in AMIRIS. Still, revisions or adaptations of marketing strategies of existing trader agents might be necessary with regard to newly developed policy instruments (see item 8 “Regulators”).

- ***ESCos:***
  It is not intended to implement ESCos in AMIRIS, since energy efficiency and contracting are out of scope. The demand level is taken from external time series.

- ***Operators:***
  As far as new market design options require further market rules or market places, these will be implemented as further instances of the class of market operators. In this respect, it is planned to implement variations of wholesale market rules directly at the corresponding market agents (e.g., new market products with shorter time units) - please refer to Deliverable D4.1 for details.

- ***Regulators:***
  Further elements for regulatory frameworks are to be implemented in AMIRIS. This comprises different RES remuneration policies (e.g., contracts for differences, several variations of market premia, or feed-in tariffs) and capacity mechanisms (e.g., capacity premia, or capacity subscriptions) as well as retail market elements to impose agents to different taxes and levies, depending on the type of agent and or application. These elements are currently under development.

4.2.2. EMLab

The current EMLab implementation uses a segmented load duration curve. This was originally designed to speed up the calculations. A major drawback is that this implementation doesn’t allow to model energy storage and demand side response. For this reason, the most suitable improvement is to couple EMLab with another model that has implemented a more detailed dispatch model. It can be coupled with an optimization dispatch model that reflects the optimal dispatch decisions or another ABM, e.g. AMIRIS.

The advantage of coupling with an optimization model is that these types of models have detailed information on generation technologies, sector coupling, cross-border flows (grid constraints) as well as the dispatch details (i.e. start-up times, ramp rates) that allow to model demand response, demand curtailment, energy storage, vRES curtailment, etc. COMPETES, for example, can model the power trade among the EU28+ countries.

Besides the replacement of the dispatch algorithm, the investment module of EMLab can also be replaced with an optimization algorithm. The native EMLab investment decisions are rule-based, where the rules model real-world investor behaviour. This logic can be replaced by optimal decision making, in which we assume that agents make investments to maximize social welfare. If such a replacement is made, the capacity mechanism (CM) of EMLab and the CO_2 market of EMLab can allow an endogenous calculation of CO_2 price and CM support.

EMLab can also be linked with agent-based dispatch models, for example AMIRIS. In comparison to EMLAB, in AMIRIS the producer agents are distinguished by technology, not by owner. For this reason, coupling of the EMLAB investment algorithm with the AMIRIS dispatch algorithm requires some adjustments to the logic of the investment iteration. Nevertheless, the myopic behaviour of the investors can be equally modelled.

Apart from the model coupling, only minor additions to EMLab are anticipated. One such enhancement is addition of the capacity subscription mechanism. This addition requires enhancements on the consumer agents in the dispatch algorithm, as described in Deliverable 4.5.

4.2.3. MASCEM

Considering the project goals and characteristics, new features will be designed and implemented, including the enhancement of the considered actor characteristics and a set of actors' behavior capabilities.

In what concerns the technology already implemented in the model, MASCEM considers inflexible demand and flexible heating and cooling (H&C) for prosumers and aggregator. It also considers the possibility of adding PV and wind generation.

Considering the existing features, during this project demand side response and electric vehicles management models are being designed for integration with prosumers and the aggregator (details in D4.1 and D4.2). In specific, a load curtailment model is being designed for the inflexible demand and a load shedding and shifting model is being developed for flexible loads. Besides the cost factor, these models consider the relative importance of end-user comfort and the effect of local produced generation and real-time pricing. The models are applied to the consumers and prosumers, taking advantage on the management role of the aggregator entity. The aggregator, besides managing and suggesting load management actions to its aggregates, will also apply new models that are being developed for resources' aggregation. The aggregation models (described in D4.2) will enable the aggregator to identify the players that should be approached for the application of demand response actions and events, considering the characteristics of these players and their influence on the power network flow. In this way, the MASCEM market models can be executed at different levels, at different timings, and considering different modes of participation from the diverse actors. As an example, the MASCEM model will enable running the wholesale market considering an aggregator that represents a fixed set of consumers and generators; or an aggregator that represents a restrictive set of consumers/prosumers, negotiating their flexibility in the market. On the other hand, the aggregator can be a negotiating player (selling or buying) in the wholesale market, but can also be a market operator in a local market executed at a zone managed by itself (including the necessary interactions with the local DSO).

Other operations that are being added for prosumers and the aggregator are related to battery storage systems and electric vehicles. For that, two models are being designed. The first considers the aggregation of electric vehicles considering their zonal distribution throughout time. This model is used to support the actions of the aggregator when negotiating energy in the market, when negotiating flexibility and also when managing local areas and running local markets. Minimum/maximum energy limit, charging/discharging power and charging/discharging efficiency are considered in this model. The second model is related to potentiating load shifting by making use of the flexibility brought by the electric vehicles and the batteries. The battery energy storage management system considering real time pricing is also being designed for the use of prosumers, producer, aggregators, wholesale market and local/community market with particular focus on potentiating demand flexibility (details also in D4.1). Pumped hydropower storage will also be designed for producers, suppliers and the aggregator.

Using the mentioned models requires that the considered players, namely the aggregator and market operators, need to interact with the TSO and DSO for the sake of power network stability. In this way, new models are also being designed for supporting the capabilities of the TSO and DSO agents. A Power Flow Service (PFS) is being developed, and details are provided in D4.5, to enable any actor with the role of power network validation (e.g. DSO, TSO, aggregator) to perform a network validation considering any type of power network (distribution or transmission network, with any topology), using any from a large set of power flow algorithms. This model aims to address all relevant aspects related to the network, including network topology, voltage limits, thermal capacity and line/node characteristics. In this way, the actors will be able to undertake network validation actions that will enable enriching the diversity of flexibility of the market models and scenarios to be experimented by the project.

The current model does not consider the automatic definition of actors' behaviour. However, considering the project objectives, some behaviours will be considered in the model:

- Utility maximization, environmental, social and sustainability concerns and legislation standards are applicable to all actors and will be considered as appropriate.
- Cost minimization and profit maximization are to be considered for prosumers, producers, suppliers, aggregator, wholesale trader, ESCo and for the local/community market.
- Comfort standards are to be considered for prosumers and the aggregator, safety standards for TSO, DSO and regulator, and, finally, attitude to risk, for prosumers, producers, suppliers and aggregator.

4.2.4. RESTrade

Under the TradeRES project, the traditional agents are going to be improved concerning the new market designs of power systems with near 100% RES. The upgrades of the agent models will be performed under a strong collaboration with ISEP. LNEG will focus on the supply side, while ISEP will have a stronger contribution on the consumers' side.

- **Producers**:
  Producer agents that own vRES power plants will adapt their participation on markets according to i) the different vRES support schemes, ii) no support mechanisms, and iii) also considering the possibility of these players participating in the balancing and reserves markets. Producers will also adapt the planning process of their traditional power plants operation, according to the new markets' gate closures and to the new time units. Producers will have their optimization formulation adapted to

consider their participation in capacity markets. The participation of vRES in bilateral markets is also considered.

- **Aggregator**:
  Within the TradeRES project, an "aggregator" is a player that aggregates the consumption and/or production of electricity acting as a single entity [77]. This player embeds different approaches/concepts being responsible for i) the interactions with the electricity markets, and ii) providing ancillary services to TSO under some concepts. Thus, several subclasses of aggregators have already been designed within the TradeRES project, such as single technology aggregation as the aforementioned wind aggregator, but also vRES aggregators, citizen energy communities (CECs), and hybrid renewable power plants (HyPPs). Each subclass is differentiated according to its intrinsic features (for example, objective function or technologies included) as presented below.

  - **Generation aggregation:** Further enhancements of the existing single technology aggregation approaches will be pursued in TradeRES using optimization strategies instead of clustering-based approaches. These approaches will be extended for solar PV to identify the potential benefits of aggregation of different vRES technologies, as reported by some authors [78]. This step is particularly important for devising an aggregation dispatch strategy that can increase the value of vRES generation into electricity markets while contributing to transform the power production from these technologies into a more reliable energy source. The aggregation strategies are defined *a priori* by indicating desirable connections (physical or virtual) of a set of vRES power plants according to the optimization strategies. The interaction with the electricity market is performed through the aggregator agent.
  - **CECs** are composed of the same parties of a typical aggregator: RES, consumers, prosumers, batteries, etc. However, it only operates on the distribution level and its main behavior comprises a cost minimization and a maximization of the efficiency regarding the use of the local energy resources considering DSM and DR [79]. It can participate in spot and bilateral markets. Its participation in balancing markets will be tested considering its technical capabilities to do so. It can negotiate bilateral agreements with producers and suppliers. Considering that this player is composed of consumers and producers a strong collaboration between ISEP and LNEG will exist while developing it.
  - **HyPPs** are co-located power plants that combine two or more renewable resources, with (or without) energy storage systems [80]. One of the main goals of this concept is to explore the natural complementarity between the primary resources of renewable energy sources within a HyPP and their synergy to attain operational set-points. It is a crucial step to obtain a smart energy management of renewable energy generation through a strategic bidding/participation in the different electricity market frameworks. Other main recognized advantages of HyPPs include [81]:

- An increased load factor of transmission lines, allowing to postpone new investments in grid infrastructure.
- An increased capacity factor and smoother power output, taking advantage of renewable resources' natural complementarity.
- Reduced power system's balancing costs due to “more dispatchable" generation, especially if a storage system is in place.
- These power plants can be operated both in stand-alone and grid-connected mode. Their behaviour typically follows a cost minimization when operating in stand-alone applications [82], [83] and a maximization of profit in grid connect applications [84].
- These power plants can participate in spot and bilateral markets. The participation of these power plants in ancillary services markets will be tested considering their technical capabilities and the regulations in place.

- ***TSO:***
  The TSO agent will be enhanced by incorporating the new market designs, mechanisms, products, and rules developed in TradeRES project [73]. This agent will interact with the traditional and new players according to the rules defined for each agent. Furthermore, the TSO will also be responsible to apply different mechanisms of the aFRR capacity procurement namely, considering also the vRES forecast and an asymmetrical procurement, which according to [85] may allow increasing the level of efficiency of this mechanism and is already in place in some countries [86]. The TSO will also be responsible for managing the cross-border balancing market considering a DyLR analysis in case of congested tie-lines between different market zones.

Table 7 illustrates the main characteristics of these agents under development

Table 7: RESTrade’s (future) agents characteristics

Class of Actor	Number of Agent(s)	New Functions	Interacts with
Producer	~10 with multiple power plants	Profit maximization considering capacity markets and vRES support schemes.	Suppliers, Aggregators TSOs and CECs
Aggregator - **vRES** - **CEC** - **HyPP**	>10 considering different types of aggregations	vRESs have the goal of maximizing their profit	Consumers, Producers, Suppliers and TSO
TSO	1	CECs have the goal of minimizing costs and maximizing energy sustainability	Consumers, Producers, Suppliers and TSO

Figure 6 presents the architecture of the RESTrade system that already has several agents and mechanisms, but also foregrounds models under development.

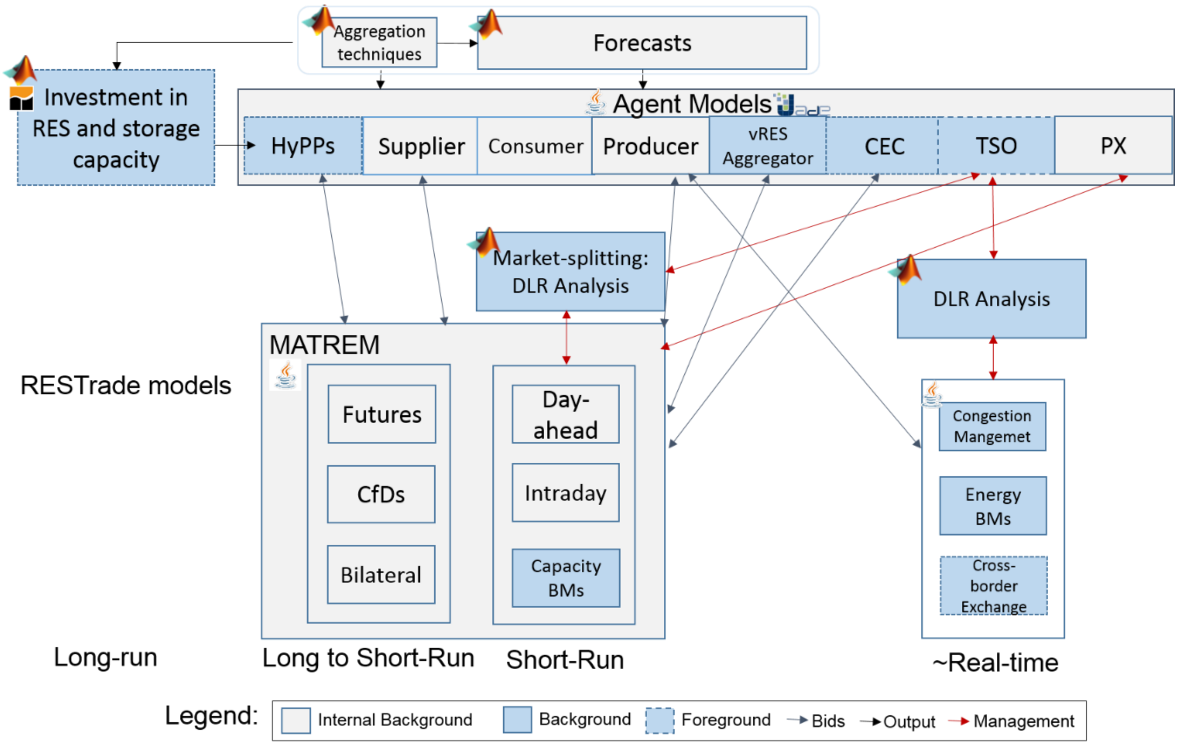

Figure 6: Main architecture of the RESTrade system. Blue-filled boxes correspond to background and foreground modules with open access within the project.

5. Conclusion

Summarizing this first version of the report about the representation of actor types and behaviours in the market simulation models, it can be said that the ABMs have been found even in their initial version to offer an extensive coverage of operational attributes and behavioural aspects identified in earlier stages of the project. The modelling enhancements related to agents, aim to provide a more complete, realistic and contemporary representation of actors in market simulation tools through agents.

Initially a detailed review of the literature has offered the necessary background for considering attributes and methods, linked and adopted by agents, respectively. After an overview of the electricity markets and the agent-related modelling approaches, an elaboration on the representation of actors through agents provides the framework for translating the operational and behavioural characteristics of actors to modelling functionalities of agents. In that context, common entities such as the producers, from both the operational and investment existence, the suppliers, the aggregators, the consumers and the prosumers are considered. Additionally, as far as the methods related to decision-making functioning are concerned, the rule-based control of agents, the adoption of generic algorithms for finding heuristically stationary points and the incorporation of adaptation/learning processes have been reviewed. It should be stated that although the ABMs that participate in TradeRES constitute an important part of the literature, they haven't been included in this review as they are analysed in more detail in the other sections.

Given these agent-based modelling principles, the characteristics of actors, as identified in earlier stages of the project, are considered. The four ABMs that are used in the project are examined under the two dimensions adopted for the characterization of actors' needs. Therefore, the coverage of the relations of market actors with (i) technologies, (ii) operational attributes and (iii) behavioural aspects offered by the initial versions of ABS is identified. Similarly, enhancing directions towards the inclusion of further relations are highlighted for the models. This process has been facilitated by the relational tables of D3.2, on top of which an extra layer of information has been added. The support to the further analysis these new enriched relational tables offered has been threefold. They assisted the identification of enhancing directions towards which modelling efforts should focus, they offered a coverage overview with respect to the actors' characterization that facilitated coordination of interventions and they enabled the monitoring the improvements added coverage and value given the pre-identified needs.

In a similar sense, the more detailed consideration of the ABMs that follows exactly after the initial evaluation of existing features, the identification of enhancing priorities and allocation of modelling improvement between models. In a per model basis, the agent instances in the initial versions of the four ABMs are described, while the scheduled improvements have been described. There have been several points where reference to other WP4 deliverables is needed, as the concepts involved may lay on the boundary or even be strongly related to the modelling of flexibility options (D4.1-D4.3) or the market design modelling requirements (D4.5).

It also needs to be highlighted that this is the first version of the deliverable related to the representation of actors in simulation models and tools, with the next final version being expected on M29, when modelling enhancing activities will be in a more mature stage and other related tasks being completed. At that point further details on agent implementations are expected to be reported, following of course the directions that have been already identified, prioritized and allocated between the ABMs.

References

[1] Bhattacharya, K., Bollen, M.H. and Daalder, J.E., 2012. Operation of restructured power systems. Springer Science & Business Media., [Online].

[2] Ventosa, M., Baıllo, A., Ramos, A. and Rivier, M., 2005. Electricity market modeling trends. Energy policy, 33(7), pp.897-913., [Online].

[3] Vasin, A., 2014. Game-theoretic study of electricity market mechanisms. Procedia Com-puter Science, 31, pp.124-132., [Online].

[4] Lise, W., Linderhof, V., Kuik, O., Kemfert, C., Östling, R. and Heinzow, T., 2006. A game theoretic model of the Northwestern European electricity market—market power and the environment. Energy Policy, 34(15), pp.2123-2136., [Online].

[5] Bjørndal, M. and Jørnsten, K., 2005. The deregulated electricity market viewed as a bilevel programming problem. Journal of Global Optimization, 33(3), pp.465-475., [Online].

[6] Ye, Y., Qiu, D., Sun, M., Papadaskalopoulos, D. and Strbac, G., 2019. Deep reinforcement learning for strategic bidding in electricity markets. IEEE Transactions on Smart Grid, 11(2), pp.1343-1355., [Online].

[7] Qiu, D., 2020. Modelling and analysing the impact of local flexibility on the business cases of electricity retailers., [Online].

[8] Ringler, P., Keles, D. and Fichtner, W., 2016. Agent-based modelling and simulation of smart electricity grids and markets–a literature review. Renewable and Sustainable Energy Reviews, 57, pp.205-215., [Online].

[9] P. Ringler, D. Keles, W. Fichtner, "Agent-based modelling and simulation of smart electricity grids and markets–a literature review.," *Renewable and Sustainable Energy Reviews,* vol. 57, pp. 205-215, 2016.

[10] Dorokhova, M., Martinson, Y., Ballif, C. and Wyrsch, N., 2021. Deep reinforcement learning control of electric vehicle charging in the presence of photovoltaic generation. Applied Energy, 301, p.117504., [Online].

[11] Whitley, D., 1994. A genetic algorithm tutorial. Statistics and computing, 4(2), pp.65-85., [Online].

[12] Marks, R., "Market design using agent-based models," *Handbook of computational economics,* vol. 2, pp. 1339-1380, 2006.

[13] Punia, S. et al. , "Deep learning with long short-term memory networks and random forests for demand forecasting in multi-channel retail," *International journal of production research,* vol. 58, no. 16, pp. 4964-4979, 2020.

[14] Qiu, D., Ye, Y., Papadaskalopoulos, D. and Strbac, G., 2020. A deep reinforcement learning method for pricing electric vehicles with discrete charging levels. IEEE Transactions on Industry Applications, 56(5), pp.5901-5912, [Online].

[15] Qiu, D., Ye, Y., Papadaskalopoulos, D. and Strbac, G., 2021. Scalable coordinated management of peer-to-peer energy trading: A multi-cluster deep reinforcement learning approach. Applied Energy, 292, p.116940., [Online].

[16] Zhou, Z., Chan, W.K.V. and Chow, J.H., 2007. Agent-based simulation of electricity markets: a survey of tools. Artificial Intelligence Review, 28(4), pp.305-342., [Online].

[17] Aliabadi, D.E., Kaya, M. and Şahin, G., 2017. An agent-based simulation of power genera-tion company behavior in electricity markets under different market-clearing mecha-nisms. Energy Policy, 100, pp.191-205., [Online].

[18] Murphy, F.H. and Smeers, Y., 2005. Generation capacity expansion in imperfectly compet-itive restructured electricity markets. Operations research, 53(4), pp.646-661., [Online].

[19] Yang, J., Zhao, J., Luo, F., Wen, F. and Dong, Z.Y., 2017. Decision-making for electricity retailers: A brief survey. IEEE Transactions on Smart Grid, 9(5), pp.4140-4153., [Online].

[20] Morstyn, T., Farrell, N., Darby, S.J. and McCulloch, M.D., 2018. Using peer-to-peer energy-trading platforms to incentivize prosumers to form federated power plants. Nature Energy, 3(2), pp.94-101., [Online].

[21] Morstyn, T., Farrell, N., Darby, S.J. and McCulloch, M.D., 2018. Using peer-to-peer ener-gy-trading platforms to incentivize prosumers to form federated power plants. Nature En-ergy, 3(2), pp.94-101, [Online].

[22] Mengelkamp, E., Staudt, P., Garttner, J. and Weinhardt, C., 2017, June. Trading on local energy markets: A comparison of market designs and bidding strategies. In 2017 14th In-ternational Conference on the European Energy Market (EEM) (pp. 1-6). IEEE., [Online].

[23] Clauß, J., Stinner, S., Sartori, I. and Georges, L., 2019. Predictive rule-based control to activate the energy flexibility of Norwegian residential buildings: Case of an air-source heat pump and direct electric heating. Applied Energy, 237, pp.500-518., [Online].

[24] Heendeniya, C.B., 2021. Agent-based modeling of a rule-based community energy sharing concept. In E3S Web of Conferences (Vol. 239). EDP Sciences., [Online].

[25] Chen, T. and Su, W., 2018. Local energy trading behavior modeling with deep reinforcement learning. Ieee Access, 6, pp.62806-62814., [Online].

[26] Wan, Z., Li, H., He, H. and Prokhorov, D., 2018. Model-free real-time EV charging scheduling based on deep reinforcement learning. IEEE Transactions on Smart Grid, 10(5), pp.5246-5257., [Online].

[27] Park, J.B., Kim, J.H. and Lee, K.Y., 2002, July. Generation expansion planning in a competi-tive environment using a genetic algorithm. In IEEE Power Engineering Society Summer Meet-ing, (Vol. 3, pp. 1169-1172). IEEE., [Online].

[28] Jain, A.K. and Srivastava, S.C., 2009. Strategic bidding and risk assessment using genetic algorithm in electricity markets. International Journal of Emerging Electric Power Sys-tems, 10(5)., [Online].

[29] Meng, F.L. and Zeng, X.J., 2016, July. A bilevel optimization approach to demand response management for the smart grid. In 2016 IEEE Congress on Evolutionary Computation (CEC) (pp. 287-294). IEEE., [Online].

[30] Sutton, R.S. and Barto, A.G., 2018. Reinforcement learning: An introduction. MIT press., [Online].

[31] G. Xiong, T. Hashiyama, and S. Okuma, “An electricity supplier bidding strategy through Q-learning,” in Proc. Power Eng. Soc. Summer Meeting, vol. 3. Chicago, IL, USA, Jul. 2002, pp. 1516–1521., [Online].

[32] M. B. Naghibi-Sistani, M. R. Akbarzadeh-Tootoonchi, M. H. J.-D. Bayaz, and H. Rajabi-Mashhadi, “Application of Q-learning with temperature variation for bidding strategies in market based power systems,” Energy Convers. Manage., vol. 47, nos. 11–12, pp. 1, [Online].

[33] H. Song, C.-C. Liu, J. Lawarrée, and R. W. Dahlgren, “Optimal electricity supply bidding by Markov decision process,” IEEE Trans. Power Syst., vol. 15, no. 2, pp. 618–624, May 2000., [Online].

[34] V. Nanduri and T. K. Das, “A reinforcement learning model to assess market power under auction-based energy pricing,” IEEE Trans. Power Syst., vol. 22, no. 1, pp. 85–95, Feb. 2007., [Online].

[35] A. C. Tellidou and A. G. Bakirtzis, “Agent-based analysis of capacity withholding and tacit collusion in electricity markets,” IEEE Trans. Power Syst., vol. 22, no. 4, pp. 1735–1742, Nov. 2007., [Online].

[36] M. Rahimiyan and H. R. Mashhadi, “An adaptive Q-learning algorithm developed for agent-based computational modeling of electricity market,” IEEE Trans. Syst., Man, Cybern. C, Appl. Rev., vol. 40, no. 5, pp. 547–556, Sep. 2010., [Online].

[37] N.-P. Yu, C.-C. Liu, and J. Price, “Evaluation of market rules using a multi-agent system method,” IEEE Trans. Power Syst., vol. 25, no. 1, pp. 470–479, Feb. 2010., [Online].

[38] M.Peters,W.Ketter,M. Saar-Tsechansky, and J.Collins,“A reinforcement learning approach to autonomous decision-making in smart electricity markets,” Mach. Learn., vol. 92, no. 1, pp. 5–39, Apr. 2013., [Online].

[39] B.-G.Kim,Y. Zhang, M.VanDer Schaar, and J.-W. Lee, “Dynamic pricing and energy con-sumption scheduling with reinforcement learning,” IEEE Trans. Smart Grid, vol. 7, no. 5, pp. 2187–2198, Sep. 2016., [Online].

[40] R. Lu, S. H. Hong, and X. Zhang, “A dynamic pricing demand response algorithm for smart grid: Reinforcement learning approach,” Appl. Energy, vol. 220, pp. 220–230, Mar. 2018., [Online].

[41] R. Lu and S. H. Hong, “Incentive-based demand response for smart grid with reinforce-ment learning and deep neural network,” Appl. Energy, vol. 236, pp. 937–949, Feb. 2019., [Online].

[42] Wen, Z., O’Neill, D. and Maei, H., 2015. Optimal demand response using device-based reinforcement learning. IEEE Transactions on Smart Grid, 6(5), pp.2312-2324., [Online].

[43] O'Neill, D., Levorato, M., Goldsmith, A. and Mitra, U., 2010, October. Residential demand response using reinforcement learning. In 2010 First IEEE international conference on smart grid communications (pp. 409-414). IEEE., [Online].

[44] Ruelens, F., Claessens, B.J., Vandael, S., De Schutter, B., Babuška, R. and Belmans, R., 2016. Residential demand response of thermostatically controlled loads using batch rein-forcement learning. IEEE Transactions on Smart Grid, 8(5), pp.2149-2159., [Online].

[45] Dang, Q., Wu, D. and Boulet, B., 2019, June. A Q-learning based charging scheduling scheme for electric vehicles. In 2019 IEEE Transportation Electrification Conference and Expo (ITEC) (pp. 1-5). IEEE., [Online].

[46] Wu, J. and Jia, Q.S., 2018, August. A Q-learning method for scheduling shared EVs under uncertain user demand and wind power supply. In 2018 IEEE Conference on Control Technology and Applications (CCTA) (pp. 601-607). IEEE., [Online].

[47] Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A.A., Veness, J., Bellemare, M.G., Graves, A., Riedmiller, M., Fidjeland, A.K., Ostrovski, G. and Petersen, S., 2015. Human-level control through deep reinforcement learning. nature, 518(7540), pp.529-533., [Online].

[48] Jia, S., Gan, Z., Xi, Y., Li, D., Xue, S. and Wang, L., 2020. A deep reinforcement learning bidding algorithm on electricity market. Journal of Thermal Science, 29(5), pp.1125-1134., [Online].

[49] Yang, Y., Hao, J., Sun, M., Wang, Z., Fan, C. and Strbac, G., 2018, January. Recurrent Deep Multiagent Q-Learning for Autonomous Brokers in Smart Grid. In IJCAI (Vol. 18, pp. 569-575)., [Online].

[50] Wang, B., Li, Y., Ming, W. and Wang, S., 2020. Deep reinforcement learning method for demand response management of interruptible load. IEEE Transactions on Smart Grid, 11(4), pp.3146-3155., [Online].

[51] Mocanu, E., Mocanu, D.C., Nguyen, P.H., Liotta, A., Webber, M.E., Gibescu, M. and Slootweg, J.G., 2018. On-line building energy optimization using deep reinforcement learn-ing. IEEE transactions on smart grid, 10(4), pp.3698-3708, [Online].

[52] Wan, Z., Li, H., He, H. and Prokhorov, D., 2018. Model-free real-time EV charging schedul-ing based on deep reinforcement learning. IEEE Transactions on Smart Grid, 10(5), pp.5246-5257., [Online].

[53] Lillicrap, T.P., Hunt, J.J., Pritzel, A., Heess, N., Erez, T., Tassa, Y., Silver, D. and Wierstra, D., 2015. Continuous control with deep reinforcement learning. arXiv preprint arXiv:1509.02971., [Online].

[54] Ye, Y., Qiu, D., Wu, X., Strbac, G. and Ward, J., 2020. Model-free real-time autonomous control for a residential multi-energy system using deep reinforcement learning. IEEE Transactions on Smart Grid, 11(4), pp.3068-3082., [Online].

[55] Ye, Y., Qiu, D., Li, J. and Strbac, G., 2019. Multi-period and multi-spatial equilibrium analy-sis in imperfect electricity markets: A novel multi-agent deep reinforcement learning ap-proach. IEEE Access, 7, pp.130515-130529., [Online].

[56] Aladdin, S., El-Tantawy, S., Fouda, M.M. and Eldien, A.S.T., 2020. MARLA-SG: Multi-agent reinforcement learning algorithm for efficient demand response in smart grid. IEEE Ac-cess, 8, pp.210626-210639., [Online].

[57] Chen, T. and Bu, S., 2019, September. Realistic peer-to-peer energy trading model for microgrids using deep reinforcement learning. In 2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe) (pp. 1-5). IEEE., [Online].

[58] Vazquez-Canteli, J., Detjeen, T., Henze, G., Kämpf, J. and Nagy, Z., 2019, November. Multi-agent reinforcement learning for adaptive demand response in smart cities. In Journal of Physics: Conference Series (Vol. 1343, No. 1, p. 012058). IOP Publishing., [Online].

[59] Lu, R., Li, Y.C., Li, Y., Jiang, J. and Ding, Y., 2020. Multi-agent deep reinforcement learning based demand response for discrete manufacturing systems energy manage-ment. Applied Energy, 276, p.115473., [Online].

[60] de Vries, L. J., Chappin, E. J. L., & Richstein, J. C. (2015). EMLab-Generation – An experimentation environment for electricity policy analysis. TU Delft, Version 1.2. , [Online].

[61] Lopes, F. (2018). MATREM: an agent-based simulation tool for electricity markets. In Electricity markets with increasing levels of renewable generation: Structure, operation, agent-based simulation, and emerging designs (pp. 189-225). Springer, Cham., [Online].

[62] Algarvio, H., Lopes, F., Sousa, J., & Lagarto, J. (2017). Multi-agent electricity markets: Retailer portfolio optimization using Markowitz theory. Electric Power Systems Research, 148, 282-294., [Online].

[63] Algarvio, H., Viegas, J., Lopes, F., Amaro, D., Pronto, A., & Vieira, S. M. (2015). Elec-tricity usage efficiency in large buildings: DSM measures and preliminary simulations of DR programs in a public library. In International Conference on Practical App, [Online].

[64] Algarvio, H., Lopes, F., & Santana, J. (2016). Multi-agent retail energy markets: contract negotiation, customer coalitions and a real-world case study. In International Conference on Practical Applications of Agents and Multi-Agent Systems (pp. 13-23). S, [Online].

[65] Conejo, A. J., Garcia-Bertrand, R., Carrion, M., Caballero, Á., & de Andres, A. (2008). Optimal involvement in futures markets of a power producer. IEEE Transactions on Power Systems, 23(2), 703-711., [Online].

[66] Ghadikolaei, H. M., Ahmadi, A., Aghaei, J., & Najafi, M. (2012). Risk constrained self-scheduling of hydro/wind units for short term electricity markets considering intermittency and uncertainty. Renewable and Sustainable Energy Reviews, 16(7), 4734-4743., [Online].

[67] Zhang, Y., Yao, F., Iu, H. H., Fernando, T., & Trinh, H. (2015). Wind–thermal systems operation optimization considering emission problem. International Journal of Electrical Power & Energy Systems, 65, 238-245, [Online].

[68] Algarvio, H., Lopes, F., & Santana, J. (2020). Strategic Operation of Hydroelectric Pow-er Plants in Energy Markets: A Model and a Study on the Hydro-Wind Balance. Fluids, 5(4), 209., [Online].

[69] Algarvio, H., Lopes, F., Couto, A., & Estanqueiro, A. (2019). Participation of wind power producers in day-ahead and balancing markets: An overview and a simulation-based study. Wiley Interdisciplinary Reviews: Energy and Environment, 8(5), e343., [Online].

[70] Algarvio, H., Lopes, F., Sousa, J., & Lagarto, J. (2017). Multi-agent electricity markets: Retailer portfolio optimization using Markowitz theory. Electric Power Systems Research, 148, 282-294., [Online].

[71] Algarvio, H., Viegas, J., Lopes, F., Amaro, D., Pronto, A., & Vieira, S. M. (2015). Elec-tricity usage efficiency in large buildings: DSM measures and preliminary simulations of DR programs in a public library. In International Conference on Practical App, [Online].

[72] Miettinen, J., Holttinen, H., & Hodge, B. M. (2020). Simulating wind power forecast error distributions for spatially aggregated wind power plants. Wind Energy, 23(1), 45–62. https://doi.org/10.1002/we.2410, [Online].

[73] Strbac, G., Papadaskalopoulos, D., Chrysanthopoulos, N., Estanqueiro, A., Algarvio, H., Lopes, F., ... & Helisto, N. (2021). Decarbonization of electricity systems in Europe: Market design challenges. IEEE Power and Energy Magazine, 19(1), 53-63., [Online].

[74] Couto, A., Duque, J., Algarvio, H., Estanqueiro, A., Pestana, R., Esteves, J., & Cao, Y. (2020). Impact of the dynamic line rating analysis in regions with high levels of wind and solar PV generation. In 2020 IEEE PES Innovative Smart Grid Technologies Eu, [Online].

[75] Algarvio, H., Lopes, F., Couto, A., & Estanqueiro, A. (2019). Participation of wind power producers in day-ahead and balancing markets: An overview and a simulation-based study. Wiley Interdisciplinary Reviews: Energy and Environment, 8(5), e343., [Online].

[76] ENTSO-E. (2009). Appendix 1 - Load-Frequency Control and Performance. ENTSO-E Operation Handbook, Cc, 1–33., [Online].

[77] Burger, S., Chaves-Ávila, J. P., Batlle, C., & Pérez-Arriaga, I. J. (2017). A review of the value of aggregators in electricity systems. Renewable and Sustainable Energy Reviews, 77, 395–405. https://doi.org/10.1016/j.rser.2017.04.014., [Online].

[78] Nuno, E., Koivisto, M., Cutululis, N. A., & Sorensen, P. (2018). On the Simulation of Ag-gregated Solar PV Forecast Errors. IEEE Transactions on Sustainable Energy, 9(4), 1889–1898. https://doi.org/10.1109/TSTE.2018.2818727, [Online].

[79] Algarvio, H. (2021). The Role of Local Citizen Energy Communities in the Road to Car-bon-Neutral Power Systems: Outcomes from a Case Study in Portugal. Smart Cities, 4(2), 840-863. , [Online].

[80] Dykes, K., King, J., DiOrio, N., King, R., Gevorgian, V., Corbus, D., ... & Moriarty, P. (2020). Opportunities for Research and Development of Hybrid Power Plants (No. NREL/TP-5000-75026). National Renewable Energy Lab.(NREL), Golden, CO (United States). , [Online].

[81] Lian, J., Zhang, Y., Ma, C., Yang, Y., & Chaima, E. (2019). A review on recent sizing methodologies of hybrid renewable energy systems. Energy Conversion and Manage-ment, 199, 112027., [Online].

[82] Duchaud, J. L., Notton, G., Fouilloy, A., & Voyant, C. (2019). Wind, solar and battery micro-grid optimal sizing in Tilos Island. Energy Procedia, 159, 22-27., [Online].

[83] Zhang, W., Maleki, A., Rosen, M. A., & Liu, J. (2019). Sizing a stand-alone solar-wind-hydrogen energy system using weather forecasting and a hybrid search optimization algo-rithm. Energy conversion and management, 180, 609-621, [Online].

[84] Carvalho, D. B., Guardia, E. C., & Lima, J. W. M. (2019). Technical-economic analysis of the insertion of PV power into a wind-solar hybrid system. Solar Energy, 191, 530-539., [Online].

[85] Regulation (EU) 2019/943 of the European Parliament and of the council on the internal market for electricity. (2019). Official Journal of the European Union, 2019(714), 54–124., [Online].

[86] MIBEL Board of Regulators. (2018). Integration of Renewable Generation and Cogener-ation in Mibel and in the Operation of Their Electrical Systems (Issue March)., [Online].

[87] D. Qiu, Y. Ye, D. Papadaskalopoulos and G. Strbac, "Scalable coordinated management of peer-to-peer energy trading: A multi-cluster deep reinforcement learning approach," *Applied Energy,* vol. 292, no. 116940, 2021.

[88] Y. Ye, D. Papadaskalopoulos, J. Kazempour and G. Strbac, "Incorporating non-convex operating characteristics into bi-level optimization electricity market models. IEEE Transactions on Power Systems," *IEEE Transactions on Power Systems,* vol. 35, no. 1, pp. 163-176, 2019.

[89] J. Li, Y. Ye, D. Papadaskalopoulos and G. Strbac, "Distributed Consensus-Based Coordination of Flexible Demand and Energy Storage Resources," *IEEE Transactions on Power Systems,* 2020.

[90] W. Nicholson and C. M. Snyder, Microeconomic Theory: Basic Principles and Extensions, Cengage Learning , 2016.