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 final version of the report that deals with the representation of electricity market actors' in the agent-based models (ABMs) used in TradeRES project and it was developed within the scope of *Task 4.2 - Representation of new actors, markets and policies*. With the ABMs available in the consortium (AMIRIS, the EMLab, the MASCEM and the RESTrade) 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 principles. Emphasis is given to 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 - Characterization of new flexible players*. The operational attributes and the behavioural 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 directions. Such modelling enhancing activities 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.

The more detailed consideration of the ABMs that follows next 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 - Market design for a reliable ~100% renewable electricity system*, this work is closely related to other WP4 deliverables. This final version of the deliverable incorporates perspectives of other subtasks of WP4 that have developed in parallel to T4.2 and have already concluded. This version also aims to be a reference for other ongoing and forthcoming deliverable reports that address flexibility options modelling (D4.1-D4.3) and the market design modelling requirements (D4.5).

Finally, the representation of the actors involved more at the local level (the supplier, the prosumer and the local energy market operator) is presented from the perspective of the Local Energy Market Simulation Framework that is to be used complementary to the participating ABMs for the study of interactions and outcomes of local markets.

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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
CP	Capacity premium
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
FMP	Fixed market premium
FIT	Feed-in tariff
GA	Genetic Algorithm
GTM	Game Theoretic Modelling
H&C	Heating and Cooling
HVAC	Heating, Ventilating and Air Conditioning
HyPP	Hybrid Renewable Power Plant
KKT	Karush-Kuhn-Tucker
LEM	Local Energy Market
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
VMP	Variable market premium
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 which are solved analytically. Difficulties with 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 causal 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, the MASCEM and the RESTrade, which have been presented in D4.6 - *Market model communication interfaces* [1]. 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 this final version of the “New actor types in electricity market simulation tools” report is building upon the development of the first version that was submitter in M19.

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 - Characterization of new flexible players* [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.

In Section 5, the representation of the actors strongly involved in the local level is presented from the perspective of the LEM Simulation Framework that is to be used in the Local Energy Communities case study. Two Local Environments are defined – the Broad and the Narrow – with the focus being different in each one of them. In the former, the focus is on the interaction between actors belonging in different layers (Physical, Aggregation, Market) and in the latter the emphasis in the local market and the internal mechanisms. In that context, the supplier, the prosumer and the LEM operator are discussed

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[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.

with the example formulations making the necessary links to the operational and behavioural dimension analysis of D3.2.

Finally, this report concludes in Section 6 with a summary of the approaches and technics adopted for the translation of actors' types to agents of the simulation models used in TradeRES project and an encapsulation of the directions 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 (electricity market) Actor-ID cards being among 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. 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 - New market designs in electricity market simulation models* [3] as well. Figure 1 depicts this information exchange between tasks and the interrelation of the deliverables.

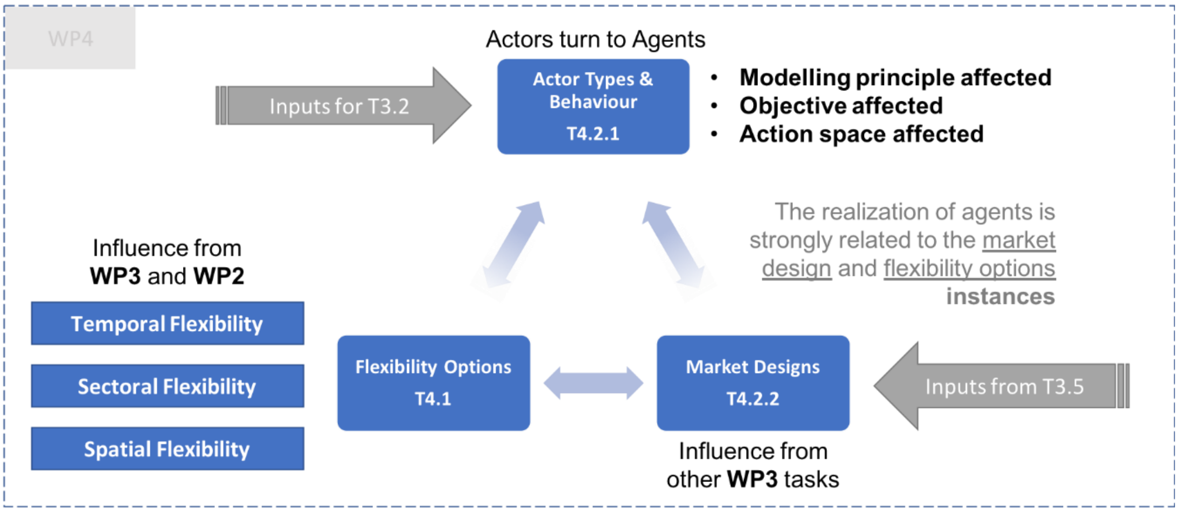

Figure 1: Schematic representation of relations with other tasks and deliverables.

This deliverable is accompanied by a series of other deliverables from TradeRES Work Package 4. The first three deliverables (D4.1 - D4.3) were published close to the first version of D4.4, while D4.5 has been developed concurrently with this report in T4.2. Please refer to the following deliverables to gain deeper insights on the specific topics:

- Deliverable 4.1 [4] covers model enhancements with respect to temporal flexibility.
- Deliverable 4.2 [5] focusses on the implementation of sectoral flexibility within TradeRES models.
- Deliverable 4.3 [6] 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.

Finally, it should be stated that this version of the deliverable has been influenced by the evolvements in WP5, where the simulations take place and the corresponding models run and are validated. It is also expected this report as well as the developments described here contribute to some of the tasks of WP5, specifically in the analysis and interpretation of the results.

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, and 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 [7]. 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 driven by appropriate market designs.

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 [8]. Other participants, due to their functionalities, may be located at each level of this framework. A detailed analysis of the actors in electricity markets 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 is 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) [9], [10], 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) [11]. 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 [12].

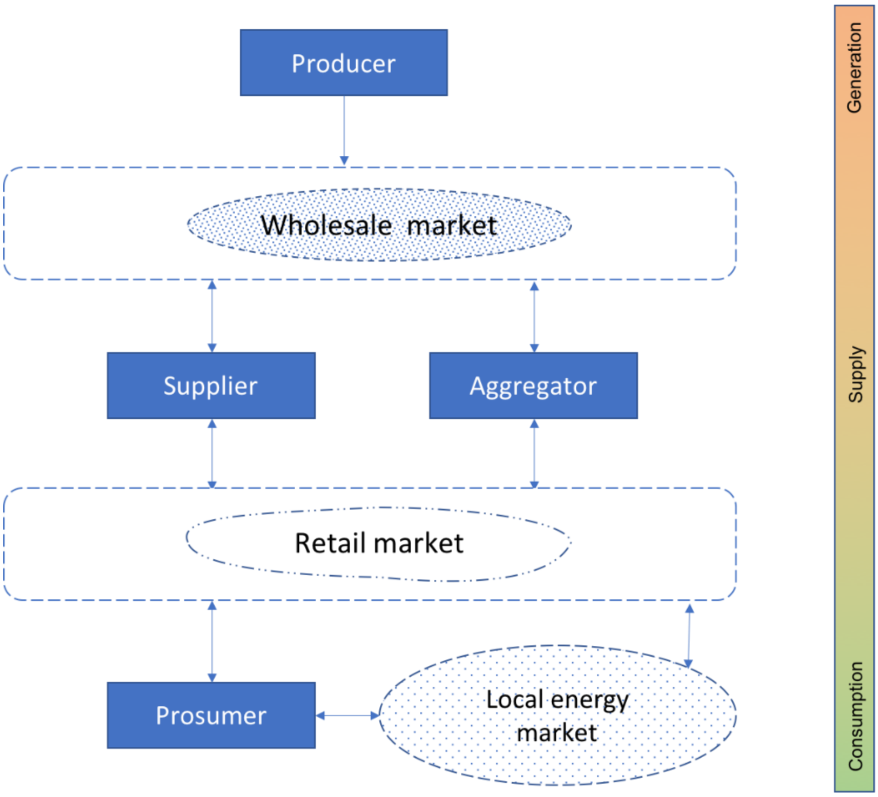

Figure 2: The deregulation of electricity markets [13].

Agent-based modelling (ABM) has received increasing attentions in recent years owing to its advantages in modelling large-scale complex and stochastic systems [14]. 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 has been successfully used for investigating many real-world complex electricity market problems [15].

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 [16]. 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 [17]. 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 [12].

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) [18]. 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) [19], and the pinpointing of strategic retail prices for consumers (e.g., RL) [20] 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 [21].

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 [22].

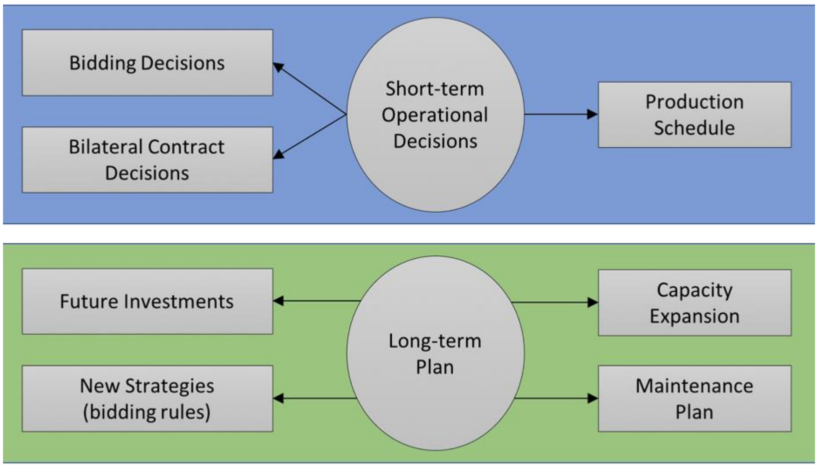

Figure 3: Two-level decision making by electricity producers.

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 [23]. 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 to study the electric power system transition at the time scales 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 [24]. 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 [25]. 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 [25].

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. [26]. 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 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 [27].

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.

The role of the energy storage in the energy markets and in trading will become more significant as the ESS technology becomes more viable in tecno-economic terms and its penetration in the energy system increases [28]. The usage of ESS may vary in scale, with the operational goals being different as well. More centralised infrastructures integrated to large-scale vRES generation (e.g., PV plants, wind farms, etc) aim to smooth and control the output of the system. Alternatively, on their distributed form, ESS can enhance self-consumption of local communities, support the active management of the distribution network and reduce the demand peaks.

The extensive adoption of EVs, which primarily aim to offer clean and cost-effective transportation, enhances the electric energy storage capabilities and not only facilitates the transition to the integrated and decarbonised energy system paradigm but also makes EVs a natural player in energy trading. The bidirectional chargers are the technical enablers of the exchange of electric power between the EVs and the grid, making the vehicles and their users interacting with other market participants under either the Grid-to-Vehicle or the Vehicle-to-Grid mode.

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) [29] 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

As conceptually RBC is based on predetermining the logic of the agents, it is very much dependent to the design approach as it requires domain-specific expertise as well as knowledge of the criteria and their importance in decision making process. In certain cases, the rule-based approach can be easily represented, communicated, and understood given that there are transparent causality links [30]. Currently, RBC is widely used for automatic control problems in smart grid applications. Authors in [31] proposed a predictive rule-based control to activate the energy flexibility of a residential building. Authors in [32] 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 [33] and EV real-time smart charging behaviour [34]. However, rule bases do not scale efficiently making the RBC approach less adequate for large problems that are characterised of high complexity.

2.3.2. Genetic Algorithm

GA is a type of evolutionary algorithm 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 [35] the authors proposed a framework for a generation expansion planning applicable in a competitive environment using GA. Authors in [36] 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 [37] 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]. General in the agent-based learning but also specifically in reinforcement learning the agent is considered the main entity and it is assumed to interact with the environment. Consequently, the Agent and the Environment objects can be described as follows:

  1. The ***Agent*** is perceiving the status of the environment (State) through its interaction and receives some feedback (Reward). The agent presents some form of intelligence as they can perform learning functioning, through which the decisions (Action) are made and improved. The decision-making process of the agent is conditional to the external environment since the selection of the action is made according to the state. The learning functionality of the agent is the observation of the external environment and the formation of a strategy according to the reward.
  2. The ***Environment*** from a practical point of view, consist of the elements that are outside the agent object, with the state being affected by the action of the agent, with the related reward being awarded to the agent.

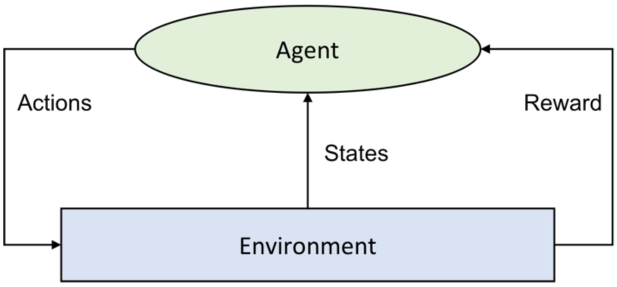

Figure 4: Agent-environment interactions in SARL [38].

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. $p(s_{t+1}|s_t, a_t) = p(s_{t+1}|s_1, a_2, \ldots, s_t, a_t)$, 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 $r: \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$, 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 a_t 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 [38]. Authors in [39], [40], [41], [42], [43], [44], [45] and [46] 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 [47], [48], [49] and [50] 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 [51], [52], [53] and EV smart charging strategies [54], [55]. 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) [38] 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 [56] 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 [57], smart pricing determinations [58], and demand response problem of consumers [59] - [60] and EVs [61]. 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 [62] featuring an actor-critic architecture, which is able to handle the high-dimensional continuous state and action spaces. The existing literature has successfully applied DDPG method to the strategic bidding problem of electricity producer in a non-convex unit commitment (UC) problem [12], strategic pricing problem of an EV aggregator considering EV discrete charging levels [20], and the real-time home energy management problem [63].

- **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 $\pi_i(a_1|o_1){:}\,\mathcal{O}_i \times \mathcal{A}_i \rightarrow [0,1]$ to choose actions executed to the environment and transit to the next state based on the transition function $\mathcal{T}{:}\,\mathcal{S} \times \mathcal{A}_1 \times \dots \times \mathcal{A}_I \rightarrow \mathcal{S}$. 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 $r_{i,t}{:}\,\mathcal{S} \times \mathcal{A}_i \rightarrow \mathbb{R}$ 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 [64], demand response problem of consumers [65], and peer-to-peer (P2P) energy trading problem [66]. 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 [67] and energy management problem for manufacturing systems [68]. 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 [21] 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, MAS-CEM 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 identified 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.

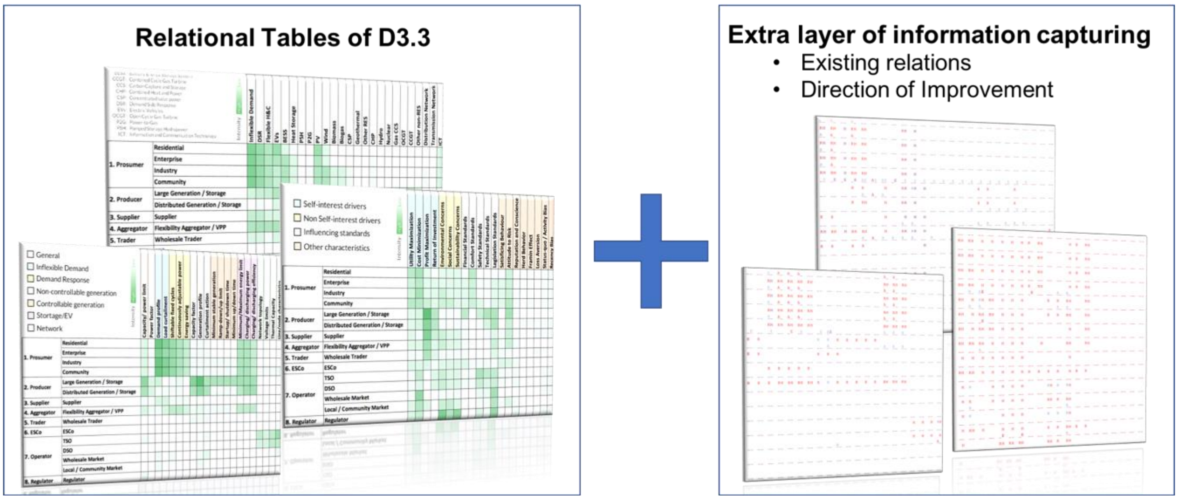

Figure 5: Development of enhanced relational tables with extra layer of information.

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, directly influence 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 consists 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, "M" for MASCEM and "R" for RESTrade.

Considering in more detail Table 1, 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, who are considered being either large or distributed and represent either generation or storage, are and will be further represented in models. EMLab, 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: Low – High

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 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 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 aggregated prosumers in the context of balancing markets, where they can provide energy balance to the power system. 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 is concerned, it used a segmented load and it is being adapted so that it uses the market clearing, including the demand representation, of AMIRIS

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 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 balancing 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: increase 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 by 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 operations 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.

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

Intensity: High – Low

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

Existing / Direction / Both

Actor		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	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—

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 have been also highlighted, especially for prosumers and the aggregator, as well as safety standards for TSO, DSO and regulator, and, finally, attitude to risk, for prosumers, producers, suppliers and aggregator.

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	Type	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 began 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 implemented enhancements are further described as well.

4.1 Initial agents and modelling principles

The presentation of the agents in the initial versions of the models is performed in 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:***
  National power demand is modelled as an aggregated block. Regarding 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 by offering power at marginal cost for each power plant.

Renewable generation can be split into power segments. These segments can consider any criterion for distinction (e.g., power limits, remuneration preconditions, location, etc.). 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 of renewable units is offered via a fixed market premium.

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.

Price 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 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. 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 are 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 [69].

The variability 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 [69].

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 operator:***
  Three agents, MIBEL (Iberian Electricity Market), EPEX (European Power Exchange) and Nord Pool (Nordic Power Exchange).

- ***Local/Community market operator:***
  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 operator and the local/community market operator 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 were planned and developed 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 [70] 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 MATREM these agents are only able to operate in retail markets and negotiate bilateral contracts with suppliers [71]. 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 [72]. On RESTrade 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) Their optimization functions have the goal of minimizing costs according to ToU rates and their flexible demand. MATREM also supports coalitions of consumers [73]. For the time being RESTrade does not models prosumers.

- ***Producers*****:**
  MATREM'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 [74], [75], [76]. 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 [77]. 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 [78].

- ***Suppliers***:
  A supplier agent can participate both in wholesale and retail markets. On MATREM 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 [79]. 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 [80].

- ***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 [81]. This aggregation is spatially limited to a control region within the power system. They only negotiate at spot markets [82].

- ***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 [83]. It is equipped with the market mechanisms of the balancing markets [84]. This agent is responsible for the aFRR capacity procurement, using the ENTSO-E and the Portuguese formulations [85]. It is also responsible for clearing the aFRR capacity and energy, and mFRR energy market based on the marginal pricing or the pay-as-bid approaches. 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 [83].The TSO is also responsible for the Imbalance Settlements of the Balance Responsible Parties imbalances. It computes the imbalance prices using the single price Portuguese rule or the double pricing Nordpool or Spanish rules.

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

Based on the current stage of the model and the purpose and characteristics of the project, some enhancements regarding the actors' capabilities were planned and developed as described in Section 4.2.4.

4.2 New agents and agent enhancements

Enhancements as well as the introduction of new agents are presented in this subsection, 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

New agents, policy measures, strategies, and evaluation options were implemented in AMIRIS in the course of TradeRES. These enhancements are described in the following. In light of recent and radical developments in the energy sector further enhancements are deemed necessary for AMIRIS. This especially includes the connection to the hydrogen sector. Therefore, it is planned to also model agents for the operation of hydrogen-fuelled power plants and electrolysers. 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:***
  The producer agents' reporting capabilities were significantly enhanced to allow for more complex simulation result assessment. This includes tracking of consumed fuels and emitted CO_2, as well as tacking of income and expenses. As mentioned above, it is planned to implement hydrogen-fuelled thermal power plants.

- ***Suppliers:***
  According to plan, supplier agents were not enhanced beyond their existing implementation.

  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.

  Multiple different real-time pricing options for load-shifting were implemented in AMIRIS. Consumer price components (i.e., procurement, grid charges, levies, taxes) can be static or time-varying according to real-time market prices. In addition, grid charges can be determined based on annual peak capacity. The load shifting operation agent was enhanced to consider these different consumer pricing mechanics during its dispatch optimisation. This optimisation can be targeted at either minimising the total system cost or maximising the agent's profits.

The optimisation of household heat pumps with heat reservoir capacities was implemented in AMIRIS. Strategies for operating at a constant temperature or between a minimal and maximal temperature were integrated into AMIRIS. Three different thermal response models for the depicted households were created. Ongoing tasks include the calibration of the thermal response models to the scenario data defined in WP2.

Without a detailed understanding of individual charging behaviour, AMIRIS would not have provided additional insights regarding demand of electric vehicles and its potential for flexibility compared to the optimisation models within TradeRES. Thus, AMIRIS will derive the demand from electric vehicle charging from results of the optimisation models.

- ***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, no further trader-agent classes were developed but existing agents were enhanced significantly with regard to policy instruments (see item 8 “Regulators”). Previous, rather rigid implementations of policy instruments and associated trading strategies were replaced to provide the necessary flexibility for policy assessments within TradeRES. Therefore, AMIRIS now supports smart trading strategies for various support policies. The trading agents for renewable energy in AMIRIS can now also manage multiple sets of different associated plant operators with individual support policies. In this way, more complex portfolios can be simulated.

  In addition, all trading agents for renewables can now be parameterised with individual power forecast error statistics. This allows to assess the impact of new market products with shorter gate-closure lead times onto the profits of renewable agents.

- ***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:***
  The wholesale market operator in AMIRIS was found to be already compatible with different proposed wholesale market rules, including new products with shorter time units and rolling-horizon market clearing - please refer to Deliverable D4.1 for details. Also, other market operators, i.e., the fuels market operator and carbon market operator are compatible with these new products. Therefore, no changes were required for the market operators.

  Albeit not developed within the scope of the TradeRES project, AMIRIS was improved with regard to market coupling during another project. This algorithm is capable of clearing multiple markets in parallel by minimising the total system cost of the linked markets considering provided transmission grid capacities. If required, this newly developed market coupling algorithm could be adapted for the needs of the TradeRES project and thus be utilized for more complex assessments with AMIRIS, e.g., within the European case study in WP5.

- ***Regulators:***
  Several different support policies were implemented in AMIRIS in a highly flexible way, thus giving modellers maximum freedom of parameterisation. This includes the following support policies: “feed-in tariff” (FIT), “fixed market premium” (FMP), “variable market premium” (VMP), “contracts for differences” (CFD) and “capacity premium” (CP). Different parameterisations can be specified for different energy carriers or remuneration sets. This enables precise parameterisation of different sets of renewable plant operators, differentiated by, e.g., location, year of construction, or capacity.

  FIT and FMP policies allow to specify a time series for the pay-out scheme. This enables the integration of multiple cohorts into a single remuneration set. For both policies, the pay-out is calculated according to the actual feed-in of the plant operator. Plant operators also receive the market revenues when using FMP in contrast to FIT.

  VMP and CFD are more dynamic policies. Their premia are calculated by taking the difference between the estimated levelized cost of electricity production (LCOE) and the average market revenues of that energy carrier. LCOE can be specified individually for each remuneration set and can vary over time. In case of CFD, operators need to pay-back market revenues exceeding their estimated LCOE.

  Finally, in case of CP policies, operators are rewarded based on their installed electricity production capacity. Again, the premium can be a time series.

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 investment algorithm of EMLab requires iterating the dispatch algorithm several times. This would require stopping the calculations, extracting information, feeding it to the second model, using the results of the second model, and restarting the calculations. This would be very complex and require large code adjustments. For this reason, EMLab that was originally written in Java, was rewritten into smaller modules in Python. A second reason is that the soft linking is executed with a Python tool, Spinetoolbox, which would facilitate the integration. The new EMLab, written in Python is called EMLabpy. Coupling the EMLAB investment algorithm with the AMIRIS dispatch algorithm requires some adjustments to the logic of the investment iteration. It requires adding modules to enable the data extraction and the data insertion into both models. The target investor logic will also be replaced by the RES support results from AMIRIS. Furthermore, a short-term investment algorithm was added. This module represents those investments made in technologies that can be quickly installed, such as PV and batteries. Instead of basing the investment decisions on a forecast of the market, the agents invest in these technologies based on the market revenues from previous simulation years. The long-term investment module kept the myopic behaviour of the investors as described in section 4.1.2. Adding a more detailed short-term market can increase the computational time exponentially, for this reason as a first approach only one energy producer agent is being considered. The agents with simple rules and accounting rules, as indicated in Table 4, have also been simplified. Apart from the model coupling, only minor additions to EMLab are anticipated. The most important enhancement is the addition of the capacity subscription mechanism. This addition requires enhancements to the consumer agents in the dispatch algorithm and it is described in Deliverable 4.5.

4.2.3. MASCEM

Considering the project goals and characteristics, new features were designed and implemented, including the enhancement of the considered actor characteristics and a set of actors' behaviour 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 (details in D4.1, subsection 3.3.2) and electric vehicles management (details in D4.2, subsection 3.2.2) models were designed and integrated into prosumer and the aggregator agents. In specific, a load curtailment model was designed for the inflexible demand and a load shedding and shifting model was developed for flexible loads (see D4.1, subsection 3.3.2.1). 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 (see D4.1, subsection 3.3.2.2). 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, also applies new models developed for resources' aggregation. The aggregation models (described in D4.3, subsection 3.2.2) allow 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. Currently, the MASCEM model enables running the wholesale market considering aggregator agents that represent a fixed set of consumers and generators as well as aggregators representing a restrictive set of consumers/prosumers, negotiating their flexibility in the market. On the other hand, while an aggregator can be a negotiating player (selling or buying) in the wholesale market, it can also be at the same time a market operator in a local market executed at a zone managed by itself (including the necessary interactions with the local DSO). The MASCEM model has the flexibility to define aggregators participating in the wholesale day-ahead market to buy/sell the forecasted demand/surplus of its clients and later (on the following day) adjust their clients' needs in both local electricity markets and flexibility markets.

Other operations that were added to the prosumer and aggregator agents are related to battery storage systems and electric vehicles. For this purpose, two models were designed and developed. The first considers the aggregation of electric vehicles considering their zonal distribution throughout time (see D4.2, subsection 3.2.2). This model supports the actions of the aggregator when negotiating electric energy in the market, flexibility, or when managing local areas and running local markets. This model considers minimum/maximum energy limit, charging/discharging power, and charging/discharging efficiency. The second model (see also D4.2, subsection 3.2.2) 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 was designed to be used by the prosumer, producer, aggregator, wholesale market operator, and local/community market operator agents with particular focus on potentiating demand flexibility (details also in D4.1, subsection 3.3.2.2). Pumped hydropower storage models were also designed for producers, suppliers, and aggregators.

To use these models, the respective players, namely the aggregator and market operators, must interact with the TSO and DSO for the sake of the power network stability. In this way, new models were designed and developed to support the capabilities of the TSO and DSO agents. To this end, the power flow service detailed in D4.5 allows any actor with the role of power network validator (e.g., DSO, TSO, aggregator) to perform an electric grid validation considering any type and topology of distribution or transmission network. The user can select from a large set of available grids and power flow algorithms. A new power network, or updates to an existing one, may also be provided by the user and added to the service's database for future reuse. This model addresses all relevant aspects related to the network, including network topology, voltage limits, thermal capacity, and line/node characteristics. In this way, the actors can undertake network validation actions that enrich the diversity of flexibility of the market models and scenarios to experiment with the project.

Regarding the actor's behaviours, considering the project's objectives, a few behaviours were considered, designed, and developed for different models, namely:

- Utility maximization, environmental, social, sustainability concerns, and legislation standards apply to all actors as appropriate. Different models (e.g., [86]) were developed for distinct actors.
- Cost minimization and profit maximization (e.g., [87]) were also considered for several players from consumers to producers, prosumers, and market operators (wholesale and local/community)
- Comfort standards were considered for prosumers and aggregators [86], safety standards for TSOs and DSOs (e.g., [88]), and attitude to risk for prosumers, producers, suppliers and aggregators [89].

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.

- **Aggregator**:
  Within the TradeRES project, an "aggregator" is a player that aggregates the consumption and/or production of electricity acting as a single entity [90]. 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.

  - **VRES 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 [91]. 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 [92]. It can participate in spot and bilateral markets. Its participa-

tion in balancing markets will be tested considering its technical capabilities to do so. It can negotiate bilateral agreements with producers and suppliers.

- **HyPPs** are co-located power plants that combine two or more renewable resources, with (or without) energy storage systems [93]. 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 [94]:
  - 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 [95], [96] and a maximization of profit in grid connect applications [97].
  - 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.

- ***Consumer/prosumer:***

  Each consumer and prosumer will inform the aggregator regarding its expected flexible and inflexible consumption/net load and respond to prices defined by the CEC or aggregator. The flexible consumption will be used to promote load shifting aiming to minimize the energy costs for this type of players. Further flexibility will be introduced in prosumer players by considering battery energy storage management systems and their technical capabilities to minimize the energy costs.

- ***TSO:***

  The TSO agent will be enhanced by incorporating the new market designs, mechanisms, products, and rules developed in TradeRES project [82]. 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 [98] may allow increasing the level of efficiency of this mechanism and is already in place in some countries [99]. 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 developed. Figure 6 presents the architecture of the RESTrade system that already has several agents and mechanisms, but also foregrounds models 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 and HyPPhave the goal of maximizing their profit. CECs have the goal of minimizing costs for the consumers/prosumers.	Consumers, Prosumers, Producers, Suppliers and TSO
Prosumer	>100 considering different power net load profiles	Computation of inflexible and flexible net loads. Cost minimization	Suppliers and CECs
TSO	1	Increase social welfare	Suppliers and aggregators.

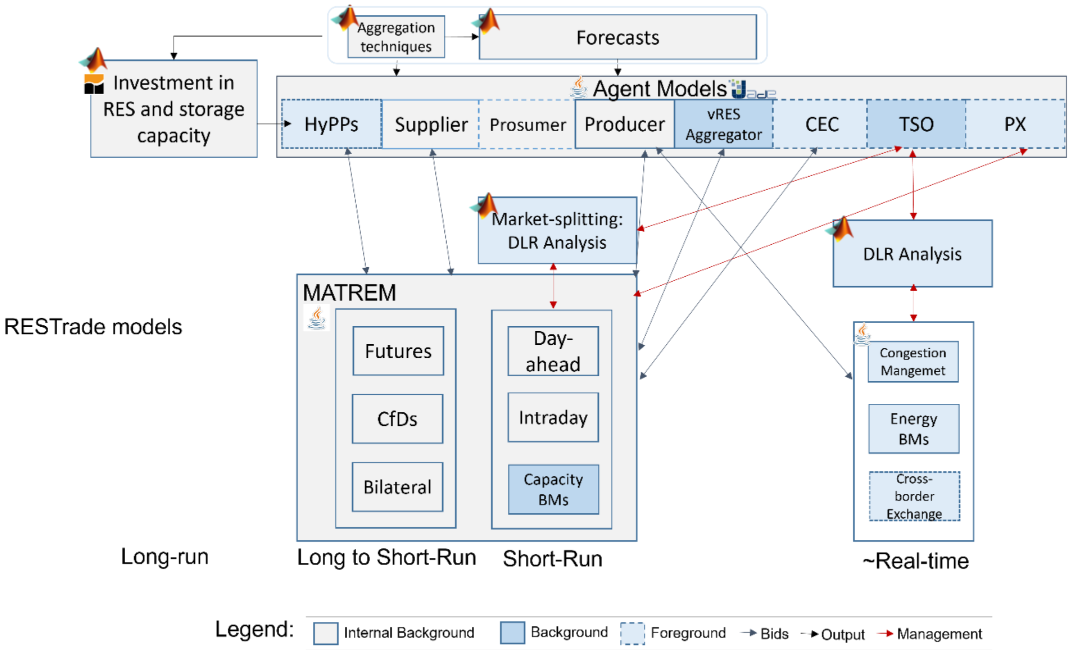

Figure 6: Main architecture of the RESTrade system.Blue-filled boxes correspond to background and foreground modules with open access within the project.

5. Actors in the LEM Simulation Framework

The Local Energy Market (LEM) Simulation Framework aims to support the more focused investigation of market design aspects that deal with the interactions within local environments. This is led by the Imperial College London and is performed complementary to the studies that exploit the previously discussed ABMs, with the simulation activities being part of TradeRES Task 5.2, which includes the performance assessment of current and new market designs and trading mechanisms for local energy community. Figure 7 depicts the areas of focus with respect to Figure 2 that sets interactions in the context of deregulated electricity markets. Two local environments are distinguished, one that sets more broad boundaries and includes the retailer and a narrower one that concentrated the interest in the interaction between the prosuming entities and the LEM. The environment of the more holistic approach can also be defined, with the integration of the wholesale market and the consideration of the networks. As it can be seen in Figure 7, the prosuming entities may be related to several vectors and technologies, while the certain instances than can be developed through the different combinations are mapped to already known and established actors. Indicative examples are the generators in their distributed and micro-scale form, the consumers that can be flexible about their demand, the energy storage asset owners, as well as the energy communities resulted by the formation of coalitions.

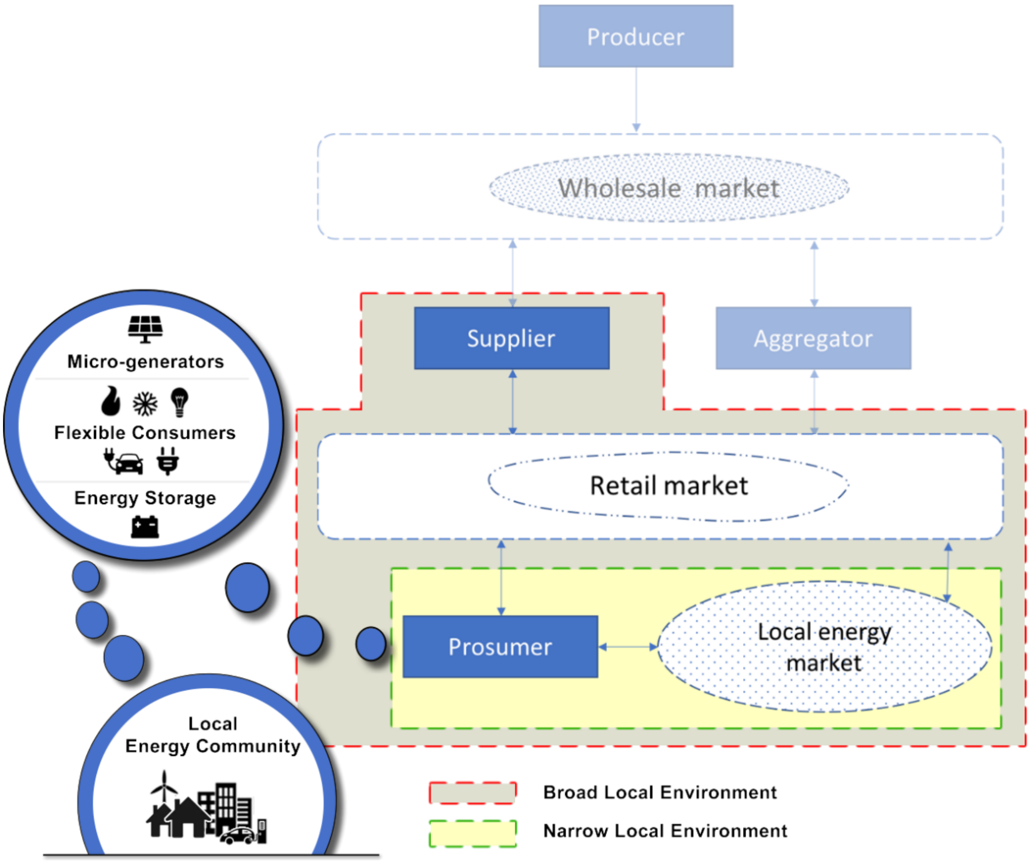

Figure 7: Areas of LEM Simulation Framework focus.

5.1 Strategic behaviour

The multi-layer interactions among competing and cooperative actors in the electricity market constitute a game and game theory offers the theoretical framework for these individual actors who can optimize their decision-makings in a strategic setting. This strategic behaviour involves the acknowledgement of the influence that the choice of an individual may have to the choices made by others and is linked to the anticipation of the expectation in the decision-making process. As discussed in Section 2, the strategic setting contrasts with the price-taker assumption, where individuals take prices as given without considering that their actions affect the formation of the price and is suitable for cases of increased competitiveness with many participants. Considering the LEM, which by definition are small market structures, the adoption of game-theoretical formulations seems appropriate as the strategic behaviour becomes even more significant. On the other hand, there is the increased complexity of reality that requires generous simplification in certain cases. Exactly on that trade-off, ABMs offer a decent compromise and specifically as far as the electricity market modelling is concerned have been continuously gaining ground.

5.2 Information levels

Another significant part deals with the information exchange and the information sets available during the decision-making process. Variations of the different levels of available information may include the extreme cases of private and perfect information respectively as well as the case where the information sets are incomplete. There are situations where the flow of information is imposed by the rules and is coordinated centrally but there are also examples where estimations or biased values are used, making the players myopic. The information flow as well as its integration in the decision-making process is know for its effect in the convergence and stability of the models [100]. Although it is common to assume the agents to be rational, there are several behavioural characteristics that can lead to deviating behaviours, as those described in Section 3.2. Deviations can also be due to the limited knowledge and understanding of the agents, who in lack of sufficient information may have to deal with a black box, making process adjustments and learning naturally attractive. Uncertainty around environmental parameters in several cases can be delt in a similar way to the adoption of a distribution for replacing the expectation but should not be related to the private information concept.

Table 8: Actor classes included in the LEM Simulation Framework.

<table>
<tr><th colspan="3">Supplier</th></tr>
<tr><th colspan="3">Prosumer</th></tr>
<tr><td>- Independent flexible consumer
- Independent micro-generator
- Independent storage owner</td><td>Generic Prosumer</td><td>Energy Community (Cluster of Prosumers)</td></tr>
<tr><th colspan="3">LEM Operator</th></tr>
<tr><td>Centralised clearing</td><td>Mid-market Rate Clearing</td><td>Double-auction Clearing</td></tr>
</table>

5.3 Sub-models of actors

The main actor classes involved in the LEM Simulation Framework, which correspond directly to the entities of Figure 7, are presented in Table 8. The subsections that follow aim to elaborate on their integration into the framework by emphasizing on the assumptions made and providing example formulations for the corresponding sub-models.

5.3.1. Supplier

By assuming a self-interested supplier, the interaction with its client base and the wholesale market is mainly governed by the aim to maximize the overall profit. The client base consists of end-users that behave independently and have predefined portfolio of assets for local micro-generation, residential consumption, and energy storage, while being characterised by distinct operating properties. The business model of the supplier is based on the provision of differentiated prices to its client base for buying and selling energy and the trading in the wholesale market for acquiring the aggregated consumption and marketizing any excess generation. Although the buy/sell prices are not differentiated between the customers for not being discriminatory, it is possible to differ between times. This can be considered more as a market design parameter, since it is related to the retail tariffs (D4.5), with the distinction being made between flat, time-of-use (ToU) and dynamic pricing regimes. The flat tariffs refer to the case where the offered retail prices (for both buying and selling energy) are constant throughout the examined daily horizon or during certain intervals of this horizon (e.g., peak and off-peak periods), while the ToU structure enables the supplier to offer hour-specific retail (buy and sell) prices to its customers. The dynamic prices can extend the differentiation of price during time, taking into account the wholesale price evolution and the network conditions, with the latter not being considered further.

An example formulation of the decision-making problem of the supplier in the context of the “Broad Local Environment” can take the following form. As a business entity main aim is the maximization of profits in its simplified form, i.e., the difference between operational revenues and variable costs, where the exact business structure and the fixed costs are not considered. The supplier perceives demand and generation endpoints as different for metering purposes, while in the case of a single prosumer i and j may correspond to the same end user. Similarly, the energy storage assets considered are operating only on a not self-consumption mode, aiming to benefit from differences in prices.

$$\max_{\{\lambda_t^b, \lambda_t^s, w_t\}} \sum_t \lambda_t^b \left(\sum_i d_{i,t} + \sum_k s_{k,t}^c + u_t n_t\right) - \sum_t \lambda_t^s \left(\sum_j g_{j,t} + \sum_k s_{k,t}^d + (u_t - 1) n_t\right) - \sum_t \lambda_t^w w_t \tag{5.1}$$

subject to

$$\lambda^{min} \le \lambda_t^b, \lambda_t^s \le \lambda^{max}, \forall t \in T \tag{5.2}$$

$$\sum_i d_{i,t} - \sum_j g_{j,t} + \sum_k \left(s_{k,t}^c - s_{k,t}^d\right) + n_t = w_t, \forall t \in T \tag{5.3}$$

The following components are included in the objective function (5.1) that sets the overall profits of the supplier:

i) its revenues from selling energy to demand points, including energy consumption of end users $\sum_i d_{i,t}$ and the charging of storage assets $\sum_k s_{k,t}^c$, as well as the energy sales to another entity (e.g., LEM) $u_t n_t$.

ii) its costs of buying energy from generation points, including the micro-generators $\sum_j g_{j,t}$, the storage assets during their discharging phase $\sum_k s_{k,t}^d$ and the other entity for when energy is sold to the supplier $(u_t - 1)n_t$.

iii) its net cost in the wholesale market, i.e., the cost or revenue of buying or selling energy w_t in the wholesale market respectively.

The retail buy and sell prices offered by the supplier λ_t^b, λ_t^s, as decision variables of the supplier and are subject to the regulatory constraints (5.2) which lower and upper bound them respectively for protecting the customers and preventing the supplier from making excessive profits. Constraints (5.3) express the energy balance constraints of the retailer, where the net energy traded with its customers should be equal to the net energy traded with the wholesale market at each period.

5.3.2. Prosumer

According to D3.2 the Prosumer actor class incorporates the final users and/or groups of users who consume, store, self-generate, participate in flexibility or energy efficiency schemes in a not primary commercial or professional way. To that extent, prosumers can be distinguished based on their type to residential, enterprise and industrial prosumers, while their grouping sets the community prosumer. For the integration of this actor class into the LEM Simulation Framework different instances are considered. For distinguishing the extreme independent instances, the flexible consumer, the independent micro-generator and the energy storage asset owner adopt the different operations separately. The generic prosumer instance incorporates all the operations (demand, supply, and storage) in which a prosumer can be involved and is considered the maximal case with respect to the technology integration aspect, while the aggregation of the aforementioned instance is forming a coalition of prosumers – the energy community – that operates under cooperative goals such as the maximization of the welfare of the community and/or the maximization of self-consumption.

5.3.2.1. Independent instances

a) Flexible Consumer

Although this player may integrate several technologies, from a behavioural perspective its total demanded energy is modelled as the continuous dependent variable of its utility function. Therefore, the flexible consumer aims to maximise the utility perceived from covering the maximum demand (exogenous time series) to the extent of his choice, given the retail (buy) prices determined by the supplier. An example formulation of this problem in the context of the “Broad Local Environment” can be the following:

$$\max_{\{d_{i,t}\}} \sum_t \left(l_{i,t}^D d_{i,t} - q_{i,t}^D d_{i,t}^2\right) - \sum_t \lambda_t^b d_{i,t} \tag{5.4}$$

subject to

$$0 \leq d_{i,t} \leq d_{i,t}^{max}, \forall i \in I, \forall t \in T \tag{5.5}$$

Equations (5.4) - (5.5) present the optimization problem of the flexible prosumer, who aims to maximizes the utility perceived, which is defined as the difference between

i) the benefit/satisfaction received from the use of energy,
ii) the cost paid for buying energy from the supplier.

Constraint (5.5) expresses the flexibility of independent flexible consumer i to modify its demand $d_{i,t}$ within certain limits $d_{i,t}^{max}$.

b) Micro-generator

The micro-generator as an independent instance of prosumer with solely producing capabilities is considered to be controllable, for its active participation to be meaningful. The objective in such case would be to maximise the returns from its operation, i.e., the profits that result from subtracting expenses from the revenues from sales. An example formulation in the context of the “Broad Local Environment” can be the following:

$$\max_{\{g_{j,t}\}} \sum_t \lambda_t^S g_{j,t} - \sum_t \left(l_j^G g_{j,t} + q_j^G g_{j,t}^2\right) \tag{5.6}$$

subject to

$$0 \leq g_{j,t} \leq g_j^{max}, \forall j \in J, \forall t \in T \tag{5.7}$$

With the selection of the generation level $g_{j,t}$, the objective function of (5.6) is maximizing the profits of the independent micro-generator j, which is given by the difference between:

i) its revenue from the energy sales to the supplier,
ii) its costs incurred in production.

Constraint (5.7) expresses the power output limits of the micro-generator.

c) Storage owner

The energy storage asset owner aims to maximise the revenues gained by selling when the price is high energy that has been purchased during periods of low prices, exploiting that way the intraday spread (referred in D3.5 as “time arbitrage”). The constraint optimization problem of the energy storage asset owner aims to set the best possible operation points (charging and discharging actions) given the prices set by the retailer for buying and selling energy. An example formulation in the context of the "Broad Local Environment" can be the following:

$$\max_{\{s_{k,t}^{c}, s_{k,t}^{d}, E_{k,t}\}} \sum_t \lambda_t^s s_{k,t}^d - \sum_t \lambda_t^b s_{k,t}^c \tag{5.8}$$

Subject to

$$E_{k,t} = E_{k,t-1} + s_{k,t}^c \eta_k^c - s_{k,t}^d / \eta_k^d, \forall k \in K, \forall t \in T \tag{5.9}$$

$$E_k^{min} \leq E_{k,t} \leq E_k^{max}, \forall k \in K, \forall t \in T \tag{5.10}$$

$$0 \leq s_{k,t}^c \leq s_k^{max}, \forall k \in K, \forall t \in T \tag{5.11}$$

$$0 \leq s_{k,t}^d \leq s_k^{max}, \forall k \in K, \forall t \in T \tag{5.12}$$

$$E_k^0 = E_{k,t}, \forall k \in K, \forall t = |T| \tag{5.13}$$

The objective function in (5.8) includes the profits of the energy storage provider k, with the formulation aiming to maximise the difference between

i) its revenues from selling energy to the retailer when discharging $s_{k,t}^d$ and
ii) its costs of buying energy from the retailer when charging $s_{k,t}^c$.

The problem is constraint, with (5.9) expressing the energy balance of the energy storage asset $E_{k,t}$ (charging/discharging losses are included), constraint (5.10) represents its minimum and maximum energy limit set by the asset's capacity and suggested depth-of-discharge (DoD), (5.11) - (5.11) include the charging/discharging power limits and (5.13) expresses the energy neutrality assumption, i.e., the energy content of the asset at the start and the end of the examined horizon are assumed equal.

5.3.2.2. Generic Prosumer

The generic prosumer instance incorporates all the operations in which a prosumer may be involved. Although the operations are again distinct, a more detailed representation of the integrated technologies is considered more appropriate for the generic case to bring further accuracy to the framework. Therefore, a wide range of small-scale DER is considered for covering the electrified versions of vectors, with the households having resources of non-shiftable demand (e.g., lighting, electronic devices such as TV and computers), different types of shiftable loads such as EV, Smart Appliance and H&C systems, as well as PV panels, and ESS. The following paragraphs aim to present those resources and establish links to the operational dimension aspects of Section 3.1, by highlighting the operational constraints that different types of DER bring to the framework.

a) Electric vehicle

The electric vehicles present storage capabilities, while the grid-to-vehicle (G2V) and vehicle-to-grid (V2G) modes of operation set the differences in modelling. In the former, the EV acts as a flexible load, with charging phase having the ability to span throughout the parking period. In the latter, the EV acts also as an energy storage asset of variable connection status, an operation complementary to that of flexible load. An example formulation in the context of the "Narrow Local Environment" would include the following constraints:

The storage dynamic model of EV battery energy E_t^{ev} at each time slot t can be formulated as:

$$E_{t+1}^{ev} = E_t^{ev} + P_t^{evc}\Delta t\eta^{evc} + P_t^{evd}\Delta t/\eta^{evd} - E_t^{com} \tag{5.14}$$

$$(1 - DoD^{ev,max})E^{ev,max} \leq E_t^{ev} \leq SoC^{ev,max}E^{ev,max} \tag{5.15}$$

$$0 \leq P_t^{evc} \leq V_t^{ev}A_t^{ev}P^{ev,max} \tag{5.16}$$

$$-(1 - V_t^{ev})A_t^{ev}P^{ev,max} \leq P_t^{evc} \leq 0 \tag{5.17}$$

$$E_{t^{dep}}^{ev} \geq \sum_t E_t^{com} \tag{5.18}$$

Equation (5.15) constitutes the storage dynamic model of EV battery energy E_t^{ev} at each time slot t. Parameters $\eta^{evc} \in (0,1]$ and $\eta^{evd} \in (0,1]$ indicate respectively the EV charging and discharging efficiency, E_t^{com} represents the energy requirement for commuting purposes at time slot t, while P_t^{evc} and P_t^{evd} indicate respectively the EV charging and discharging power. The power rate of EV is $P_t^{ev} = P_t^{evc} + P_t^{evd}$ since P_t^{evc} and P_t^{evd} are assigned with different signs, i.e. $P_t^{evc} \geq 0$ and $P_t^{evd} \leq 0$.

The EV energy content is limited by its battery energy capacity $E^{ev,max}$, and is also related to its battery maximum depth of discharge rate $DoD^{ev,max}$ and the maximum state of charge rate $SoC^{ev,max}$, respectively as it can be seen in (5.15).

The charging and discharging power variables, i.e., P_t^{evc} and P_t^{evd}, are less than the power capacity of the EV at each time slot t and this is ensured by constraints (5.16) and (5.17), where $P^{ev,max}$ is the maximum charging and discharging power rate of the EV. A_t^{ev} represents the connection to the grid status of the EV; $A_t^{ev} = 1$ for the time slot $t \in [0, t^{dep}) \cup (t^{arr}, T]$ and $A_t^{ev} = 0$ for the time slot $t \in [t^{dep}, t^{arr}]$, where t^{dep} and t^{arr} denote the departure and arrive time of EV, respectively. The binary variable $V_t^{ev} \in \{0,1\}$ that represents the charging mode ($V_t^{ev} = 1$) or discharging mode ($V_t^{ev} = 0$) of the vehicle are used to avoid the simultaneous charging and discharging.

Finally, (5.18) ensures the charging level of the EV upon departure at t^{dep} to be sufficient for the travelling plan.

b) Smart appliances

The load of smart appliances that operate in fixed and deferable cycles is an indicative case of flexible loads that can enable the response of the demand side to price signals.

Wet appliances such as the dishwashers, the washing machines and the dryers constitute typical examples of appliances of which the demand depends on the mode of operation and modes correspond to certain energy consumption levels having fixed durations.

The deferability of the cycles up to a maximum delay limit set by the user can the flexibility such smart appliance can offer. Although there can be pauses during the cycles (e.g., dryers) or between the modes the cycles are considered non-adjustable and interruptible so that after the activation occurs the phases cannot be modified and the appliance operated according to the modes until the end of the cycle. D4.5 includes a schematic comparison between the cases of continuously adjustable power with flexible shift intervals and fixed cycles with discretized power states.

By assuming one activation of a single operational cycle per day, an example formulation in the context of the "Narrow Local Environment" takes into account the earliest initiation time t^{in} and latest termination time t^{ter} set by the user during the temporal horizon and can be based on the following constraints:

$$\sum_{t=t^{in}}^{t^{ter}-T^{dur}+1} V_t^{wa} = 1 \tag{5.19}$$

$$P_t^{wa} = \sum_{\tau=1}^{T^{dur}} V_{t+1-\tau}^{wa} A_t^{wa} P_\tau^{cyc} \tag{5.20}$$

Constraint (5.19) imposes one activation on the eligible time frame, given the duration of the cycle of the smart appliance T^{dur}, through the binary variable V_t^{wa} that indication the initiation of the cycle at time point t ($V_t^{wa} = 1$ at the initiation time point; $V_t^{wa} = 0$ otherwise). The demand of appliance at time t, P_t^{wa}, is expressed with respect to the activation binary variable V_t^{wa}, the scheduling availability parameter A_t^{wa} ($A_t^{wa} = 1$ for the appliance scheduling period $t \in [t^{in}, t^{ter}]$ and $A_t^{wa} = 0$ otherwise), and the power demand at each time slot τ of the cycle P_τ^{cyc}.

c) *Heating and Cooling (H&C)*

Heating and cooling systems such as the heating, ventilating and air conditioning (HVAC) systems can be controlled by the households to maintain the indoor temperature to comfort levels by warming the space in the winter and cooling it in the summer. Through the operation of an HVAC system the electric energy is transformed to thermal, offering the comfort living conditions that the user specifies. The exact power demand is difficult to be determined due to the many factors (weather conditions, indoor temperature, insulation, energy efficiency, etc) that influence the dynamic behaviour of the system. Nevertheless, the flexibility in operation of HVAC systems lies in the thermal capacity of the building and the allowance of an indoor temperature range by the users, within which their thermal comfort is preserved.

An example formulation in the context of the "Narrow Local Environment" would incorporate the following constraints:

$$H^{min} \leq H_t^{in} \leq H^{max} \tag{5.21}$$

$$H_{t+1}^{in} = H_t^{in} - (H_t^{in} - H_t^{out} + \eta^{hvac} R^{hvac} P_t^{hvac})\Delta t/(C^{hvac} R^{hvac}) \tag{5.22}$$

$$0 \leq P_t^{hvac} \leq P^{hvac,max} \tag{5.23}$$

Constraints (5.21) ensure the thermal comfort by setting the indoor temperature at time t, H_t^{in}, within the range that H^{min} and H^{max}, minimum and maximum indoor temperature, define. Given the outdoor temperature H_t^{out} and the slack the indoor temperature H_t^{in} offers, the operation of the HVAC system can be scheduled by the optimal specification of its power demand, P_t^{hvac}. Equation (5.22) is the difference equation that models the indoor temperature evolution based on the thermal capacity (C^{hvac}) and resistance (R^{hvac}) of the building and the energy efficiency η^{hvac} of the HVAC system, which acts as a constraint. Finally, the power consumption of the system P_t^{hvac} is assumed to be a continuous variable within certain operation limits as it can be seen in (5.23). This assumption is totally realistic since time t stands for a time interval (slot) during which the system may transition between different discrete operation states, allowing P_t^{hvac} to take any value between the consumption of the no-operation and full-operation during the slot cases.

d) Energy Storage System

Although there can be different technologies in the implementation of an ESS, the selection of which depends highly on the scale of the application and is highly related to technical and economic concerns, the constraints of the example formulation in the context of the "Narrow Local Environment" are quite general closely related to the storage owner sub-model of Section 5.3.2.1.

$$E_{t+1}^{es} = E_t^{es} + P_t^{esc}\Delta t \eta^{esc} + P_t^{esd}\Delta t/\eta^{esd} \tag{5.24}$$

$$(1 - DoD^{es,max})E^{es,max} \leq E_t^{es} \leq SoC^{es,max}E^{es,max} \tag{5.25}$$

$$0 \leq P_t^{esc} \leq V_t^{es}P^{es,max} \tag{5.26}$$

$$-(1 - V_t^{es})P^{es,max} \leq P_t^{esd} \leq 0 \tag{5.27}$$

The difference equation of (5.24) is time-coupling constraint that encapsulated the dynamic model of the ES energy level E_t^{es} at each time t. The charging and discharging efficiency coefficients are parameters η^{esc} and η^{esd} respectively, while P_t^{esc} and P_t^{esd} and the charging and discharging power of the ESS. Here again the power variables are assigned with different signs (i.e., $P_t^{esc} \geq 0$ and $P_t^{esd} \leq 0$), while constraints (5.26) and (5.27) impose the power rating limits of operation. The energy stored in the ESS is limited by its capacity $E^{es,max}$, and is also related to its maximum depth of discharge rate $DoD^{es,max}$ and the maximum state of charge $SoC^{es,max}$.

5.3.2.3. Energy Communities

The establishment of a union with local communal characteristics and common goals, strongly related to energy has been considered as a significant facilitator towards the realization of the distributed paradigm in a decentralised, citizen-engaging and socially efficient way. According to D3.2, the energy community as an actor has been considered to belong to the Prosumer class since the consumption, generation and storage of energy can be the main activities in which it is involved. Although many business models are foreseen for communities, the most promising ones are related to the maximization of self-consumption, the minimization of peak demand, the participation in local markets, the provision of ancillary services, and the development/operation of local assets (e.g., EV charging stations, public dimmable lighting, etc.). In [101] four main categories are presented and reviewed with respect to barriers and the applicability potential. The foreseen report of T5.2 is expected to discuss and analyse further this topic from the same perspective, given that the market design assessment is strongly related to the LEM simulation framework considered here. Finally, in the context of the framework, the energy communities are considered as coalitions of individuals, with the assets being grouped together and their operation considered joint.

5.3.3. LEM Operator

Considering the ongoing decentralisation and decarbonization, the fundamental structure of power system is altered by the increasing penetration of large-scale small-size prosumers with DERs and the enhancement of the system's flexibility. However, this paradigm greatly complicates the operation of the system, as the effective coordination of such large numbers of prosumers involves very significant communication and computational scalability challenges as well as privacy concerns. The local markets have recently emerged as approaches to deal with the coordination challenge of localized prosumers in distribution grid.

The operators of such markets enable prosumers to trade locally, but also coordinate the energy exchanges between prosumers and the upstream grid and address local network problems. In the context of D3.2, the Local Energy Market Operator is considered to belong to the Operators class which includes the entities that are responsible for the operation of a system of an either physical or economic interpretation. Moreover, the local market beyond the coordination benefit can reduce net demand peaks and network losses, resulting in avoidance or deferral of capital-intensive network reinforcements.

In the "Broad Local Environment", where the supplier is included in a strategic manner offering the strategic retail prices, the emphasis is on the interaction that spans in the three layers defined in D3.2, the physical layer that includes the prosumers, the aggregation layer and market layer. Therefore, the focus is more on the interaction among different layers and less on the internal operation process of the LEM itself. As such, the assumption of centralised operation in Table 8 can be made, where the LEM operator is collecting information from all the participants and proceeds with the clearing. An example formulation in that context can be based on the following problem:

$$\max_{V^{lem}} \sum_{i',t}\left(l^D_{i',t} d_{i',t} - q^D_{i',t} d^2_{i',t}\right) - \sum_{j',t}\left(l^G_{j'} g_{j',t} + q^G_{j'} g^2_{j',t}\right) - \sum_t \lambda^b_t u_t n_t + \sum_t \lambda^s_t (u_t - 1) n_t \tag{5.28}$$

where

$$V^{lem} = \{d_{i',t}, g_{j',t}, E_{k',t}, s^{c}_{k',t}, s^{d}_{k',t}, u_t, n_t\} \quad (5.29)$$

subject to

$$\sum_{i'} d_{i',t} - \sum_{j'} g_{j',t} + \sum_{k'}\left(s^{c}_{k',t} - s^{d}_{k',t}\right) = n_t : \lambda^{lem}_t, \forall t \in T \quad (5.29)$$

$$u_t \in \{0,1\}, \forall t \in T \quad (5.30)$$

$$0 \leq d_{i',t} \leq d^{max}_{i',t}, \forall i' \in I', \forall t \in T \quad (5.31)$$

$$0 \leq g_{j',t} \leq g^{max}_{j'}, \forall j' \in J', \forall t \in T \quad (5.32)$$

$$E_{k',t} = E_{k',t-1} + s^{c}_{k',t}\eta^{c}_{k'} - s^{d}_{k,t}/\eta^{d}_{k}, \forall K' \in K, \forall t \in T \quad (5.33)$$

$$E^{min}_{k'} \leq E_{k',t} \leq E^{max}_{k'}, \forall k' \in K', \forall t \in T \quad (5.34)$$

$$0 \leq s^{c}_{k',t} \leq s^{max}_{k'}, \forall k' \in K', \forall t \in T \quad (5.35)$$

$$0 \leq s^{d}_{k',t} \leq s^{max}_{k'}, \forall k' \in K', \forall t \in T \quad (5.36)$$

$$E^{0}_{k'} = E_{k',t}, \forall k' \in K', \forall t = |T| \quad (5.37)$$

The objective function seen in (5.28) is the total surplus of the LEM as it includes the total benefit of all the independent instances of the prosumer that participate in the market, the total cost faced by the participating micro-generators and the costs or revenues emerging from buying or selling transaction with the supplier. The LEM operator, given the perfect information sharing context, takes into account the operational constraints of the participants (5.31) - (5.37).

Constraints (5.29) express the energy balance for the LEM, ensuring that the excess demand or generation n_t is traded with the supplier. The dual variables (λ^{lem}_t) of these constraints constitute the clearing prices of the LEM. The binary nature of decision variable u_t is imposed by (5.30), for the LEM being able to either buy energy ($u_t = 1$) from the retailer or sell energy ($u_t = 0$) to the supplier at each period. The LEM operator in such case provides the operation schedules to independent prosumers that participate into the market and makes decision on the trading of the market with the supplier.

Finally, in the case of the "Narrow Local Environment" where the subject matter turns to be the interaction of individual prosumers within the markets, the interest is transferred to the internal operation of the LEM. This constitutes the ideal environment for setting up a peer-to-peer (P2P) trading case where prosumers are incentivized to trade energy locally using a structure of local market that can be facilitated by a platform, as depicted in Figure 8. As such, the options of each prosumer to supply its consumption loads are diverse. First, prosumers can manage their installed energy portfolios to supply their own loads. Second, prosumers can trade electricity with each other in the P2P energy trading platform following the well-designed market clearing rules. Third, prosumers are still allowed to buy/sell their unbalanced energy with the suppliers at the retail import/export tariffs. The trading processes are repeated for each time slot across a daily horizon, with the objective of minimizing energy cost. For each participant, it is assumed to have a home energy management system for the management of its energy schedules and trading strategies that may consist of price-quantity bids (or quantity bids only) in the P2P energy trading platform.

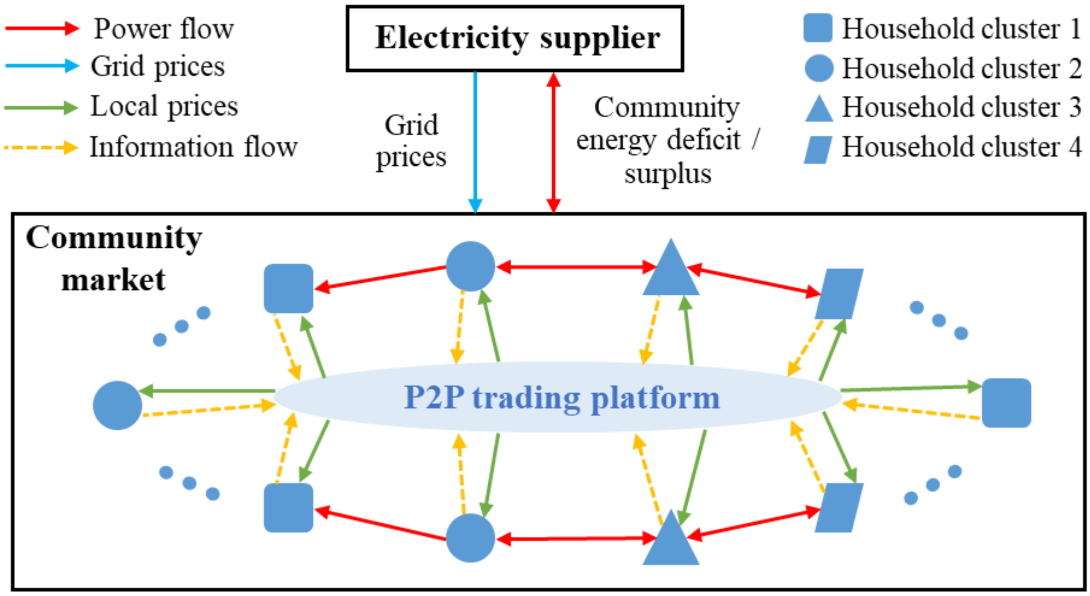

Figure 8: P2P trading platform interaction schematic [21].

To that extent, the local market operator manages the normal operation of P2P energy trading and matches multiple buyers (prosumers with energy deficit) and sellers (prosumer with energy surplus) who are interested in energy trading. When the local market opens, it allows the prosumers to submit their bids/asks with the corresponding price and/or quantity information. Then, the local market operator clears the market (whenever a new transaction exists between buyers and sellers) and publishes the market outcomes (trading prices and quantities) until the market is closed, which are also public for all market participants (prosumers) to adjust their trading strategies at the next round of local market clearing. Currently, mid-market rate and double auction are two popular market clearing rules for P2P energy trading. Further specifications of the process, with the clearing methods and the corresponding algorithms inclusive, are subject to market design choices and out of the scope of this deliverable.

6. Conclusion

Summarizing the analysis performed in this final version of the report that deals with the representation of actor types and behaviours in the market simulation models, it can be said that the ABMs that participate in TradeRES incorporate several agents and present great modelling capabilities. The initial versions of the models, i.e., the versions before the start of TradeRES, have been found to offer an extensive coverage of operational attributes and behavioural aspects identified in earlier stages of the project. The modelling enhancements related to the agents that have been described in this deliverable, aim to provide a more complete, realistic, and contemporary representation of actors in market simulation tools through agents.

The detailed review of the literature that has been performed has provided the necessary background for considering attributes and state-of-the-art 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 time frame, 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 separate 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 of added coverage and added 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 has been made, 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).

The detailed description of the actors that constitute the local environments has been an addition to the final version. The supplier, the prosumer and LEM operator actors have been examined from the agent/player point of view in the context of the LEM Simulation Framework, a development that enables the game-theoretic modelling of interactions at the local level. Aspects emerging from the operational dimension and the extensive analysis that has been performed in T3.2 have been integrated into the sub-models and the provided formulations are an indicative example of their mapping to the simulation models.

Finally, it should be stated that the work of enhancing the representation of the actors in the simulation models and tools has been one direction of improvement within the TradeRES project. All the enhancements in both the operational and behavioural dimension complement the strengthening of the models for the more accurate representation of reality that will lead to more realistic simulations. Together with the other two directions of improvement that deal with the representation of flexibility and of the market designs, this work is expected to contribute to the simulations that will be performed in WP5.

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