**D5.2, June 2017**

# Modelling of Renewable Energy Auctions: Game theoretic & Energy system Modelling **Methodology Report**

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Modelling of Renewable Energy Auctions

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# Content

# Executive Summary

This report describes the methodology of modelling renewable energy auctions and their outcomes from a game theoretic perspective (agent-based model) as well as from the overall energy system model perspective (Green-X model).

The agent-based model can depict a variety of auction schemes and their respective design elements as well as regulatory features as e.g. restrictions to participation. Pay-as-bid and uniform pricing auctions can be shown, either as a one-shot auction or a multi-round auction that allows participants and the auctioning entity to learn. It is furthermore possible to model the agents in a very detailed manner, to depict the respective auction participants in a country or to investigate a certain question concerning the auction outcome. Several applications of the model in AURES D7.3 “Model-based analysis of specific cases” will make this clearer.

Within the course of AURES we have extended the applicability of auction-based RES support in TU Wien’s Green-X model, a well-established (sectorial) energy system model that allows for conducting RES-related energy policy assessments in the European context. The extended version of the model will be applied in the AURES project to conduct a comparative assessment of the performance of auctions to other instruments used for incentivising of renewable energy deployment. Within this report we introduce the modelling system, inform on key assumptions and provide an outlook on the envisaged application, shedding light on how the EU can reach the 2030 RES target by use of auctions or through alternative policy instruments.

# 1 Introduction

This methodology report is dedicated to provide the theoretical and conceptual background information on how auction schemes are represented in modelling done in the course of the AURES project. We will thereby also inform on the planned application of the models developed / extended. Please note however that the outcomes of the analyses performed / planned are not part of this report – these can be found in the forthcoming AURES report D7.3.

As a first step, we describe in the subsequent section 2 our game theoretic approach concerning the modelling of RES-related auction schemes. More specifically, we inform the interested reader how we model the outcome of different auction designs as developed in AURES WP2 “Framing and conceptual aspects of auctions for RES-E” and WP3 “Auction designs, implications, and application options for RES-E”. Based on that, we derive possible implications on auction outcomes in country, regional and EU wide modelling exercises which are presented in WP7 “Future implementation possibilities for auctions in Europe”. The model will formally capture the incentive structures of RES investors from auctions and reveal the consequences on societal support costs. We show different auction design elements the policy maker can make use of to set incentives in a way that desired outcomes can be fulfilled. The analysis includes the integration of incentive structures at different levels of detail and aggregation. This micro-economic perspective will deliver new insights on investment incentives for RES investors under different auction designs. The newly developed game theoretic model can display strategic behaviour by market participants and very closely model different EU member states’ auction schemes.

Furthermore, a top-down perspective will be adopted within section 3 of this report. Here we put auction design options into the broader energy policy context. This allows analysing their impact on societal support costs and their comparative performance. This will be done by use of TU Wien’s Green-X model – a well-established simulation model for assessing the impact of energy policy instruments on future RES developments. In this section we describe the modelling approach, inform briefly on the undertaken extension in the course of AURES and provide an outlook on the planned application of this tool in the course of AURES. Generally, the work planned aims for complementing the perspective of considering particular cases in WP4 and WP6 with information on the impact of auctions for all EU MS.

# 2 Game theoretic modelling of RES auctions

This section defines the overall modelling framework and develops and calibrated a game-theoretic model. The tool provides insights and concrete guidance on how to employ certain auction design elements (as quotas or limits for participation or penalties and pre-qualification criteria) and delivers, in combination with AURES task 6.3 “Alternatives to auctions”, the tools for a realistic and fine-tuned energy system modelling. The model is agent-based, programmed in Python and is informed by auction theoretic insights.

In the modelling of auctions, the focus is on strategic behaviour, specifically learning between auction rounds but also on individual optimization of bidding strategies given the respective background, incentives, and planning horizon of the auction participants. Furthermore, the variation of design criteria of auctions requires rethinking the strategic behaviour. We also consider how policy makers pursue additional policy objectives like agent diversity, and compare them with alternative options.

To best reflect the underlying market structure and the number and size of the actors involved, the agent-based modelling approach proved to be best suited to tackle our research questions. The model is based on auction theoretic foundations and includes empirical data (on RES technology costs, the structure of different technological sectors and previous auction results) to the highest resolution possible.

Different market structures have been modelled by adjusting the following parameters: the participants in the auction, the technology and its costs, the size and structure of the market and the auction design (including e.g. timing, ceiling prices, scope, technology focus and policy goals to be achieved among others). Selected auction designs, namely uniform pricing and pay-as-bid (PAB) have been tested. These have been equipped with various design features that were previously established in WPs 2 and 3.

The overall modelling framework ensures consistency throughout the different modelling approaches within this work package with respect to the applied parameters and methodologies. It is intended to calibrate the models to assess selected case study regions or countries in WP7. The definition of the regions will draw on the case studies that are selected in WP7, in order to create a strong link between the quantitative analysis of this task and the case cooperation.

## 2.1 Literature Review and Theoretic Background

The model has its foundation in two large areas of economic research, auction theory and agent based modelling. This short literature overview gives insight into the underlying theory and justifies the choice of methods for the analysis that follows in AURES D7.3 “Model-based analysis of specific cases”.

The first important strand of literature deals with **auction design elements.** Auctions for renewable energy (with a few exceptions, as e.g. offshore wind) are multi-unit auctions – and there have so far been few theoretical analyses of this particular setting. The most important auction theoretic design elements that have been introduced into our model and the depiction of the agents participating in the auctions are shown in the following. For more detailed information on the respective design elements, please refer to AURES WP2 "Framing and conceptual aspects of auctions for RES-E".

Auctions are one form of market-based allocation mechanisms, which provide an efficient[1] approach whenever information asymmetry between an agent and a principal exists (McAfee and McMillan, 1987). Allocating the support for RES via an auction can improve the efficiency of the allocation and thereby the overall efficiency of the support system (Klessmann et al., 2015). The present model can be applied for pay-as-bid (PAB) and uniform pricing auctions[2] as these pricing rules are the most widely used "in situations in which the marginal values are declining - that is, the value of an additional unit decreases with the number of units already obtained" (Krishna, 2010). This is also true for renewable energy auctions, where multiple goods are auctioned.[3]

Onshore wind power auctions are examples of such multi-unit auctions, as are auctions for large-scale PV projects. Precisely, a certain capacity of power is tendered. In each round, different bidders enter with their projects of different scopes and sizes. Since the auctioning entity ( for simplifying reasons named auctioneer) procures a specific capacity, the good can be defined as homogeneous from an auctioneer's point of view according to the theory of (Myerson, 1981).

Besides the pricing rule, a variety of other design elements distinguishes auctions. These elements help derive efficient outcomes and adapt the auction to the needs of the auctioneer and the market environment (see e.g. Kreiss et al., 2017). In the following, a (non-exhaustive) overview on the most important design elements used in RES auctions is presented.

[1] Efficiency here and in all following parts of this paper refers to the concept of allocative efficiency i.e. the distribution of the resources (support for renewables in a pareto efficient way).

[2] We distinguish static auctions, which include the two assessed formats (pay as bid and uniform pricing) and dynamic auction formats. Dynamic auction formats allow agents to react on their competitors' bidding behaviour during the course of an auction, whereas static auctions are so-called "one shot" auctions, meaning that each agent submits a bid and theses bids are then ranked in order of their respective amount.

[3] Single unit auctions, on the other hand, are usually applied when only one good with uncertain valuation to the auctioneer is sold (Krishna, 2010). In RES auctions, this is the case when a certain project is auctioned for realization, e.g. the offshore wind power auctions in Germany or in Denmark, in which the participants bid for the right of implementing one specific offshore wind farm, for which the plans have been already outlined.

Price limits (minimum- or ceiling prices) are an important auction design feature that is regularly used in renewables auctions. How to set this price is a crucial issue since it affects the level of competition and technological diversity (Del Río, 2015). Price limits can be implemented in our model, in a static or dynamically adapting manner.

In some market environments, it makes sense to introduce certain measures to ensure actors' diversity and reduce market power. Such design elements include restricting the number and size of bids, setting a minimum participation number for the auction to be carried out or limiting the number of rounds a bidder can participate. These measures can be implemented in our model as well, depending on the respective market that is simulated (e.g. restrictions for arable land in the German PV auctions).

As shown in AURES D7.3 "Model-based analysis of specific cases", the auctioneer can define penalties and pre-qualifications. Furthermore, the model allows comparing technology neutral and technology specific auctions. Restrictions on agent participation and their impact on auction results are also shown. All details of these implementations and their results are also shown in AURES D7.3.

There are many other additional features from auction design that can be made use of in auctions for renewable energy. This overview has presented only the features that have been implemented throughout the case studies assessed by our game theoretic model and is not yet exhaustive. We however intend to make the model's possibilities and limitations clear in the following sections and thus close the theoretical overview with these main features. The interested reader can refer to other reports of the AURES project where the complete technical and theoretical background is presented in more detail: An assessment of various implementation and design strategies for RES-E auctions in the EU is provided by the AURES project (del Río et al., 2015; Haufe & Ehrhart, 2016). An analysis of key elements to designing RES auctions is provided by IRENA (2015). A comprehensive overview of experiences and best practices is shown in Wigand et al., 2016.

The second important section of this literature review is on **previous applications of agent based modelling** (ABM) in the energy or more specifically the electricity sector. This is especially important, as our model uses an agent-based approach and as the respective bidders' behaviour over time is approximated with a learning algorithm which also stems from agent based modelling.

The following overview shows past applications of ABM in energy research. Several studies applying the ABM approach were published in energy research, whereas they often model an electricity (spot) market with a vast amount of agents in frequently occurring auctions, as e.g. power market simulations in Fraunhofer ISI's model PowerACE (Genoese and Fichtner, 2012) or the EMLab Generation Model by TU Delft (Chappin, 2013). Furthermore, a substantial amount of literature exists where ABM has been used to display and model complex interactions on the broader electricity market, i.e. modelling different agent's (TSOs, generators, regulatory institutions, consumers) behaviour and their respective interacting and sometimes contradictory objective functions and constraints, see e.g. Kiose and Voudouris (2015) and Widergren et al. (2006). ABM has also been used to assess different market design elements and policies for renewable subsidies, as shown in currently published research by Iychettiria (2016). Auctions for renewable energy have, to our knowledge, not yet been analysed using an ABM design. Among the studies on agent-based electricity market models, comparing PAB and uniform pricing has been a popular research question in the past (Weidlich and Veit, 2008). Further scientific energy-related auction literature applying an ABM approach is e.g. Kiose and Voudouris (2015), Veit et al. (2009), Bunn and Oliveira (2001), or Li and Shi (2012) among others.

Adaptation is also an important feature of agent-based modelling (Dam et al., 2013). As this paper focuses on the procurement auctions of renewable energies with a very clear time horizon and only a limited amount of rounds, the possibility of learning effects for the agents is limited. Nevertheless, a certain amount of learning is still implemented as shown in the following section.

Finally, **empirical literature on auctions for renewables** has been consulted for our model. This section is kept brief. A substantial amount of assessments took place in the various countries that tested auctions for renewable energy subsidies or even permanently implemented a support system based on auctions. However, many of these assessments are confidential, so the empirical literature consulted is usually restricted to studies by renewables associations, regulators or third parties. The literature most relevant for the country cases we analysed is presented in the modelling cases in AURES D7.3. This literature specifically concerns sources for our input data, namely size of markets, distribution of market participants, prices and design criteria. For further information, please refer also to AURES WP4, which treats empirical aspects of auctions for RES.

## 2.2 Modelling Framework

Figure 1 depicts a modelling framework, explaining how the agents' behaviour and the auction outcome are interlinked. There are several points of interlinkage and feed-back and a lot of information on the market and technologies has to be taken into account when assessing auctions for renewable energy.

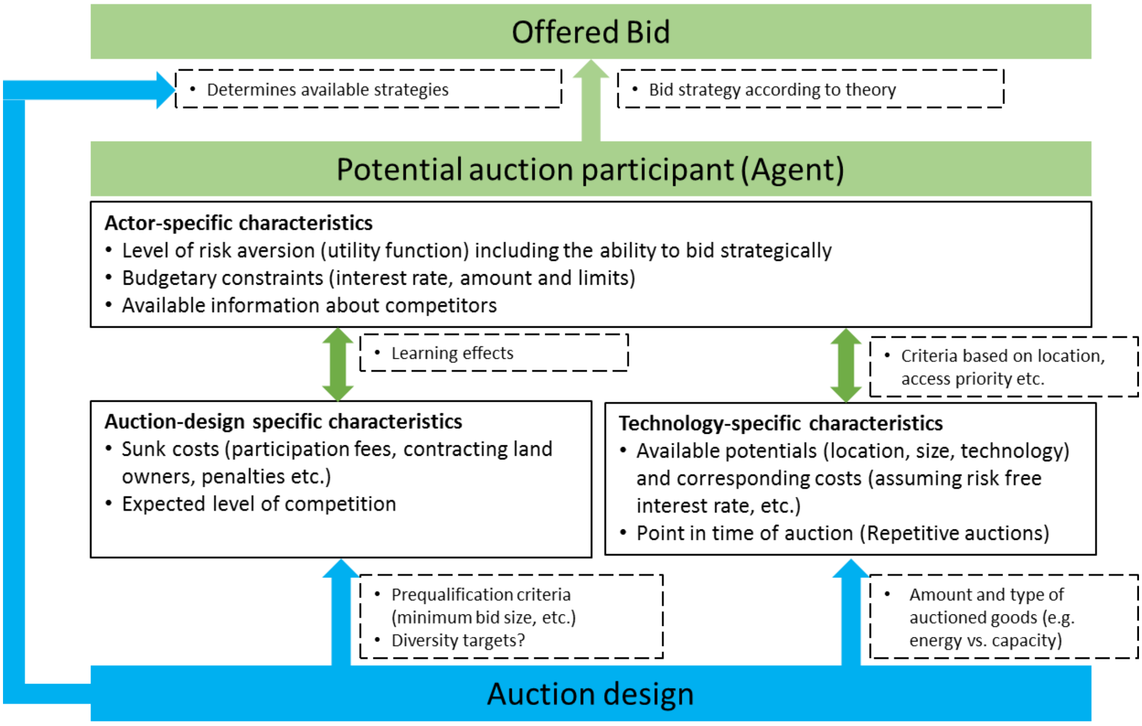


**Figure 1: Modelling Framework for RES Auctions**

### 2.2.1 Agent-specific characteristics

When simulating auctions, an agent is assumed to behave rationally, i.e. bid her own costs and try to maximize her possibility of winning (over time). Furthermore, the agent is characterized by her attributes, namely the size of her wind power project, and her bidding behaviour – the bid function and the implemented learning algorithm.

To take a certain degree of learning effects due to multiple realized projects and overall learning effects in the industry into account, the model includes an optional cost digression. Whenever an agent's bid is successful in an auction, her cost in ct/kWh decreases by a certain factor due to economies of scale. Furthermore, overall costs decrease per round for all agents equally, depending on the technology. This can be further adapted depending on the time horizon and specifics of the auction design that is assessed. In a one-shot auction where an agent can bid into multiple bidding years, the agent assumes different cost for each year. In sequential auctions, costs decrease accordingly. Furthermore, as agents get to know previous auction results, in sequential auctions agents can refine their bids by learning about competition and previous price levels. These parameters are implemented into the agent's bid function in the pay-as-bid auction format (we assume bidders to always bid their true costs in Uniform pricing, according to theory). All these features are adaptable and interchangeable and allow a very detailed modelling of the respective auction scheme in different countries.

In order to design the model efficiently, types of model agents have to be selected. The agents can differ in size, costs, long-term planning horizon, legal restrictions (i.e. when they bid for restricted areas as the arable land in Germany) and other features. This task obviously requires some aggregation and depends on data availability. Data assessed for this task were e.g. reports by renewables associations, official statistics, previous auction results if available or other studies on the respective markets. Implementing the correct share of each agent type participating in the auctions is crucial for a realistic simulation of the auctions. It is furthermore important to implement how the agent distribution changes in multi-annual auctions. In all auctions that include multiple rounds, a number of new agents are drawn to participate in the next auction after each round. Their numbers are drawn from a discrete uniform distribution. How this is implemented again depends on a variety of factors: ceiling prices, available areas, restrictions in participation agent's planning horizon etc. To model this, we either make use of empirical auction outcomes, or, if these are not (yet) available, we make assumptions according to the respective technology sector in the specific country analysed. A variety of these design elements have been taken into account to the extent feasible and necessary for answering the respective policy questions in different country cases in AURES D7.3. In these applications, the procedure will become clearer.

The corresponding quantity offered by each agent is also drawn from a discrete uniform distribution. To model the difference in the ability of realizing certain sizes of projects, agent types can be assigned a different distribution.

Agents' bidding behaviour over multiple rounds can also differ. The time until re-entry into the auction is modelled as a uniformly distributed, discrete random variable that can be varied. Due to model simplification reasons, we do not have bidders enter multiple projects in one round. Successful bidders can however immediately participate in the next round with a new power quantity that is again drawn randomly from their assigned distributions.

Risk aversion can also be accounted for in our model. It is assumed that larger agents can bear higher risks since they can better diversify their portfolio and command the resources for long-term optimization. The smallest auction participants can thus bear the least risk (Klessmann et al., 2015). We assume that winning a bid in a future round is less preferable for them compared to larger participants who have more options for bidding strategically and diversifying, e.g. see del Río and Linares (2014). They thus discount future revenues more heavily. Furthermore, risk aversion and strategic behaviour can be depicted via the bidding function. An agent receives a certain signal, i.e. a range from which he or she derives the costs and the resulting bid. We always assume agents to behave rationally. However, in case when agents do not receive a penalty or when they do not have any sunk costs due to prequalification criteria, there is an incentive for them to bid at the lower range of their assumed costs, thus increasing their risk bidding below their true costs. This change in risk aversion due to different auction designs can also be accounted for in the model.

### 2.2.2 Bid functions

In auction theory, the bid function maps an agent's cost for realizing the project (or valuation of a good) to a bid price. Agents can receive b (their bid) in PAB, the highest accepted or lowest not awarded bid in uniform pricing, or 0 depending on the auction's outcome and try to maximize their profit (Krishna, 2010).

#### Uniform Pricing

Uniform pricing means, that all successful bidders receive the same remuneration, which is in our model determined by the lowest rejected bid. The bid function is derived from auction theory. Several studies have shown, that bidding one's own cost in a multi-unit auction with uniform pricing (when the agent only places a bid for one unit) or in a second price auction – the single unit equivalent – is a weakly dominant strategy (Milgrom, 2004).

$$b_i = c_t$$

In our model, agents therefore bid truthfully (their exact costs $c_t$) in every round of uniform pricing. According to theory, the outcome of a functioning uniform pricing regime is incentive compatible (Klemperer, 2004). Uniform pricing serves as a benchmark case in the analysis, as the bidding strategy is not influenced by parameters other than the agent's cost.

Pay as bid

Under discriminatory pricing rules (first-price sealed-bid and PAB), successful agents are paid exactly their bid $b_t$. Due to this fact, bidders will at least bid their individual cost, usually with a certain margin on top. In auction theory, this behaviour is known as ”bid-shading” (Menezes and Monteiro, 2005). Under the PAB pricing mechanism, the agent maximizes her expected profit π over her chance of winning and the amount received in case of being successful by adjusting her bids accordingly and taking into account the possibility to win in the following rounds. In general, the higher her bid is, the lower her probability to win in the auction but the higher the profit in case of winning (e.g. Samuelson (1986), McAfee and McMillan (1987)). If the auctions are designed as sequential multi-unit auctions, the bid vector b contains all the bids from the current round t until the last round in T. The discount factor is $0 < \delta < 1$, since winning in a future round is less favourable (Sugianto and Liao, 2014), and $c_t$ is the agents' specific cost in round t. If we look at a one-shot auction, the model is implemented in a similar way but without learning.

Assuming that the agents participate with only a single project in each round, they can only take part in the following rounds with their specific project if their current bid is unsuccessful. Consequently, the expected profit in one of the following rounds has to be adjusted by the probability of losing in the past auctions. Thus, the current bid not only influences the current expected profit, but also the future ones, as the profit of the specific project is maximized taking into account a specific period of time and the expected probability of winning over all auction rounds. Adjusting the discount factor $\delta^t$

enables to account for the specific risk aversion of each agent type. The expected utility is calculated in each round, with T being the final round.

for t=0,1,2,...,T

$$E\big(\pi(\boldsymbol{b})\big) = \sum_{i=t}^{T} \delta^{i-t} \cdot (b_i - c_t) \cdot Pr(\text{"}successful\ bid\ in\ round\ i\text{"}) \prod_{x=1}^{i-t} Pr(\text{"}unsuccessful\ bid\ in\ round\ i-x\text{"}))$$

As agents should include the level of competition into their expected profit, the concept of order statistics (Ahsanullah, Nevzorov, & Shakil, 2013) has been implemented: In order to determine the probability of submitting a successful bid, the agent assumes n-1 participants (without her) with $n_s$ (successful) bidders being able to win in the auction round. Therefore, at least the $n_s^{th}$ lowest out of the n − 1 other participants' bids has to be higher than her own one $b_t$. The agents assume the competition and the number of winners to be the same as in the preceding auction round. Due to a lack of information in the first round, they there assume a certain amount of competitors and a certain number of successful bidders. This again depends on the market characteristics and auctioned capacity among other factors. We further introduce a cumulative distribution function (CDF). This function F(·) which captures an agent's belief on the other participants bid distribution and specifically, the probability that another bid $b_j$ is lower, hence Pr ($b_j < b_i$). Consequently, $1-F(b_i)$ depicts the probability of her own bid being lower than her opponent's. Based on the approach in Ahsanullah et al. (2013), we can calculate the probabilities in the following way:

$$\mathrm{E}(\pi(b)) = \sum_{i=t}^{T} \delta^{i-t-1}(b_i - c_t) \sum_{j=0}^{n_{t-1,s}-1} \left(\binom{n_{t-1}-1}{j} \mathrm{F}(\mathrm{b}_i)^i (1-\mathrm{F}(\mathrm{b}_i))^{n_{t-1}-1-j}\right)$$
$$\cdot \prod_{x=1}^{i-t} \sum_{k=n_{t-1,s}}^{n_{t-1,s}-1} \left(\binom{n_{t-1}-1}{j} \mathrm{F}(\mathrm{b}_{i-x})^i (1-F(b_{i-x}))^{n_{t-1}-1-k}\right)$$

Although the above equation is based on the auction-theoretic concept of first-price sealed bid auctions (McAfee & McMillan, 1987), we won't derive a bid function taking into account the other bidders' behaviour. In this simulation, the above equation will be solved using maximization algorithms.

### 2.2.3 Learning algorithms

Agents, as autonomous entities, should be able to adapt their behaviour to changes in the system to simulate a realistic environment and learn from past occurrences. Information provided by the auctioneer flows into the learning algorithm implemented in the simulation for the PAB pricing rule. Each agent optimizes his expected payoff over the entire time horizon. As shown previously, the expected profit depends on the parameters of the cumulative distribution function (CDF). The CDF is modelled as a normal distribution, similar to modelling the distribution of the market clearing price in electricity markets (Azadeh et al., 2012, Bhattacharya 2000, Rahimiyan and Rajabi Mashhadi, 2008, Rahimiyan and Rajabi Mashhadi, 2007. This function $F(\cdot)$ which captures an agent's belief on the other participants bid distribution and specifically, the probability that another bid bj is lower, hence Pr ($b_j < b_i$). Consequently, $1-F(b_i)$ depicts the probability of one's own bid being lower than an opponent's.

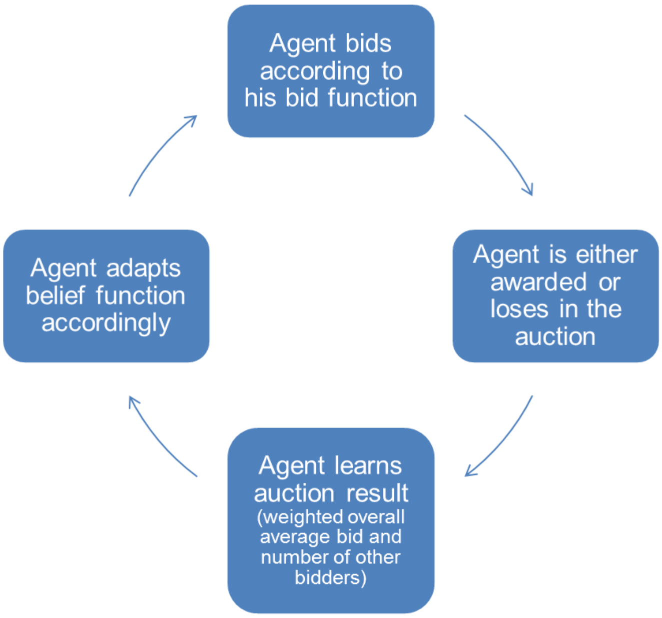


**Figure 2: Simplified learning algorithm**

Therefore, the mean value (μ) can be seen as a central configuration parameter besides the standard deviation. The agents' learning algorithm consists of adapting μ to new information generated throughout the course of the auctions. In the first round, the assumptions on μ of F(·) are based on each agent's own signal (her cost) which is the best approximation regarding the other agents' bids (Krishna, 2010). In the course of the auctions, new information becomes available, which is incorporated by the agents: they adjust the CDF, by updating μ with the last round's overall mean bid. This definition of learning is one of the main properties of ABM (Woolridge & Jennings, 1995): the environment – in our particular case the overall mean bid and the number of (successful and overall) participants – influences the agents' behaviour and in return the agents' individual bids have an impact on the overall average bid.

### 2.2.4 Simulation rounds

In order to derive an accurate answer to the research question, pricing rules are simulated in a number of iterations to receive a representative simulation result. The exact number of rounds of course depends on the respective case modelled. Each agent's bid vector is calculated before the auction round takes place by using a so-called "SLSQP algorithm" (Kraft, 1988)[4]. Using this specific algorithm has the advantage of defining boundaries for the optimization and thus not obtaining extreme values, which would be a possible result from applying a standard normal distribution. We employ the agents' own cost as initial guess for the maximization algorithm. In all simulations executed, algorithm and model generate realistic values: Within each bid vector, the corresponding bids decrease over all rounds, i.e. the later an auction takes place, the more aggressive the agents' bids become. This also leads each round's current bid ($b_t$) – which determines the specific auction's outcome – to decrease (c.p.) over time.

## 2.3 Outlook: Application of the model

The forthcoming AURES D7.3 report will contain three separate assessments made with the game theoretic model: one for the UK, Germany, and Denmark respectively. Each of these modelling cases treat a different auction related policy question. Specifically, we investigated technology neutrality vs. technology differentiated auctions, agent behaviour in auctions with participatory restrictions, and the influence of penalties and prequalification criteria. These applications show the wide range of auction-design related questions that the model is already able to cover. With the code being made open source, these questions can be expanded or assessed with different input data for other countries or time spans. Overall, the agent-based model serves as a very useful tool for policy advising. The forthcoming report AURES D7.3 will show this in more detail. Furthermore, some forthcoming scientific publications will give even further theoretical insights into the model's game theoretic background.

[4] SLSQP optimizer is a sequential least squares programming algorithm which uses the Han–Powell quasi–Newton method with a BFGS update of the B–matrix and an L1–test function in the step–length algorithm. The optimizer uses a slightly modified version of Lawson and Hanson's NNLS nonlinear least-squares solver (http://www.pyopt.org/reference/optimizers.slsqp.html).

# 3 Prospective renewable energy system modelling

In this task the approaches developed in tasks 4.1 and 4.2 will be used to more accurately calibrate and implement auction based support instruments in the Green-X model.

Within the course of this project we have extended the applicability of auction-based RES support in Green-X, building on the methods developed and findings gained in tasks 5.1 and 5.2. This will allow to model auctions in a more realistic fashion – since in the model's representation of auction designs a distinction between pay-as-bid and uniform pricing has been established. Moreover, the user can select to apply auctions at different layers: for single technologies, for baskets of technologies – at national as well as at multi-national level (e.g. European or regional level). Considering these improvements taken we will conduct a comparative assessment of the performance of auctions to other instruments used for incentivising of renewable energy deployment. Thus, the improved representation of auctions in the model will be used to develop scenarios of future RES-E deployment in the 2030 context that will inform about the policy support expenditures of different auction designs and their performance compared to other options for RES-E support.

Please note that the scope and the selection of scenarios was done in accordance with the cases undertaken in WP3 and WP6, as well as the analysis from WP5, in order to create additional synergies between the Work Packages and to support policy recommendations with quantitative results in as many areas as possible.

Below we introduce the modelling framework and inform on key assumptions. Next to that, an outlook on the planned / assessed cases is taken.

## 3.1 Approach and key assumptions

### 3.1.1 The applied modelling system (Green-X, complemented by HiREPs)

The analysis will build on modelling works undertaken by the use of TU Wien's Green-X model (cf. Box 1). More precisely, a quantitative policy analysis of various scenarios on future RES deployment up to 2030 within the EU will be used to assess the performance of auction-based RES support in comparison to other instruments.

**Box 1 Brief characterization of the Green-X model**

*Green-X is an energy system model that offers a detailed representation of RES potentials and related technologies in Europe and in neighbouring countries. It aims at indicating consequences of RES policy choices in a real-world energy policy context. The model simulates technology-specific RES deployment by country on a yearly basis, in the time span up to 2050[5], taking into account the impact of dedicated support schemes as well as economic and non-economic framework conditions (e.g. regulatory and societal constraints). Moreover, the model allows for an appropriate representation of financing conditions and of the related impact on investor's risk. This, in turn, allows conducting in-depth analyses of future RES deployment and corresponding costs, expenditures and benefits arising from the preconditioned policy choices on country, sector and technology level.*

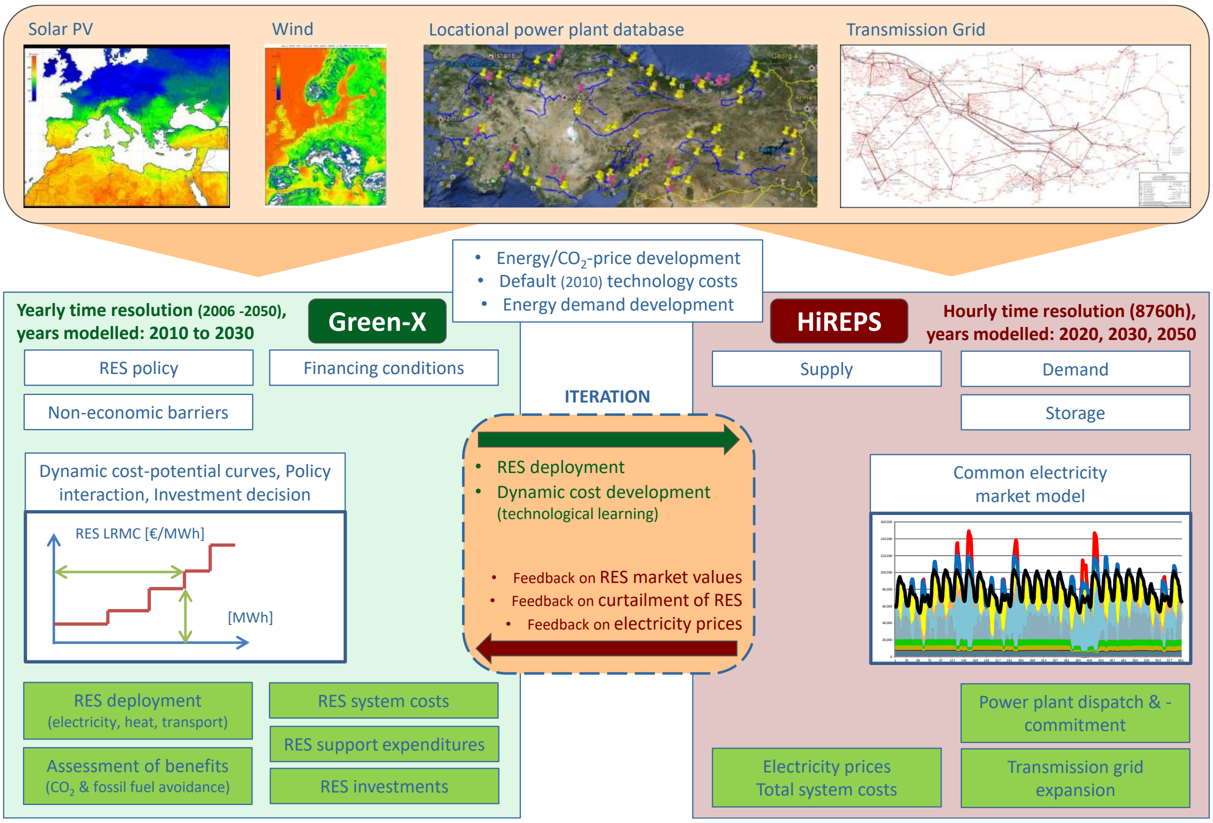


**Figure 3 Model coupling between Green-X (left) and HiREPS (right) for a detailed assessment of RES developments in the electricity sector**

For specific purposes, e.g. for assessing the interplay between RES and future electricity market design that involves an analysis of the merit order effect and related market values of the produced electricity for variable and dispatchable renewables, Green-X was complemented by its power-system companion – i.e. the HiREPS model – to shed further light on the interplay between supply, demand and storage in the electricity sector thanks to a higher intertemporal resolution than in the RES investment model Green-X.

Figure 3 gives an overview on the interplay of both models. Both models are operated with the same set of general input parameters, however in different spatial and temporal resolution. Green-X delivers a first picture

[5] For this exercise model calculations will be however limited to the period up to 2030.

of renewables deployment and related costs, expenditures and benefits by country on a yearly basis (2010 to 2030 (and up to 2050 for specific purposes)). The output of Green-X in terms of country- and technology-specific RES capacities and generation in the electricity sector for selected years (2020, 2030 (and 2050)) serves as input for the power-system analysis done with HiREPS. Subsequently, the HiREPS model analyses the interplay between supply, demand and storage in the electricity sector on an hourly basis for the given years. The output of HiREPS is then fed back into the RES investment model Green-X. In particular the feedback comprises the amount of RES that can be integrated into the grids, the electricity prices and corresponding market revenues (i.e. market values of the produced electricity of variable and dispatchable RES-E) of all assessed RES-E technologies for each assessed country.

### 3.1.2 Key parameter

In order to ensure maximum consistency with existing EU scenarios and projections the key input parameters of the scenarios presented in this report are derived from PRIMES modelling and from the Green-X database with respect to the potentials and cost of RES technologies. Table 1 shows which parameters are based on PRIMES, on the Green-X database and which have been defined for this study. The PRIMES scenarios used for are the latest publicly available reference scenario (European Commission, 2016) and the climate mitigation scenarios PRIMES euco27 and PRIMES euco30 that build on the targeted use of renewables (i.e. 27% RES by 2030) and an enhanced use of energy efficiency compared to reference conditions – i.e. 27% (euco27) or 30% EE (euco30) by 2030, respectively. Please note that all PRIMES scenarios are intensively discussed in the EC's winter package, cf. the Impact assessment of the recasted RED (SWD (2016) 410 final).

Although a target of 30% for energy efficiency has already been fixed for 2030, we show ranges with regard to the actual achievement of energy efficiency to cover both, a higher or substantially lower level of ambition in terms of energy efficiency policy: Under reference conditions an improvement in energy efficiency of 23.5% compared to the 2007 baseline of the PRIMES model is projected for 2030, whereas in the PRIMES euco27 scenario, assuming a strong ambition level for energy efficiency, an increase to 30% is assumed.

**Table 1 Main input sources for scenario parameters**

| Based on PRIMES | Based on Green-X database | Defined for this assessment |
|---|---|---|
| Primary energy prices | Renewable energy technology cost (investment, fuel, O&M) | Renewable energy policy framework |
| Conventional supply portfolio and conversion efficiencies | Renewable energy potentials | Reference electricity prices |
| $CO_2$ intensity of sectors | Biomass trade specification | |
| Energy demand by sector | Technology diffusion / Non-economic barriers | |
| | Learning rates | |
| | Market values for variable renewables | |

## 3.2 Outlook: Application of the model

In the forthcoming AURES D7.3 report we will present the outcomes of our energy system modelling exercise on the performance of RES auctions in the EU context.

More precisely, we will build our model-based assessment of the performance of auction-based RES support on a recently conducted exercise done in the course of the IEE project towards2030-dialogue (cf. www.towards2030.eu). Therein various pathways on future RES-E support have been assessed at an EU level in the 2030 context – in accordance with the given 2030 EU RES target (i.e. of at least 27% RES by 2030). We thus build on certain scenarios and undertake a complementary comparative assessment targeted to analyze the performance of auction-based RES support. Below we introduce the envisaged scenario scope.

In general terms the analysis will shed light on the required RES uptake for meeting 27% RES by 2030 and on RES-related costs & benefits – with a focus on the resulting policy costs (i.e. support expenditures). Distinct scenarios will be conducted that allow for a comparison of the performance of auction-based RES support with alternative policy approaches.

*Overview on RES policy scenarios used in this exercise:*

| | |
|---|---|
| **Harmonised Quota** | Harmonised (RES) support post 2020 (EU-wide quotas with certificate trading for RES-E) |
| **Stringent State Aid Guidelines** | Stringent implementation of State Aid Guidelines (National auctions for RES-E support through sliding premiums with partial or full market opening) |
| **National Policies with common Guidelines** | National Policies with common guidelines (National quotas with certificate trading for RES-E or national auctions for RES-E support through sliding premiums without market opening) |

A list of RES policy (convergence) pathways has been identified in the course of the towards2030-dialogue project. These pathways build from a conceptual viewpoint on either a top-down (i.e. those forms of convergence in RES policy driven by European Institutions) or a bottom-up process (i.e. those forms of convergence driven by Member States cooperating with each other). In our assessment of auction-based support we focus on the first category (top-down) involving the following pathways:

Harmonised Quota: As the most prominent representative of an EU-wide harmonised RES-E support we assume under this pathway that an EU-wide harmonised quota scheme will be implemented for supporting investments in new RES-E installations post 2020. More precisely, we take the assumption that an EU-wide harmonised support scheme is put in place for supporting new RES installations in the electricity sector that does not differentiate between different technologies. In this case the marginal technology to meet the EU RES-target sets the price for the overall portfolio of RES technologies in the electricity sector. The policy costs occurring in the quota system can be calculated as the certificate price multiplied by the RES generation under the quota system. These costs are then distributed in a harmonised way across the EU so that each type of consumer pays the same (virtual) surcharge per unit of electricity consumed.

Stringent State Aid Guidelines: Another form of top-down convergence is the prescription of specific types of (market-based) instruments by the EU institutions to be implemented by Member States (e.g. strengthening of current state aid guidelines in the period 2020-2030). Specifically, we take the assumption that a feed-in premium system (with sliding premiums) – where support levels are determined in an auction procedure (with pay-as-bid) – would be the prescribed instrument to support investments in new RES-E installations post 2020. Moreover, two sub-scenarios were analysed: **national auctions with partial or full-market opening** whereby the latter is equivalent to an EU-wide auction scheme in terms of performance.

National Policies with common Guidelines: Here the EU would prescribe common guidelines that Member States have to respect when implementing RES-E support post 2020. This would facilitate the convergence process and the implementation of best practices in policy design but would leave the choice of a support instrument in the hands of the Member States. Consequently, we assess here two distinct policy approaches: National quotas with certificate trading for RES-E (without international trade), and **national auction for RES-E support through sliding premiums (without market opening)**.

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AURES is a European research project on auction designs for renewable energy support (RES) in the EU Member States.

The general objective of the project is to promote an effective use and efficient implementation of auctions for RES to improve the performance of electricity from renewable energy sources in Europe.

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