The Strategy and Architecture of a Winner Broker in a Renowned Agent-based Smart Grid Competition

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Abstract. Local energy production and distributed energy storage facilities will take a prominent position in the future smart grid along with the challenge of sustainability. To cope with that, smart grid simulation platforms are needed in order to analyze the problems of two-way data and energy flow. The Power Trading Agent Competition (Power TAC) provides an open source, smart grid simulation platform to enable various smart grid studies from the perspective of sustainability. In this paper, we present AgentUDE, which competed in the Power TAC 2014 and 2015 Final games as a broker agent. Here, we create and formalize information system artefacts for the electricity trading problem in a continuous and competitive environment. The main trading problem is partitioned to smaller problems to reduce the complexity. Therefore, wholesale and retail electricity market activities are individually discussed for AgentUDE14. In 2015 competition, we added a capacity control capability to AgentUDE14, which was introduced as AgentUDE15. We show that AgentUDE is a successful broker agent in many metrics, analyzing its performance in controlled experiments and international tournaments. We have also reviewed the tournament data from the winner agent's point of view.

Keywords: Smart grid, trading agent, electricity markets, power trading, brokers

1. Introduction

Smart grids have turned into an exciting area for researchers and business. New power actors with exciting concepts and ideas constantly join the market and reshape its structure and course of actions. Electric vehicles and power-to-gas plants open the door for the storage of renewable energy in a distributed way. On the other side, some governments have already declared their energy transition policies, e.g. Germany with its Energiewende concept. Within Energiewende, Germany will permanently shut down all its 17 nuclear power plants by the end of 2022 [9]. Meanwhile, fossil fuel based electricity production is likely to be replaced by massive renewable energy production capabilities [5,16].

After all, data, money and power interactions between these energy actors have to be simulated within a robust smart grid simulation platform. Power TAC is an open source, smart grid simulation platform that provides a solution to this challenge. The Power TAC homepage describes its purpose and structure very well: "Sustainable energy systems of the future will need more than efficient, clean, low-cost, renewable energy sources; they will also need efficient price signals that motivate sustainable energy consumption as well as a better real-time alignment of energy demand and supply". In Power TAC, agents act as retail brokers in a local power distribution region, purchasing power from a wholesale market as well as from local sources, such as homes and businesses with solar panels, and selling power to local customers and into the wholesale market. Retail brokers must solve a supply-chain problem in which the product is infinitely perishable, and supply and demand must be exactly balanced always.

This paper discusses and analyzes the trading performance of *AgentUDE* in international competitions and controlled experiments. We take the broker's trading problem as individual trading

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problems for each of the market that *AgentUDE* involved.

In the wholesale market, we design a responsive hybrid model for price forecasting, using dynamic programming techniques and Markov Decision Process. We use a belief function to adjust predicted values, derived from exponentially smoothed values of market clearing prices (MCP).

In the retail market, *AgentUDE* focuses on the manipulation of tariff parameters to earn more from customers' penalties. This was a quite new strategy for the Power TAC 2014 Final games and resulted in decent amount of profit. However, analysis showed that *AgentUDE* performs better in case of a tough competition. Less competitive environment reduces the overall profitability ratio. Detailed investigations into the effects of the AgentUDE14 business strategies showed that *AgentUDE14* achieved a serious portion of its profit through Early Withdrawal Penalties (EWP) and Bonus Payments (BP).

In 2015, we introduced *AgentUDE15* to enable its trading capability in the balancing market (BM). In the paper, we benchmark the profitability levels of battery storage customers, offering these capacities to distribution utility (DU). We use a simple ablation method by creating different variations of the broker in controlled experiments. Each variant publishes a battery storage tariff with different up-regulation and down-regulation prices. The results show that battery storage customers may provide extra profit for the broker when its capacity is strategically traded in the BM. On the other side, they help stabilizing the grid with up and down regulations.

Thanks to its overall business strategy and, especially, its aggressive tariff strategy, *AgentUDE14* won the Power TAC 2014 finals despite being the newest kid on the competition.

2. Related Work

This section explains relevant researches of the concept of this paper. Since autonomous trading is a highly interdisciplinary research field, we first introduce agent-based systems in smart to align the big picture first. Then, we introduce the works in autonomous trading, to show similar works in the literature. Then we explain more specific machine learning methods which are similar or alternative to the methods in the paper.

2.1. Agent-based Modelling and Simulation in Smart Grid

According to U.S. Department of Energy, the principal characteristics of smart grid are defined as reliability, resiliency, flexibility, and efficiency whereas the most important smart grid programs are given as self-healing and demand response [16]. Within this vision, smart grids studies need more robust multi-agent systems to enable decentralization process.

Smart grid multi-agent systems were applied in many complex applications, using open-source agent platforms, such as JADE [17], Agent.GUI [18], ZEUS [19] and JACK [20]. The leading application area is microgrids [21,22,23], especially in resource scheduling and cost optimizations.

In the field of competitive markets, Power TAC is one of the leading frameworks, which enables competitive benchmarking in many dimensions (see Section 3) [1,2,30].

2.2. Autonomous Trading

One of the most related paper was published by the *TacTex* team, the winner of the Power TAC 2013 competition. *TacTex* uses a Markov Decision Process-based design to minimize its energy costs in the wholesale market. On the other side, it optimizes its future demand, prices and predicted energy costs to pick a suitable tariff among pre-created, fixed-rate candidate tariffs [3].

Another publication is from the *AstonTAC* team. It focuses on the trading in the wholesale market using Markov Decision Processes for price optimizations and Non-Homogeneous Hidden Markov Models for predictions of future trends [4].

The last broker-related paper was published by the *cwiBroker* team, who were very successful in the 2013 and 2014 competitions. They won the second place in both tournaments, utilizing a trading technique that uses the equilibrium in continuous markets [8].

The most comprehensive review paper was published by [7] about the Power TAC 2014 competition. In this paper, brokers are compared based on pre-defined key performance indicators (KPI). Retail and wholesale market activities, including market shares and proximities of future time slots, are discussed in some detail.

2.3. Machine Learning in Smart Grid

One of the most comprehensive research papers is published by [25]. The paper reviews reinforcement learning approaches from the decision-support perspective in smart electricity markets. In this work, retail and wholesale trading problems are handled separately in a broker-centric environment. Besides this work, many existing papers have confirmed that MDP is one of the proven ways of handling time-sequential problems [3,4,27].

In our wholesale market module, we use a hybrid electricity price forecasting approach, using several reinforcement learning methods [28,29] and MDP, which is a modified version of MDP design, introduced by [3]. We use an exponential smoothing operator along with a belief function which is proposed by [27].

3. The Power Trading Agent Competition

Smart grid simulation platforms have become more and more popular as liberalized electricity markets and decentralized power generation challenge the volatile balance of electricity demand and supply. Simulations aim to address these challenges to create a vision of sustainable smart grid ecosystems. Power Trading Agent Competition (Power TAC) is probably the most powerful and robust open-source smart grid simulation platform. Power TAC is a data-driven platform that brings electricity brokers and smart market concepts together. Fig. 1 depicts the high-level structure of Power TAC.

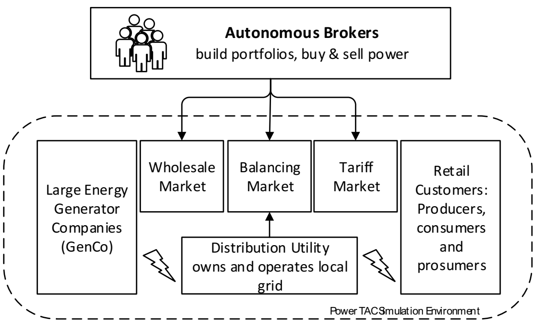

Fig. 1. Major elements of a Power TAC scenario.

Power TAC models the high complexity of contemporary and future energy markets, allowing for large scale experimentation. Main entities are the customers, representing consumers, producers and "prosumers" and brokers, who act as intermediary profit maximization parties. Customer models represent households, small and large businesses, multi-residential buildings, wind parks, solar panel owners, electric vehicle owners, etc. Brokers aim at making profit through offering electricity tariffs to customers and trading energy in the wholesale market, while carefully balancing supply and demand.“[1]

In this Power TAC scenario, broker agents remotely trade in simulated electricity markets to increase their profits. Brokers are challenged to match their supply and demand by means of trading in retail and wholesale electricity markets. The broker that achieves the highest overall profit over all runs of the finals is the winner of the competition. The 2014 version of Power TAC is best described in [1,2].

The platform integrates various smart grid actors such as customer models, retail markets, wholesale markets, a distribution utility (DU), and autonomous electricity brokers within a single distribution area, currently a city. Autonomous electricity brokers are intermediaries between end-customers and large power generators. They are supposed to trade in heterogeneous markets to match their customer-dominated power demand and supply. Since smart markets are complex, data-oriented marketplaces its participants need to deploy smart agents that trade on behalf of them. The main actors within Power TAC are now described in more detail:

– *Electricity Brokers* are business entities that trade as intermediaries to attain good results for their own accounts. They try to attract customers by publishing electricity tariffs in the retail market, i.e. tariff market. The so-called DU closely monitors all brokers in order to evaluate their demand and supply behavior. Imbalanced energy is subject to penalties, which may result in a profit loss that is approximately twice as high as the mean wholesale market price. Therefore, brokers have to trade in the Wholesale Market in order to cover their net demand. Net demand refers to the offset after coupling the local production and consumption commitments. All the transactions are controlled and executed by DU in real-time. Brokers are ought to build a customer portfolio and predict customers’ consumption patterns in order to apply their strategies as profitable as possible. On the other side, they have to compete with other brokers. Brokers need a complex,

[1] cf. http://www.powertac.org/ accessed 3.12.2016

dynamic design to sustain their profitability even in a highly competitive environment.

– *Customers* are small and medium sized consumers and producers such as households or small companies but also electric vehicles. They interact with the environment through electricity tariffs. An aggregator may act on behalf of a group of customers, e.g. parking lots. They can buy or sell electricity, subscribing to appropriate tariffs which are defined in power type, time and money domains. Customers subscribe to a fixed-rate, time-of-use or variable-rate tariff based on their consumption or production profile.
– *Generator Companies* represent the large power generators or consumers. These actors trade in the Wholesale Market and manage their commitments for the next few hours up to several weeks.
– *The Distribution Utility* operates the grid and manages the imbalances in real-time. It is assumed that the distribution utility owns the physical infrastructure. It charges brokers for their net distributed energy per kWh, known as distribution fee. It also manages imbalances and charges brokers for their imbalanced energy, called balancing fee. The balancing fee is usually higher than the actual wholesale price for electricity. Therefore, brokers are advised to build predictable customer portfolios.

While Power TAC is available all year-round for all kinds of simulations its highly prestigious international competition is conducted only once a year. Research institutes are encouraged to develop and pre-test their own smart energy brokers. A Power TAC tournament consists of a set of games, grouped in different game sizes, e.g. with three, five and seven players. The game size indicates the number of competing broker agents. In addition to competing teams, a built-in default broker is always included in the games, i.e. it means two brokers and the default broker compete in a three-player game. The default broker is the only retailer for all customers at the beginning of each game, during the so-called bootstrap period. During this period, activity logs are stored to give first relevant, necessary information to the competing brokers. Once all brokers are permitted to join in, they are meant to compete for customers.

After all games have ended, profits are summed up and normalized on the basis of each individual game size. The broker with the highest aggregated profit is the winner.

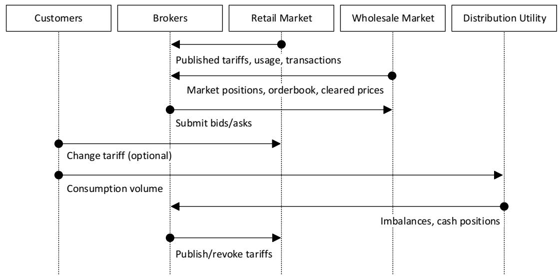

Fig. 2.Timeslot sequence diagram from a brokers' point of view.

A Power TAC game takes up to a random time slot count, starting from one, cf. Fig. 2 for the activities in a time slot. In the paper, we refer to the current time slot t and time distance δ to future auction hour (see Table 1 to read more about the notation):

1. Brokers receive signals at every timeslot, like current cash balance, cleared prices of timeslots $cp_t, cp_{t+1}, \dots, cp_{t+23}$, and published tariffs by all brokers.
2. Brokers ought to submit orders to the Wholesale Market in order to procure an energy amount E^f, based on the demand patterns of their tariffs. Note that brokers have no knowledge about future demand and market prices. They are expected to create predictive models to fill order parameters, i.e. price and energy amount.
3. At the end of a timeslot, a broker's cash account is updated based on the profit $\sum_i T_i E_i^t - \sum_j^{24} cp_t^j E_t^j$. T_i is the tariff price of the energy unit (kWh) and E_i^t denotes the distributed energy amount at timeslot *n*, under tariff *i*. $\sum_j^{24} cp_t^j E_t^j$ denotes the cost of procuring the energy amount E_t^j at timeslot *t*. Imbalance penalty $\left(\sum_i E_i^t - \sum_j^{24} E_t^j\right)P$ is debited from the broker's cash account, using the balancing fee of *P* (per unit).
4. In addition to the tariff value, tariff activities like customer sign ups or withdrawals are subject to payment due to bonuses or early withdrawal payment parameters of the according tariffs. A bonus payment is a money transfer from a broker to its customer c whenever c subscribes to a tariff from the broker. Likewise, an early withdrawal penalty is to be paid by a customer to its broker whenever the customer exits its tariff before its expiry date. Tariff publications and revocations are also subject to fees.
5. Brokers pay a distribution fee for each energy unit if power is to be distributed/transferred or if local power is traded in the Wholesale Market. The fee is exempted in case of market brokerage. Another exemption applies if local production (energy

from customers) is consumed in the same area (by customers). In other words, exemptions are issued for a certain amount of energy which is traded in the same market, e.g. retail or wholesale market. Brokers are encouraged to combine producer and consumer tariffs to avoid costly distribution fees.

6. At the end of the timeslot, all brokers get all necessary information, like information about net distribution, imbalance volumes, as well as tariff transactions.
7. Customers initially subscribed to the tariff of the default broker. After all other brokers joined in they evaluate at each timeslot the existing tariffs based on their energy profile. [11] presents a comprehensive explanation of the consumption model. Due to fact that "set and forget" is a common customer behavior, an inertia factor $I_a = (1 - 2^{-n})I$ drives the motivation of customers. Here, *n* denotes the timeslots after the latest subscription. In other words, this factor determines the probability that a customer will not evaluate tariffs during a particular period of time.

Apart from the modules mentioned above, the simulation platform acts as a top-level coordinator for customers, brokers and the DU. It especially also provides necessary real-world data, such as weather forecasts, and manages the tariff market.

Table 1.Information availability from brokers' point of view.

Not Available	Available
Future wholesale prices.	Weather data.
Future customer demand.	Current market prices & volumes.
Situation of the economic environment.	Tariff transactions.
Decisions of competitors.	Smart meter readings.

Table 1 compares the data that brokers ought to deal with. Weather forecast and reports, cleared wholesale market prices publicly available to all participants. However, brokers may/should use predictive models to resolve uncertainties using the available data from above.

3.1. Controllable Capacities

In Power TAC, controllable capacities are represented as customer models, which allow brokers to control their consumption or production for a specific time slot. There are two kinds of demand responses in Power TAC:

- *Balancing Control Event*: This order targets real-time power regulations. Orders must be delivered at current time slot. Battery storage, water pumps and heat pump customers are typical models that respond to balancing control events.
- *Economic Control Event*: Interruptible customers are typical consumers or producers with the ability of shifting the power consumption or production to a future time slot. Orders must be delivered before the event. A typical example of this customer model is a smart washing machine, which can be programmed remotely. EV batteries can also be considered as interruptible since their charging or discharging speeds are adjustable.

At a timeslot, controllable capacities are characterized by the maximum and minimum rates as well as desired energy amount to be used. They share those parameters with DU at the beginning of each time slot. Thus, customers consume or produce the desired energy in kWh at the balancing order time.

Brokers may want to use controllable capacities to avoid balancing charges and reduce wholesale energy costs. Balancing orders (see next section) authorize a DU to exercise controllable capacities whereas economic control orders apply to a future time. Economic control events are out of the scope in the paper.

Transmission Systems Operators (TSO, i.e., Independent System Operator in North America) closely monitor the grid to keep its frequency, voltage level and power factor stable. However, this task is getting more and more difficult as the share of partially predictable energy resources increases. In many European countries (e.g., Germany), due to guaranteed payment for renewable energy production, TSO's have to take care of produced power, feeding in from old-tech windmills, solar panels, etc. However, some of new-tech panels and windmills are not harmful for TSO's due to spinning ability [12,13].

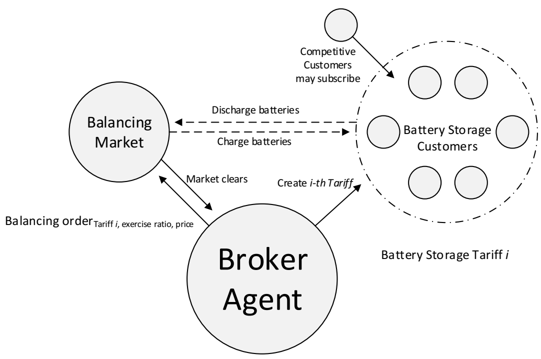

Fig. 3. Event diagram for the BM mechanism. Brokers may ask the DU to control specified tariff, given a specific exercise ratio. Orders

only apply to the relevant tariff in the extent of benefit broker will gain.

Power TAC offers DU to fulfill those balancing operations. Since there is no transmission layer in the simulation (see assumptions in [2]), the DU has only access to the balancing market portion of the wholesale ancillary services. Brokers may take some of the balancing responsibilities by allowing DU to exercise their controllable capacities. Brokers grant that permission by submitting a balancing order, in which a tariff, an exercise ratio and a regulation price are specified. As seen in Fig. 3, a balancing order has to target a tariff so that only the subscribers of that tariff are affected from the power regulation. If a balancing order clears, the broker is paid or pays for the exercised capacity. In most cases, brokers receive a payment. Once the capacity is consumed, the broker and the customer financially settle, based on the regulation rates of the tariff. Therefore, payments between brokers and the DU are fully isolated from the payments between brokers and customers.

Customers also benefit from the regulation in the extent of the gap (difference of up-regulation – down-regulation price), specified as regulation rates in the subscribed tariff. In the presence of monopoly or duopoly situation, the gap is expected to be small whereas tough competitions enlarge the gap.

In principle, the BM performs a non-profit balancing process, charging brokers as low as possible. Therefore, the main goal is to give an incentive to the brokers that contributes to the solution. Apart from the tariff price, the BM requires a separate price to exercise balancing orders on behalf of them. The price in the balancing order is expected to be equal or less than the price in the tariff to guarantee the success of the order. Note that exercise ratio only indicates the regulation direction for battery storage customers.

$$Regulation = \begin{cases} up - regulation & if\ exerciseRatio\ > 0 \\ no\ regulation & if\ exerciseRatio\ = 0 \\ down - regulation & if\ exerciseRatio\ < 0 \end{cases} \quad (1)$$

Formula 1 depicts the regulation direction, given an exercise ratio. For example, given a positive exercise ratio at a time, the DU assesses the balancing orders for the up regulation. Note that balancing orders remain effective until a new order arrives. If up and down regulation orders are submitted at the same time, the DU exercise the one which contributes to the balancing solution, and the other one is ignored.

Vickrey–Clarke–Groves (VCG) auction is a sealed-bid auction, which is first introduced in a paper, written by William Vicrey, Edward H. Clarke and Theodore Groves [14]. Bidders submit orders without knowing the bids of others. Basically, the clearing mechanism charges bidders in the extent of harm they cause to other participants. To clear a VCG auction, the BM requires to include dummy orders with an infinite capacity to represent the balancing cost at c_0 (x_{RM}), for the traded energy amount x_{RM}. Formula 2 defines the balancing cost.

$$c_0(x_{RM}) = \begin{cases} P^+(s) + \emptyset^+ x_{RM} & if\ up - regulation \\ P^-(s) + \emptyset^- x_{RM} & if\ down - regulation \end{cases} \quad (2)$$

$\emptyset^+$ and $\emptyset^+$ are the slopes of up and down regulations respectively. P^- and P^+ refer to basis prices for up-regulation and down-regulation, respectively. For up-regulation, all balancing orders are sorted, starting from the lowest bid up to the needed amount. Likewise, down-regulation requires sorting from highest to lowest bid. Generally, the bid in the last position partially clears whereas others fully clear [13].

In addition to VCG price, brokers are also responsible for their imbalances. Let X and C be the net imbalance and controllable capacity respectively whereas broker b has corresponding values x_b and C_b. Then the balancing cost is denoted as $BC_X^{(C/C_b)}$, and the payment of a non-contributing broker b with an imbalance x_b is calculated through Formula 3.

$$imb_b(x_b) = \frac{BC_X^{(C/C_b)}}{X}\ x_b \quad (3)$$

Payment of a contributing broker b is calculated through an extra step to make sure that the payment covers the costs of non-contributing brokers B. To do that, capacities of non-contributing brokers are excluded from payment. The process is formulated in Formula 4.

$$imb_b(x_b) = \frac{BC_X^{(C/\{C_b \cup C_k : k \in B\})}}{X}\ x_b \quad (4)$$

At the end of a time slot, broker b pays the sum of VCG and imbalance payment.

3.2. Overview of Power TAC 2014

In order to proof the success of a broker, multiple games are meant to be played with different game sizes. This eventually results in a "Big Data" problem since all of the transactions and events are logged in a file, called state file. State files are created after every game. However, information is stored in raw format. In order to deal with this problem, the open-source Power TAC Log Analysis (PLA) framework was extended. It now stores data in a relational database system. Therefore, all transactions, e.g. order book transactions, market transactions or tariff transactions are associated with timeslots, brokers, and competitions. We used MATLAB R2015b for computations and its graphical presentations.

The following teams participated in the finals of Power TAC 2014:

– *AgentUDE* - University of Duisburg-Essen [15]
– *cwiBroker* - CWI Amsterdam [8]
– *CrocodileAgent* - University of Zagreb [7]
– *Maxon* - Westfaeliche Hochschule
– *Mertacor* - Aristotle University of Thessaloniki
– *coldbroker* - National Institute of Astrophysics
– *TacTex* - University of Texas at Austin [3]

In the Power TAC 2014 Finals, 72 games were played. Out of these, 16 games were with 8 players, 35 games were with 5 players and 21 games were with 3 players. As already mentioned, Power TAC includes a default broker which is included in all games.

Table 2. Official results of the Power TAC 2014 finals.

Broker	**3 player**	**5 player**	**8 player**	**Total**
AgentUDE	0.279	1.499	1.976	3.754
cwiBroker	1.557	1.026	0.600	3.183
Croco.	0.952	-0.893	-0.560	-0.501
Maxon	-0.921	0.142	-0.643	-1.423
Mertacor	-0.945	-0.492	-0.865	-2.302
coldbroker	-0.922	-1.281	-0.509	-2.712
TacTex	-	-	-	-

Table 2 shows the official results of Power TAC 2014 Final games. Here, the total profits of the brokers are summed up and normalized for each game size using a standard deviation. Then they are summed up to generate the final value as seen in the last column. Note that game sizes represent the number of competing agents. Originally, 7 brokers were meant to compete in the tournament. However, *TacTex* was withdrawn from the tournament at the last minute, thus did not produce any results. At first sight, it can be seen that *AgentUDE* and *cwiBroker* dominated the games by realizing the best profits. *AgentUDE* took the first place in game sizes 5 and 8 and third place in game size 3.

4. AgentUDE14 at a Glance

The broker abilities of *AgentUDE* can be divided into three groups: Wholesale, retail and balancing market activities. *AgentUDE* has a local repository to store historical data. Besides, it has a tariff and a wholesale module which evaluates the data in the repositories and creates future values that will be used in the retail and wholesale markets. Each module has its own predictive model and data structure to create and transmit order messages to the Power TAC core. Fig. 4 illustrates the model based structure of the simulation environment as well as the internal structure of *AgentUDE*. The environment basically consists of market implementations and a number of power actors, e.g. customers, brokers, generators.

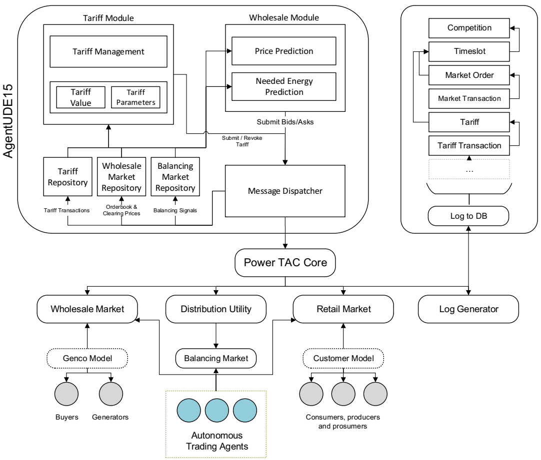

Fig. 4. Model-based structure of AgentUDE and Power TAC.

The wholesale trading module of *AgentUDE* uses a hybrid dynamic programming approach, which tracks historical market data. This enables the broker to predict market trends regardless of weather conditions. Statistics revealed that wholesale market costs of brokers do not vary much from each other (see Table 4). Therefore, retail activities are better understood by interpreting the diversity of the individual tariff publication policies of the brokers. On the other side, *AgentUDE* deploys an aggressive tariff strategy. Especially in the beginning of a game it is trying to offer the cheapest tariff. The idea is to speculate on contract length, EWP and BP. There are two main goals in the retail strategy: To provoke other brokers to publish cheaper tariffs and in order to persuade customers to change their tariffs. This triggers tariff penalties which translate into profit. The results of this strategy are presented in the next subsections.

Table 3. Summary of all relevant notations.

Symbol	Definition
t	Current time slot t, i.e., order hour.
δ	Time slot proximity. Time slot distance of t to the power delivery hour.
$cp_{t,\delta}$	MCP of the wholesale market ordered at t with δ.
$\widetilde{cp}_{t,\delta}$	Price-driven forecasted price at t with δ.
EWP	Early withdrawal penalty, which is paid from customers to brokers.
BP	Bonus payment is paid to customers, in case of a successful tariff subscription.
C	Number of customers with respected attribute, e.g. subscriber, total customers.
D_t	Distribution volume at timeslot *t*.
$N_{t,f}$	Needed power, calculated at timeslot *t*. for the procurement at future timeslot *f*.
P	Payment for a certain amount of energy.
E	A certain amount of energy.

Table 3 defines the key parameters that are used in the paper. In addition to the notations above, we need to explain a number of terms as well. The time slot proximity refers to time between order hour and delivery hour. For example, bidding at 18:00 for the power delivery at 20:00 means that the proximity is 2.

4.1. Wholesale Market Activities

Wholesale trading is a vital issue for all brokers to minimize their imbalanced energy. Additionally, brokers are challenged to buy the cheapest possible energy in order to be more flexible in future reactions to activities of competitors. For profitability reasons customers tend to switch to the cheapest tariff available according to their knowledge.

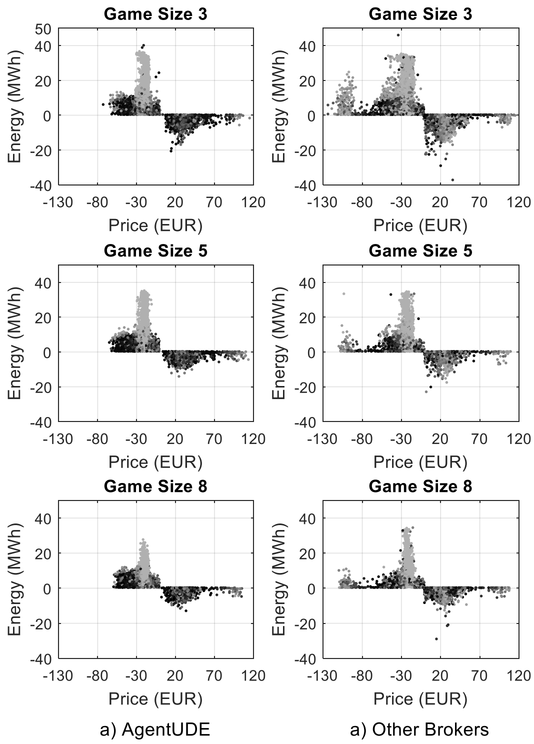

Fig. 5. Cleared bids and asks of AgentUDE and other brokers in Power TAC 2014 Finals. Negative prices show the payments from brokers for a certain amount of bought energy. In the same way, a positive price refers to a received payment for a certain amount of sold energy. Grey tones indicate the time proximity. The light grey color indicates a time slot in the far future of the game. The latter can mean up to 24 hours. Likewise, the black color indicates the near future; i.e., a sooner delivery.

Fig. 5 shows the cleared bidding and asking prices of *AgentUDE*. Altogether, the main bidding spectrum of *AgentUDE* is between 15 and 25 €/MWh. The average buying price is realized at 22.70 €/MWh and the selling price at 28.90 €/MWh (see Table 4). Surely, these cost prices make sense if the balance of the market is not important. The cost can be decreased by a stingy bidding policy. However, it eventually results in a poor market balance performance. Therefore, the broker developers are encouraged to deploy tactical and strategical decision-support models so that the net imbalance can be avoided. Then, the overall wholesale costs decrease.

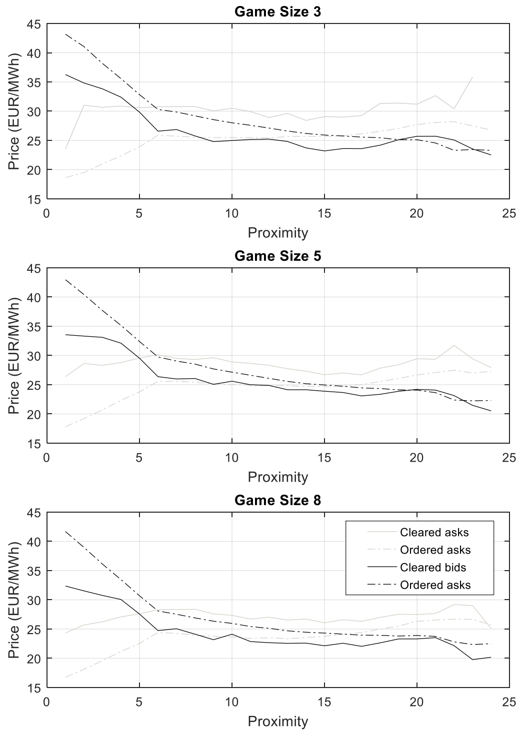

Fig. 6. The average cleared wholesale prices and the trading performance of AgentUDE.

Fig. 6 illustrates the prediction performance of *AgentUDE* under different game sizes. In 8 player games, the success rate is higher than with smaller game sizes since the market is more stable due to the large number of participants. Before the fifth future time slot, selling prices are always lower than buying prices. Therefore, this area is regarded to be a risky area due to the approaching delivery time. Brokers may submit extraordinary high bids in order to avoid imbalance penalties. These panic orders can easily be seen in Figure 2 as blue colored prices close to 100 €/MWh.

Table 4. The number of tariffs and wholesale trading averages of the brokers.

Broker	$N_{tariffs}$	Freq.	P_{bids} *(€/MWh)*	P_{asks} *(€/MWh)*
AgentUDE	3791	27	22.70	28.90
cwiBroker	1071	97	22.49	27.60
Crocodile	1106	94	43.11	13.08
Maxon	1426	73	23.15	53.30
Mertacor	2732	38	26.36	-
coldbroker	607	171	27.87	27.49
default	144	725	29.10	26.49
TacTex	1670	62	22.94	19.81

Table 4 lists the number of tariffs and the wholesale bidding and selling costs of brokers. "$N_{tariffs}$" is the total number of published tariffs. Frequency expresses the publication cycle in terms of time slots. "P_{bids}" and "P_{asks}" stand for the average bidding and asking prices. The energy consumption share of *AgentUDE* of the total energy consumption is 22.9 %. Furthermore, after *cwiBroker AgentUDE* is the second best broker when it comes to lowest market costs. However, these values are close to each other and do not provide a serious contribution to the overall profits of the brokers. Therefore, the retail activities are discussed in more detail in the next section.

AgentUDE's bidding process takes place in two steps: Electricity price forecasting and strategic bidding. In the first step, future prices are predicted, using a number of machine learning techniques. In the final step, these forecasted prices are transformed into strategic prices, taking balancing cost into account.

4.1.1. Electricity Price Forecasting

In this section, we outline the design of our MCP-based forecasting model and benchmark its performance, using different learning rates. Additionally, we compare our wholesale bidding performance with other broker agents in Power TAC environment, using strategic prices which are built on forecasted prices.

Price forecasting is one of the most established area in the time-series analysis. However, due to reasons given in the abstract and introduction of the paper, energy markets are getting closer to a non-stationary position. Daily price spikes, rapidly changing trends require a hybrid forecasting solution.

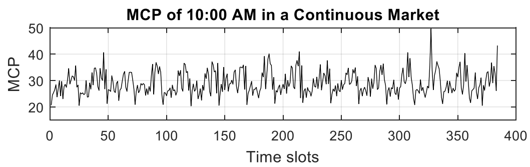

Fig. 7. MCPs of 10:00 AM in Power TAC's continuous wholesale market.

Fig 7. Illustrates a price signal from a Power TAC game. As seen, the signal is stationary and seasonal. Therefore, we can pick a simple seasonal autoregressive integrated moving average (SARIMA) model, analyzing the autocorrelation and partial autocorrelation coefficients in Fig. 8.

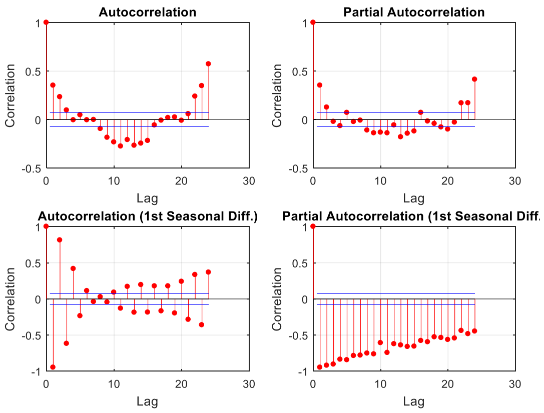

Fig. 8. Autocorrelations and partial autocorrelation coefficients, using the signal in Fig. 7. From left to right, we firstly take the autocorrelation and partial autocorrelation of the signal. The second column indicates the correlations after the first-order order seasonal difference.

As noticed in Fig. 8, there is a strong seasonality at lag 24 as well as a non-seasonal spike at lag 1. For simplicity, we ignore the moving averages and take $SARIMA(1,0,0)x(0,1,0)_{24}$ model to describe the forecasting problem. Therefore, the formula can be rewritten as:

$$\hat{Y}_{t+1} = (Y_t - Y_{t-24}) + Y_{t-23} \tag{5}$$

where $\hat{Y}_{t+1}$ is the prediction of the next time slot at current time slot t whereas Y values denote historical prices. The problem in the formula is the age of some regression terms such as Y_{t-23} and Y_{t-24}. Motivating from the strong correlation in partial autocorrelation of seasonal difference, we replace those aged regression terms with a robust model, using dynamic programming technique so that our forecasting model can avoid price spikes caused by outlier historical prices.

In this section, we outline the design of our forecasting model. On the background, we use a dynamic programming technique to implement the similar-hour concept [27]. The similar-hour concept is based on searching past data for hours with characteristics similar to the predicted hour. For example, the trader agent has the same historical patterns at 02:00 on different days of the week. In other words, the agent uses the same data, while submitting bids to 03:00, 04:00, …, 02:00 (next day). Therefore, we use MDPs to handle our time-sequential decisions, as formally described by [29]. Each hour of day (24) is represented by a Markov Process. It means that at each time slot, there are 24 concurrent bidding processes. Each process has 25 states. One of those states is terminal state {completed}. The rest of the states denote the timeslot proximity between order hour and delivery hour. Let P_{14} be the process of delivery hour 14:00. Then P_2 is in the state 6 and 1 at the order hours 08:00 and 13:00, respectively. Our MDP is defined as follows:

– *States*: $S \in \{1, \dots, 24, completed\}$
– *Terminal state*: $\{completed\}$
– *Reward*: $R(s', a) = \begin{cases} 1 : & s' = \{completed\} \\ 0 : & otherwise \end{cases}$
– *Actions*: $a_s \in \mathbb{Z}$
– *Transitions*: State s transitions to '$completed$', if a bid clears. Otherwise, it transitions to $s - 1$.

Here, action values are limit prices, provided by a value function $V^*(s)$. The value function basically maximizes the sum of expected sum of rewards, and theoretically replaces the term $(Y_{t-23} - Y_{t-24})$, given in Formula 5. The model of the environment is represented by a belief function $f(s, a)$, which is a modified version of a work by [3] and influenced by Q-learning concept [28]. However, Tesauro keeps the probability of a given price by harvesting historical data. In our case, we only keep the weights of changes of two sequential MCP's as the problem defined in Formula 5. Therefore, the belief function $f(s, a)$ points to weights of $a \in \xi_a$, given a state s, where higher values mean higher probability of reward occurrence where ξ_a is the set of actions, $\{a \in \mathbb{Z} \mid -500 \leq a \leq 500\}$. Since our reward function is a kind of counting process, we are interested in the reward occurrence in the belief function. The action with highest probability ought to result in transition to $\{completed\}$.

As time proceeds to $t+1$, the belief functions $f(s, a)$ is updated for $\forall a \in \xi_a$, as MCPs broadcasted to brokers. In brief, MCP's are supervising and reforming the belief function based on the market results. Therefore, the agent does not need to act to learn and update its model. Following formula updates the belief function, using a learning rate α and a reward function. Note that only MCP's are positively rewarded whereas other actions are rewarded with a zero value (Formula 7). This way, in turn, provides a normalization process on the action-state vector:

$$f_{t+1}(s_t, a_t) = f_t(s_t, a_t) * \alpha + R(s_{t+1}, a_t) * (1 - \alpha) \tag{6}$$

$$s_{t+1} = \begin{cases} 'completed': MCP = a_t \\ s_t - 1 : \ otherwise \end{cases} \quad (7)$$

where (1) and (2) are subject to $0 \le \alpha \le 1$.

To solve MDP, we use value iteration method to find the expected sum of rewards. The value function $V^*(s)$ takes a probability density function (pdf), $F_s(a)$ where μ and σ parameters of the normal distribution are obtained from the values of $f(s,a)$, given a state s for $\forall a \in \mathbb{Z}$. Following value function, $V^*(s)$ solves our MDP and creates a bid value, using an exponential smoothing operator. Here, the exponential smoothing operator refers to the non-seasonal auto regression term in Formula 5.

$$V^*(s) = \begin{cases} cp'_s : s = 24 \\ cp'_{s+1} + arg \max_{a} F_s(s) : \ otherwise \end{cases} \quad (8)$$

Where exponential smoothing operator is defined as $cp'_s = cp_s\,(\beta) + cp'_s(1-\beta)$ and subject to $0 \le \beta \le 1$. Since there is no seasonal difference available at state s, we only use an exponential smoothing value.

4.1.2. Experimental Setup for Price Forecasting

In the experiments, we use our broker agent *AgentUDE15* to benchmark our model. For more details, see the publication which describes the algorithms used in *AgentUDE* [15].

We arranged a tournament to create different game variations, and picked well respected and competitive brokers of the recent years: *cwiBroker15*, *CrocodileAgent15*, *Maxon15* and *TacTex14*. The suffixes, at the end of broker names indicate the year of release. Due to the number of available brokers, all the games are defined as 3-player to diverse the trading environment. Since we use *AgentUDE15* as a test-bed application, it is included in all games. Therefore, 3-player game actually means that *AgentUDE15* competes with two other brokers as well as a default-broker. All brokers have the same chance of competing with *AgentUDE15*. The requirements above make 6 game combinations possible. We multiplied the number of games by two and set 12 games in total. We used 1.3.0-Snapshot version of the Power TAC environment and the relevant output was processed in MATLAB 2015b.

AgentUDE15 starts a game without offline data, i.e. belief matrix. The belief matrix is filled along the game. We set a symbolic energy procurement amount as 0.1 MWh to make it price taker. The broker has no activity in the retail and balancing market.

An absolute error loss function L measures the accuracy of the predictions:

$$L(\widetilde{cp}, cp) = \left(\frac{\widetilde{cp} - cp}{cp}\right)^2 \quad (9)$$

Here, the lost function converges to zero, as the output and estimated price get close to each other. Since it is a quadratic function, error values are always positive and the higher error values mean the less prediction accuracy.

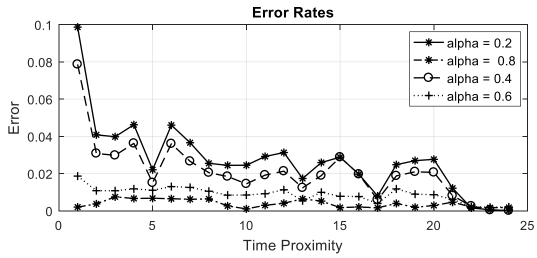

Fig. 9. Error rates of forecasting model, given learning rates, α=0.2, α=0.4, α=0.6 and α=0.8. The higher α values mean more conservative behavior (far-sighted).

Fig. 9 summarizes the simulation results from a graphical perspective. Comparing different learning rates, the model seems to be successful at far-sighted mode. This output meets the expectation, found in the figure of partial auto correlation of seasonal difference (see Fig. 8). Therefore, the historical price signal seems partially stationary. However, the proposed method can also be used in non-stationary markets due to exponential smoothing terms in it.

Table 5. Average and weighted errors.

	α = 0.2	α = 0.4	α = 0.6	α = 0.8
Average Loss	0.027	0.021	0.009	0.004
Weighted Loss	0.017	0.013	0.006	0.003

Table 5 summarizes the overall performance by learning rate. Here, average loss refers to arithmetic mean of all time slot proximities, whereas weighted loss uses weighted arithmetic mean, considering trading volumes. Let L and actual market price be 0.0029 and 25 EUR, respectively. Then 26.34 EUR and 23.66 EUR would be the upper and lower boundaries of the forecasting model.

4.1.3. Strategic Bidding

Forecasted prices usually known as truthful information. However, these predictions are not directly submitted to markets by brokers. In order to make the model comparable, forecasted prices must be transformed into strategic prices. Forecasted prices constitute 24 price distributions where μ_{hour} and σ_{hour} are mean and standard deviation of an hour. We finalize the transformation in two steps:

- Strategic prices $[1, 2, \ldots, 24] = [balancingPrice, \ldots, (\mu_{t+24} - \sigma_{t+24})]$
- Strategic prices $[1, 2, \ldots, 24] *= [1 + p_{t+1,\delta=1}, \cdots, 1 + p_{t+24,\delta=24}]$

where probability of $p_{t,\delta}$ is defined as:

$$p_{t,\delta} = \frac{\sum^{clearingProximity=\,proximity} trading\ volume_t}{\sum trading\ volume_t} \qquad (10)$$

In the first step of the transformation, we assign prices to enabled auctions, starting from the first standard deviation before the mean up to the balancing price. The balancing price is a dynamic variable which is recalculated at every time slot, based on the balancing market reports. Higher proximities are likely to get lower prices. In the second step, we take trading volume into the account. To do that, we scan historical trading volumes, tracking the same bidding proximities. Higher volume probability means higher strategic price for the given proximity.

We repeated the tournament with the same settings as the previous experiment. This time, *AgentUDE15* is fully functional on the Power TAC markets, and submits strategic prices instead of forecasted prices. The procurement amount is determined through a demand prediction process, which is out of the scope in the paper.

Table 6. Average and weighted errors.

Broker	Avg. Bidding Cost (EUR)	Weighted Bidding Cost (EUR)	Avg. Imbalance per TS (kWh)
AgentUDE15	61.04	52.95	460
CrocodileA.15	70.32	67.65	-170
cwiBroker15	55.55	52.93	-1738
Maxon15	45.93	43.80	-3460
TacTex15	54.06	54.29	-473

Table 6 summarizes the bidding performances. The weighted bidding cost is the realistic indicator which takes clearing volume into account. *AgentUDE15* performs on a decent level, having a positive average imbalance per time slot. Besides, there are two extreme bidding schemes in the table: CrocodileAgent15 and Maxon15 follows a generous and stingy bidding policies, respectively. However, those policies eventually result in either high or low imbalance activity. Therefore, brokers have plan their procurements considering the balance of cost and imbalance penalties.

4.2. Retail Market Activities

AgentUDE applied a unique strategy on the retail side in the competition, which substantially differentiated it from the other brokers: It first published aggressive tariffs, usually the lowest tariff values, complemented by customer binding measures such as EWP and BP. Due to the competition this strategy provoked other brokers to publish lower tariffs. This lower prices smoothly convinced customers of *AgentUDE* to switch their tariffs. This triggered the payment of EWPs, which resulted in additional profit. This strategy provided a 20 % contribution to the overall profit of *AgentUDE* (see Figure 7).

Table 7. The tariff activities of the brokers in the Power TAC 2014 finals.

Broker	M_{cons}	M_{prod}	S_{cons}	S_{prod}	E_{cons}	E_{prod}
AgentUDE	6.0	1.52	6.3	1.52	22.9	30.9
cwiBroker	7.8	-	7.8	-	21.5	-
CrocodileA	7.1	1.58	9.7	1.58	13.4	25.6
Maxon	522	-	7.7	-	7.0	-
Mertacor	7.3	-	6.7	-	4.4	-
coldbroker	5.3	-	5.4	-	8.2	-
default	50	1.50	50	1.50	0.2	43.5
TacTex	7.3	-	5.6	-	22.4	-

Table 7 shows the tariff statistics of the brokers. The domain of the first four columns is Euro whereas last two columns express percentage. "M_{cons}" and "M_{prod}" are the mean price of consumption and production tariffs. "S_{cons}" is the average price for the energy that is sold to the customers. Similarly, "S_{prod}" refers to the price for bought energy. Customer shares, "E_{cons}" and "E_{prod}" are energy consumption and production shares of brokers, respectively.

As can be seen from Table 5, *AgentUDE* changed its tariffs by far the most with a publication cycle of 27. On the other side, only *AgentUDE*, *CrocodileAgent* and the default broker published some production tariffs. The production tariff policy of *AgentUDE* relies on a simple rule: If the sum of the minimum production tariff value and the distribution fee is less than the wholesale market cost, then the production tariffs are published. Otherwise, the local producers are not considered.

All the games start with a number of uncertainties such as market status (production and consumption capacities) and the number of competitors. Broker agents are not aware of their competitors' trading strategies. Thus, initial tariffs have to be set carefully. The following algorithm calculates the initial tariffs of *AgentUDE*.

Table 8. The algorithm for the calculation of the initial tariffs.

Publishing Initial Tariffs

```
Calculate tariff value
tVal = mMean + dFee + pMargin
FOR tNum = 1 to 5
  publishTariff(tVal + tNum, EWP - tNum)
END FOR
```

In Table 8, "mMean" and "dFee" are the market mean price and the distribution fee, respectively. These parameters are announced at the beginning of each game. The integer value of the tariff number, "tNum", is a fixed number, since five tariffs of each power type are visible to customers. Therefore, it is used to limit the different tariff variations to exactly five . "pMargin" is the profit margin which is set heuristically. The early withdrawal penalty is formulated as a function of EWP based on the number of brokers. Customers might be highly sensitive or ignorant to the new tariffs due to the inertia parameter, defined by $Ia = I * (1 - 2^{-n})$. It is always between zero and one. Therefore, EWP's are extremely useful parameters to bind customers to the tariffs. Eventually, after some time, customers' loyalty will increase due to this inertia parameter. Customers tend to stay within the tariff even if the tariff is not the cheapest one. As a part of the retailer strategy, *AgentUDE* always sets an EWP value if the tariff value to be published is the currently lowest in the market.

Table 9. Algorithm to improve existing tariffs.

Improve Tariffs

```
monopolyTest()
revokeUselessTariffs()
IF isPublicationCycle() = True
  Return
ELSE
  IF subscriptionRate < targetShare
    IF competitorsMin < marginalCost
      publishTariff(marginalCost, NULL)
    ELSE
      publishTariff(competitorsMin, EWP)
    END IF
  END IF
END IF
```

Table 9 describes this process. Intentionally, this method differentiates between two kinds of consumer tariffs. If the offered price is the lowest on the market it is published with an EWP fee. Otherwise, EWP is not set and the tariff value is adjusted considering the market costs.

AgentUDE executes a number of procedures during its tariff determination process. One is the "monopolyTest" method. This method is triggered if a huge price gap appears between *AgentUDE* and its closer competitor. Another incident that triggers this method is the disconnection of all its competitors. Especially in 3 player games, broker agents may disconnect due to connectivity problems. In this case, *AgentUDE* revokes all its low priced tariffs and offers only the default tariff.

Another procedure is the "revokeUselessTariffs" method which removes all potentially harmful tariffs. It is quite possible that wholesale clearing prices tend to increase due to high demand or weather conditions. In this case, some of the old tariffs might be outdated and harmful in terms of profitability. This method simply removes such tariffs from the broker's repository.

The marginal market cost is calculated by the "marginalCost" method and takes all cleared wholesale market prices and the distribution fee into account. The following formula shows the content of the method:

$$marginalCost_t = \frac{\left(\sum_{n=0}^{60} \sum_{m=1}^{24} P_{m,n}\right)}{\left(\sum_{n=0}^{60} \sum_{m=1}^{24} E_{m,n}\right)} + dFee + pMargin \quad (11)$$

where P and E refer to payments and energy transactions. The formula can include up to 60 of the last hours and 24 of the next future auctions of the wholesale market. Consequently, the division in the formula yields an average cost price by dividing the total payment by the total energy. After all, the formula represents the breaking point in terms of profitability. Additionally, there are a number of relevant variables that are calculated by methods as well. One of these variables is "competitorsMin", whose underlying method basically scans the tariff repository and finds the competitors' minimum tariff value. Other controllers are "targetShare" and "subscriptionRate". They represent the goal and the current situation, respectively. Target share represents the threshold of subscribed customers that *AgentUDE* has to reach. Subscription rate reveals the percentage of currently subscribed customers.

The subscription rate and critical rate shape the EWP fee. The number of subscribed customers is proportional to the EWP fees based on the formula below. Altogether, the calculation of the early withdrawal penalty fee can be formulated as

$$EWP_t = \frac{(targetShare * C_{total} - C_{subscribed})}{targetShare * C_{total}} \quad (12)$$

This formula also measures the distance between the current and the target portfolio in terms of subscribed customers. The target share is defined as $\frac{(nominalShare)}{targetShare * C_{total}}$, where nominal share is the number of currently subscribed customers.

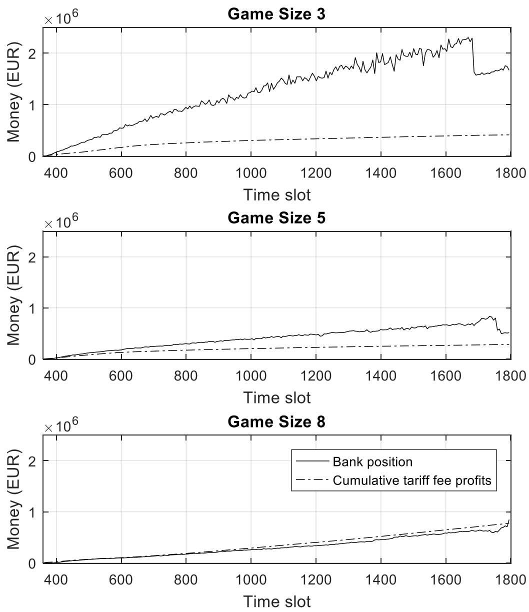

Fig. 10. The total cash position and the cumulative sum of EWP and BP.

Fig. 10 shows the overall cash balance and the collected money from tariff fees as a result of the strategy. In the same figure, the red area shows the cumulative sum of tariff fees which is the most relevant portion of the overall cash position. This rate increases in 8 player games due to tough competition. In other words, a high number of tariffs means higher fluctuation in terms of customer subscriptions and withdrawals.

Table 10. Overall average profits of brokers from tariff fees.

Broker	Game Size 3 (EUR/game)	Game Size 5 (EUR/game)	Game Size 8 (EUR/game)
AgentUDE	410.893 (6 games)	277.335 (20 games)	698.067 (14 games)
CrocodileAgent	13.583 (5 games)	12.835 (17 games)	8.537 (14 games)
Mertacor	4.615 (4 games)	3.168 (17 games)	987 (8 games)
TacTex	811.864 (2 games)	599.021 (6 games)	508912 (14 games)

Table 10 compares the tariff fee performances of all brokers. Surprisingly, only *AgentUDE* and *TacTex* benefitted from tariff fees. Here, the profit increases with the increase of the number of players.

To gain even more profit from this strategy, some requirements have to be met: Active customer and a tough competitor. First, customers have to see some profitable tariffs on the desk before leaving their current retailer. If not, customers tend to ignore the existing tariffs and stay in their tariff. In this case, the strategy offered by *AgentUDE* does not work well. Second, a broker has to offer competitive tariffs so that customers can see them and change their tariffs if it is really profitable for them. As a proof of this claim, competitive and non-competitive brokers are tested in 3 player games below.

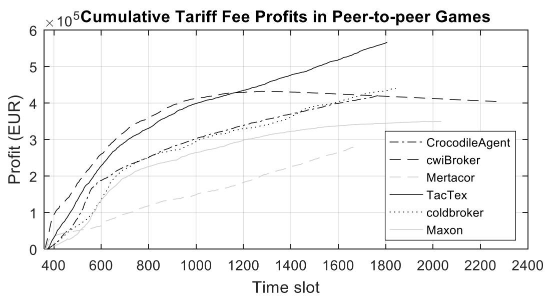

Fig. 11. Cumulative tariff fee earnings of AgentUDE that are collected through 3 player games.

Fig. 11 reflects the tariff fee earnings of *AgentUDE* in the 3 player games between *AgentUDE* and the other competing broker (other than the default broker). Apparently, *TacTex*, *CrocodileAgent* and *cwiBroker* allowed *AgentUDE* to gain more profitwhile *Mertacor*, *Maxon* permitted less. In the same fashion, this symbiotic relationship is proportional to the official results given in previous sections. Another result is that *TacTex*, *cwiBroker* and *AgentUDE* offer the most profitable tariffs to the customers and convince them to change their tariffs.

4.3. Balancing Activities

Brokers have to meet their demand and supply. If not, they might lose a serious portion of their profits for paying a huge imbalance fee. The most challenging issue at this point is to predict future consumptions. *AgentUDE* uses the consumption data of customers to make predictions. However, this method does not always provide reasonable results since it does not consider changing conditions such as the weather. The balancing market tool signals brokers to pay attention to their imbalance status. However, brokers are challenged to predict their future demand. *AgentUDE* considers such predictions by formula 13:

$$N_{t,f} = N_{t-1,f} * \omega + \left(D_t * \frac{D_{T-24}}{D_{t-24}}\right) * (1-\omega) \tag{13}$$

where N is the needed energy and D is distribution volume at the current time slot t for the future time slot f. The weight is $0 < \omega < 1$. Consequently, needed energy is adjusted with imbalance signal and the final amount of needed energy is submitted to the wholesale market.

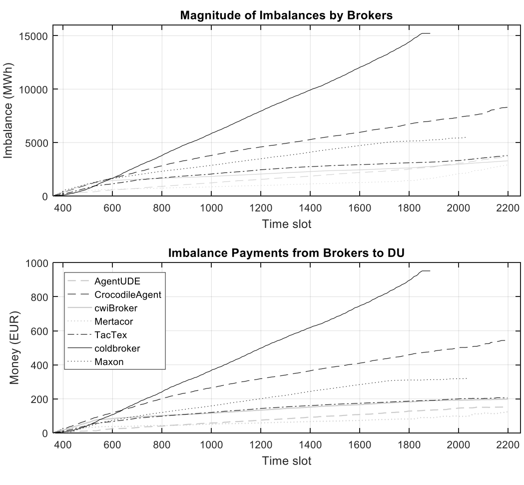

Fig. 12. The cumulative volume of negative and positive imbalances.

Fig. 12 illustrates the cumulative imbalance volumes. In this figure, negative and positive volumes are regarded as absolute values, thus, summed up regardless of their signs. Compared to other game sizes, 3 player games lead to the best result for *AgentUDE*. Since the figure illustrates the volumes, increasing number of participants makes it difficult for *AgentUDE* to adjust its imbalance due to changing demand. Besides, customers have more tariff options in game size 8 in comparison to game size 3. Therefore, withdrawal or sign up activities of customers eventually result in last-minute imbalances.

AgentUDE is the second best broker who pays the least money to the DU. However this payment only consists of imbalance penalties since the total imbalance energy is close to zero line as shown in Figure 12. For a typical negative imbalance, brokers have to pay the sum of penalty fee and the price of imbalanced energy. *TacTex* and *cwiBroker* paid 100k € for their 1700 MWh and 1450 MWh imbalanced energy, respectively. If a comparison is needed at 70k €, where the imbalanced energy of *AgentUDE* is almost zero, *TacTex* and *cwiBroker* pay 70k € plus 17.6 €/MWh and 20.6 €/MWh, respectively for their negative imbalances. In respect to wholesale market costs shown in Table 2, *TacTex* and *cwiBroker* have a good deal on the balancing market over *AgentUDE*.

5. AgentUDE15: Utilizing Controllable Capacities

AgentUDE15 was built on its ancestor, *AgentUDE14*. It extents the existing capabilities by utilizing controllable capacities to its portfolio. For this reason, overlapping features, e.g. retail and wholesale activities, will be omitted in this section to present more details about controllable capacities and their potentials. To show off these potentials, we design a controllable experiment, using the following setup.

5.1. Experimental Setup

In this experiment, we improve our broker agent *AgentUDE15* and create its variants to benchmark the balancing contribution of battery storage customers (cf., Table 2 for the broker settings). In default, we use all of the market functionalities of *AgentUDE* (serving to consumers) to generate casual imbalances. Therefore, the broker attracts customers and serve to those customers by means of trading in the wholesale market.

We arranged a tournament to create different game variations in as 4-player games in which well respected and competitive brokers (*cwiBroker15*, *CrocodileAgent15*, *Maxon15*, *TacTex15*) of the recent years compete. The suffixes, at the end of broker names indicate the year of release.

In the tournament, all the games are defined in 3-player size in which one of *AgentUDE* and its variants is included. Therefore, 3-player actually means that *AgentUDE* or its variants compete with two brokers in the games. Unfortunately, few broker binaries are released in 2015. Therefore, we avoided running 4 or 5 player games to diverse broker activity patterns. All the brokers have the same chance to compete with *AgentUDE*, *AgentUDEr1* and *AgentUDEr2*. Note that battery customers in the tournament are assumed to be captive customers. In other words, only *AgentUDE* publishes battery storage tariffs.

Table 11. Simulation settings.

Setting	Description
# of games	18 games: 6 per agent variant in Table 12
# of batteries	30 *(90 kW / each and max. transfer rate: 40 kWh / each)*
# of competing brokers	4 *(excluding default-broker)*
Game length	1460 + 360 bootstrap time slots
Game size	3-players.

Table 11 explains the settings used in the tournament. We use a constant number of captive battery storage customers. Each customer has a 90 kW of battery storage size and maximum transfer rate of 40 kWh. Thus, the maximum charging or dis-charging rate is limited to 1.2 MWh whereas the full capacity is 2.7 MW. If, e.g., brokers start charging it takes 3 time slots to fully charge or discharge the batteries. Besides, batteries have an internal-discharging rate, which refers to the power loss over the time.

Table 12. Broker variants. All units are in €/kWh.

Broker	BM Regulation Price		Customer Regulation Price	
	Up BM Pays	**Down** broker pays	**Up** broker pays	**Down** customer pays
AgentUDE	-	-	-	-
AgentUDEr1	0.24	0.08	0.24	0.08
AgentUDEr2	0.24	0.18	0.24	0.18

Table 12 lists the price settings of the broker variants. As seen in the table, the same up-regulation and down-regulation prices are used in battery storage tariffs and balancing orders. *AgentUDE* participates in BM auctions by offering its battery capacities for up- and down-regulation. As defined in the previous section, DU may decide to use one of the orders depending on the overall imbalance. This is a fixed behavior in all the games.

In order to converge the validity proposed approaches, multiple games are meant to be played, which creates many large log files. To deal with this challenge, open-source Power TAC Log Analysis (PLA)[2] framework was extended to store the raw data (logs) into a relational database model. We use MATLAB R2015b to deal with database management system and produce figures. The version of the Power TAC release which hosted the experiment is 1.3.1.

5.2. Results

Out of 18 games, 12 games were dedicated to *AgentUDE* variants (*AgentUDEr1* and *AgentUDEr2*) and 6 games were played without BM activity (*AgentUDE*). Therefore, we monitor the broker activities, competing *AgentUDE* and its variants with two other competitive brokers, listed in Section 5. The following figure shows a snapshot of the average cumulative profits.

[2] https://bitbucket.org/markuspeters/pla accessed on 03.12.2016.

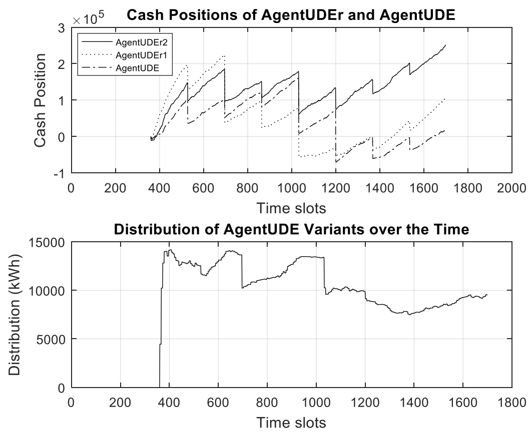

Fig. 13. Cash positions of the brokers (above) and distribution volume (below) over the time. Distribution volumes are identical for all variants since they have the same retail and wholesale market behaviors. Regulation activity has no clear contribution to the overall cash balance of AgentUDEr1 over AgentUDE.

Fig. 13 depicts the cash positions (i.e., cumulative profit) of the brokers starting from time slot 360 and until time slot 1700. Just looking at the profit level, *AgentUDEr2* seems to have a clear profit advantage over others. As noticed in the figure, there are some regular sharp decreases in the profit. The reason behind is that peak-demand assessment has been introduced in the 1.3.1 version of the Power TAC [2], instead of fixed rate distribution fee. Now, brokers pay peak-demand charges at every 168 time slots, depending on the level of harm they cause to distribution system. Since brokers initially have no idea about the distribution costs, they are expected to adjust their profit-cost balance after the peak-demand assessments.

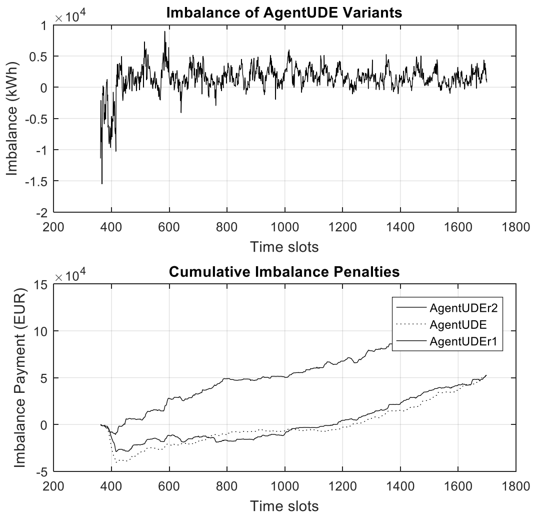

Fig. 14. Imbalanced energy amount (above) of brokers (average imbalance amounts of AgentUDE, AgentUDEr1, AgentUDEr2) and cumulative imbalance penalties (below), paid by our experimental brokers. Positive imbalance payments refer to the payment that brokers receive whereas positive imbalance denotes surplus energy that brokers procured.

Fig. 14 illustrates the average values of imbalanced energy amount and cumulative imbalance payments. Payments graph (Fig. 15, below) show that *AgentUDEr2* received the highest payment from the distribution utility. Note that the payment shown here is accounted for the net imbalance, taking the brokers' controllable capacity into account (see Formula 3 and Formula 4).

As noted previously, BM activities are financed in a different mechanism and therefore require balancing orders from brokers which have controllable capacities. In the variants, *AgentUDEr1* and *AgentUDEr2*, we use battery storage tariffs to use those capacities in the BM.

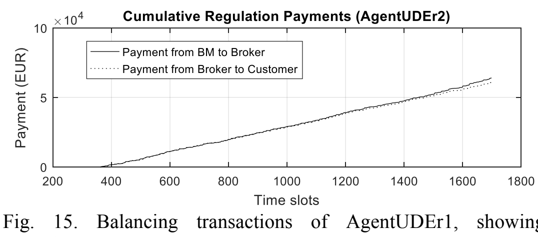

Fig. 15. Balancing transactions of AgentUDEr1, showing Cumulative payments for the regulation power, traded in the BM (up-regulation price: 0.24 €/kWh, down-regulation price: 0.08 €/kWh). The second line (dotted) shows all associated payments to customers.

Fig. 15 illustrates the BM payments and corresponding broker payment for the storage capacity, used in the up and down regulation. The positive or negative payments may be gained from either the BM or the customers, depending on the direction of regulation. In most cases, brokers gain profit, which is exactly $Payment^{BM} - Payment^{Customer}$. As noticed, the cost and profit lines are close to each other since the tariff prices in the balancing order are highly customer-friendly. On the customer side, they are the most beneficiaries of this business model as they keep getting high profit due to big gap between up-regulation and down-regulation price, specified in the tariff.

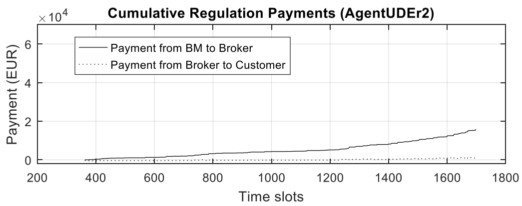

Fig. 16. Balancing transactions of AgentUDEr2, using a different pricing (up-regulation price: 0.24 €/kWh, down-regulation price: 0.18 €/kWh). The change in the tariff price has significantly changed the profit-cost balance.

Fig. 16 illustrates a similar case as in Fig. 15, this time having different prices (see the description in Table 12). Likewise, those prices are identical with the prices in the customer tariff. As noticed, we only changed the down-regulation price and keep the up-regulation price same as in Fig. 15. Since the gap between buy and sell price is now smaller, brokers have more opportunity to gain decent level of profit on the down-side. For example, given the clearing price for down-regulation at 0.08 €/kWh, broker gains net 0.1 €/kWh for that regulation. On the customer side, the net customer payment still has a positive sign which shows that the regulation business is a win-win business model for brokers, customers and DU (as reliability).

6. Future Work and Conclusion

AgentUDE seems to be a successful broker in terms of efficiency. However, there are still pending issues to be improved prior to the next Power TAC competition. One of the more important issues is to improve efficiency in the wholesale trading business. Even though *AgentUDE* has a decent performance in comparison to other brokers it still requires more accuracy to increase its competitiveness over other brokers. One chance for improvement is to better integrate weather forecasts in the price predictions for the wholesale market.

Another improvement is the utilization of unused power actors. In the Power TAC environment there are a number of new generation power actors such as storage units or controllable customers. However, most of the brokers as *AgentUDE* do not benefit from them. On the other side, the DU encourages brokers to publish producer tariffs by means of waiving distribution fee if the produced energy is consumed in the same local area. Despite this attractive offer, only *AgentUDE* and *CrocodileAgent* benefitted from this opportunity. However, it is officially announced at the Power TAC developer website that the number of producers and electric vehicles will be increased dramatically. It means that another improvement is needed to balance local production and consumption. No doubt, utilizing these components improves the overall efficiency and profitability of the broker.

For the 2015 competitions, we developed a trading capability in the BM for AgentUDE to offer capacity to DU. In the controlled experiments, we revealed the profitability potential of battery storage customers in the BM. We employed our broker agent and its variants to offer battery storage tariffs to use those capacities in the BM. The results showed that the BM provides an incentive-based clearing mechanism to satisfy all parties, which contributes to the balancing process. The main goal is to keep the overall system balance stable and reliable. Apart from that, it also offers the chance for a profitable business model for the brokers (e.g., retailers, utilities) as well as for the customers. Even though we relied on non-dynamic bidding by using fixed rate prices for customer tariff as well as in the BM balancing orders contributed positively to the overall profit of the broker.

In order to turn balancing orders from the brokers' perspective into a more profitable business model we see several strategies for future work:

- More attractive tariff prices from the customers' point of view trigger the balancing mechanism as well.
- Using the same price on the tariffs and balancing orders can only maximize the probability of winning an auction. However, differentiating the prices may increase the profit, however, on the down side, reduces the probability of clearing the auction.

This paper presented the trading strategies of *AgentUDE*. Based on the statistics which were discussed in this paper three significant outcomes for the retail, wholesale and balancing market activities can be identified:

Firstly, the wholesale market performances of the given brokers do not differ much. It can clearly be seen that all the brokers deliver a decent market performance based on their demand profiles. Thus, the first outcome is wholesale activities do not contribute much to the overall profit outcome of brokers.

Secondly, the retail strategies of the brokers reveal a great deal of variety. What allows *AgentUDE* to be one step ahead of its competitors is its aggressive tariff strategy. The results show that *AgentUDE* earns a serious portion of its profit by tariff fee speculations. This strategy leaves *AgentUDE* in a more comfortable and flexible position against other brokers.

Thirdly, the variance of the balancing activities is similar to the variance of the retail market activities. As shown in Figure 12, the average gap between brokers is 35,000. - €. This means that the balancing penalty is one of the most decisive factors with respect to the overall profit. Brokers pay imbalance penalties three times as high as the overall expenditures on distribution fees.

It is noteworthy to remark that all the data and results presented in the paper are valid for the specific releases of the brokers and Power TAC during the 2014 competition. The simulation environments as well as the brokers get stronger and stronger with time and growing experience. Additionally, new teams bring nice fresh wind to the competition. The Power TAC core modules have also been updated. At this point, success remains a relative term, especially in such a dynamic and progressive simulation environemnt. *AgentUDE* team will continue to update its broker as part of the smart grid studies at the University of Duisburg-Essen.

References

[1] Ketter, W., Collins, J. and Weerdt, M.: The 2016 Power Trading Agent Competition. ERIM Report Series (2016).

[2] Ketter, W., Collins, J. and Reddy, P.: Power TAC: A competitive economic simulation of the smart grid. Energy Economics, 39, 262–270 (2013).

[3] Urieli, D. and Stone, P.: TacTex'13: A Champion Adaptive Power Trading Agent. Proceedings of the Twenty-Eighth AAAI Conference on Artificial Intelligence. 465-471 (2014).

[4] Kuate, R. T., He, M., Chli, M. and Wang, H. H.: An Intelligent Broker Agent for Energy Trading: An MDP Approach. Proceedings of the Twenty-Third International Joint Conference on Artificial Intelligence. 234-240 (2014).

[5] Federal Environmental Agency (FEA). Energieziel 2050: 100% Strom aus erneuerbaren Quellen. Available at: http://www.umweltbundesamt.de/publikationen/energieziel-2050, accessed on 04.11.2014.

[6] Somani, A. and Tesfatsion, L.: An agent based test bed study of wholesale power market performance measures. IEEE Computational Intelligence Magazine. 56–72 (2008).

[7] Babic, J. and Podobnik V.: An Analysis of Power Trading Agent Competition 2014. Agent-Mediated Electronic Commerce. Volume 187, 2014, 1-15 (2014).

[8] Liefers, B., Han P. L., and Hoogland J.: A Successful Broker Agent for Power TAC. Agent-Mediated Electronic Commerce. Volume 187, 2014, 99-113 (2014).

[9] Morris C. and Pehnt M.: Energy Transition: The German Energiewende. Heinrich Böll Stiftung (2014).

[10] LaViola, J.J., 2003, May. Double exponential smoothing: an alternative to Kalman filter-based predictive tracking. In Proceedings of the workshop on Virtual environments 2003 (pp. 199-206). ACM.

[11] Reddy, P.P. and Veloso, M.M., 2012, July. Factored Models for Multiscale Decision-Making in Smart Grid Customers. In AAAI.

[12] RES, EU. "Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30." Off. J. of the EU, European Commission 5 (2009): 16-62.

[13] Vandezande, Leen, Leonardo Meeus, Ronnie Belmans, Marcelo Saguan, and Jean-Michel Glachant. "Well-functioning balancing markets: A prerequisite for wind power integration." Energy Policy 38, no. 7 (2010): 3146-3154

[14] Clarke, Edward H. "Multipart pricing of public goods." Public choice 11, no. 1 (1971): 17-33

[15] Ozdemir, Serkan, and Rainer Unland. "A Winner Agent in a Smart Grid Simulation Platform." 2015 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT). Vol. 2. IEEE, 2015.

[16] Smart Grid, http://energy.gov/oe/services/technology-development/smart-grid, accessed on 10.12.2016.

[17] Bellifemine, Fabio, Agostino Poggi, and Giovanni Rimassa. "JADE–A FIPA-compliant agent framework." Proceedings of PAAM. Vol. 99. No. 97-108. 1999.

[18] Derksen, Christian, Cherif Branki, and Rainer Unland. "Agent. gui: A multi-agent based simulation framework." Computer Science and Information Systems (FedCSIS), 2011 Federated Conference on. IEEE, 2011.

[19] Nwana, Hyacinth S., et al. "ZEUS: a toolkit and approach for building distributed multi-agent systems." Proceedings of the third annual conference on Autonomous Agents. ACM, 1999.

[20] Howden, Nick, et al. "JACK intelligent agents-summary of an agent infrastructure." 5th International conference on autonomous agents. 2001.

[21] Logenthiran, T., et al. "Multi-Agent System (MAS) for short-term generation scheduling of a microgrid." 2010 IEEE International Conference on Sustainable Energy Technologies (ICSET). IEEE, 2010.

[22] Logenthiran, Thillainathan, Dipti Srinivasan, and Ashwin M. Khambadkone. "Multi-agent system for energy resource scheduling of integrated microgrids in a distributed system." Electric Power Systems Research 81.1 (2011): 138-148.

[23] Logenthiran, Thillainathan, Dipti Srinivasan, and David Wong. "Multi-agent coordination for DER in MicroGrid." 2008 IEEE International Conference on Sustainable Energy Technologies. IEEE, 2008.

[24] Joskow, Paul L. "California's electricity crisis." Oxford Review of Economic Policy 17, no. 3 (2001): 365-388.

[25] Peters, M., Ketter W., Saar-Tsechansky M., Collins, J., A reinforcement learning approach to autonomous decision-

making in smart electricity markets. Machine learning 92, no. 1 (2013): 5-39.
[26] Weron, R. (2014). Electricity price forecasting: A review of the state-of-the-art with a look into the future. International Journal of Forecasting, 30(4), 1030-1081.
[27] Tesauro, G., & Bredin, J. L. (2002, July). Strategic sequential bidding in auctions using dy-namic programming. In Proceedings of the first international joint confer-ence on Autono-mous agents and multiagent systems: part 2 (pp. 591-598). ACM.
[28] Watkins, Christopher JCH, and Peter Dayan. "Q-learning." Machine learning, no. 3-4 (1992): 279-292.
1.
[29] Sutton, R.S. and Barto, A.G., 1998. Reinforcement learning: An introduction (Vol. 1, No. 1). Cambridge: MIT press.
[30] Ozdemir, Serkan, Rainer Unland, and Wolfgang Ketter. "Analysis of the Effects of Storage Capabilities Integration on Balancing Mechanisms in Agent-Based Smart Grids." German Conference on Multiagent System Technologies. Springer International Publishing, 2016.